

WIFO

1030 WIEN, ARSENAL, OBJEKT 20
TEL. 798 26 01 • FAX 798 93 86

 **ÖSTERREICHISCHES INSTITUT FÜR
WIRTSCHAFTSFORSCHUNG**

Measuring Competitiveness

Edited by
**Michael Peneder (WIFO),
Christian Rammer (ZEW)**

January 2018

Measuring Competitiveness

Edited by Michael Peneder (WIFO), Christian Rammer (ZEW)

January 2018

Authors: Michael Peneder, Andreas Reinstaller, Stefan Weingärtner (WIFO), Florence Blandinières, Niklas Dürr, Stefan Frübing, Sven Heim, Bettina Peters, Christian Rammer (ZEW)

Internal review: Jürgen Janger (WIFO)

Disclaimer:

This report has been prepared for the European Commission, DG GROW, under Specific Contract No SI2-750358 implementing the Framework Service Contract ENTR/300/PP/2013/FC-WIFO coordinated by the Austrian Institute of Economic Research (WIFO, coordinator: Andreas Reinstaller).

The information and views set out in this study are those of the author(s) and do not necessarily reflect the official opinion of the Commission. The Commission does not guarantee the accuracy of the data included in this study. Neither the Commission nor any person acting on the Commission's behalf may be held responsible for the use which may be made of the information contained therein.

Abstract

The study serves as a background document for the European Commission and is conducted in close cooperation with the ZEW Mannheim. The main tasks are to define the concept of competitiveness at the micro, meso, and macro levels of economic activity, to establish a set of indicators that is suitable for comparing the competitive performance of EU countries, to develop a systematic grid of indicators and policy objectives, and to determine the strengths and weaknesses of commonly used indicators, including their associated measurement problems or biases.

Please refer to: michael.peneder@wifo.ac.at

2018/005/S/WIFO project no: 8516

© 2018 Austrian Institute of Economic Research, Centre for European Economic Research

Medieninhaber (Verleger), Herausgeber und Hersteller: Österreichisches Institut für Wirtschaftsforschung, 1030 Wien, Arsenal, Objekt 20 • Tel. (+43 1) 798 26 01-0 • Fax (+43 1) 798 93 86 • <http://www.wifo.ac.at/> • Verlags- und Herstellungsort: Wien

Verkaufspreis: 70 € • Kostenloser Download: <http://www.wifo.ac.at/wwa/pubid/60838>

Content

Measuring Competitiveness	1
1 Introduction.....	6
2 Defining Competitiveness	8
2.1 Firm Level.....	8
2.1.1 Introduction	8
2.1.2 Competitive Performance	10
2.1.3 Competitive Potential.....	12
2.1.4 Firm Capabilities	13
2.1.5 External Factors.....	14
2.1.6 A Hierarchical Model of Firm-level Competitiveness Indicators	15
2.2 Sector Level	16
2.2.1 Introduction	16
2.2.2 Competitiveness Indicators.....	16
2.2.3 Intra-sector vs. Inter-sector Competitiveness	19
2.3 Economy-wide	20
2.3.1 Introduction	20
2.3.2 The “Iceberg” Model	21
2.4 Relation between Different Levels	26
3 Competitiveness Indicators for the European Semester	29
3.1 Cost-related Competitiveness	30
3.1.1 Motivation.....	30
3.1.2 Data.....	30
3.1.3 Empirical Analysis of Indicators.....	31
3.1.4 Conclusions	47
3.2 Innovation-related Competitiveness	48
3.2.1 Motivation.....	48
3.2.2 Data Sources.....	49
3.2.3 Empirical Analysis of Indicators.....	54
3.2.4 Conclusions	78
3.3 Export Competitiveness	80
3.3.1 Motivation.....	80
3.3.2 Data Sources.....	80
3.3.3 Indicators	85
Summary and Conclusions	125

4	Data Availability and Quality of Selected Competitiveness Indicators.....	127
4.1	Total/Multi Factor Productivity	128
4.1.1	Concept and Definitions	128
4.1.2	Data sources	129
4.1.3	Data quality.....	131
4.1.4	Data validity	134
4.1.5	Data analysis	136
4.2	Labour Productivity.....	138
4.2.1	Data Sources.....	138
4.2.2	Data Quality	139
4.2.3	Data Validity.....	141
4.2.4	Data Analysis.....	141
4.3	Unit Labour Costs	144
4.3.1	Data Sources.....	144
4.3.2	Data Quality	145
4.3.3	Data Validity.....	146
4.3.4	Data Analysis.....	146
4.4	Energy Costs	149
4.4.1	Data Sources.....	149
4.4.2	Data Quality	150
4.4.3	Data Validity.....	151
4.4.4	Data Analysis.....	151
4.5	R&D	154
4.5.1	Concepts and definitions	154
4.5.2	Data Sources.....	154
4.5.3	Data Quality	156
4.5.4	Data Validity.....	158
4.5.5	Data Analysis.....	160
4.6	Innovating Firms	169
4.6.1	Concepts and Definitions.....	169
4.6.2	Data Sources.....	170
4.6.3	Data Quality	172
4.6.4	Data Validity.....	176
4.6.5	Data Analysis.....	178
4.7	Openness	186
4.7.1	Concept and definitions	186

4.7.2	Data sources	187
4.7.3	Data quality.....	187
4.7.4	Data validity	189
4.7.5	Data analysis	190
4.8	Terms of Trade	196
4.8.1	Definition.....	196
4.8.2	Data Sources.....	199
4.8.3	Data Quality	200
4.8.4	Data Validity.....	202
1	Data Analysis.....	204
5	Conclusions.....	208
6	References	211
7	Appendix A: Indicator Sheets for Selected Competitiveness Indicators.....	219
7.1	Cost Competitiveness	219
7.2	Innovation-related Competitiveness	227
7.3	Export Competitiveness	233
8	Appendix B: Micro-level Analysis of Competitiveness Indicators.....	236
8.1	Introduction	236
8.2	Data.....	236
8.3	Results	238

1 Introduction

Michael Peneder and Christian Rammer

Competitiveness can have a number of different meanings depending on whether one refers to individual firms, to groups of firms, to economic sectors, to the entire economic activities within a region, or to an entire national economy or a group of economies. While competitiveness of an individual firm is usually related to its ability to survive in the market and to make profits (at least in the medium term), competitiveness of an industry rather refers to its competitive strengths and weaknesses in the international market in relation to the same industry in other countries. At the country level, a definition used in the past by the Commission relates competitiveness to the ability of an economy to provide citizens with improving living standards on a sustainable basis and broad access to jobs for those willing to work. It is clear that whilst these definitions are not unrelated, they are fundamentally different when it comes to empirically measure competitiveness and choose specific indicators.

The purpose of this study is to serve as a background document for European Commission publications, notably the 2017 Report on Integration and Competitiveness in the EU and its Member States and country reports in the context of the European Semester. Moreover, the study aims to inform policy-making in the Commission.

The main objectives of this study are as follows:

- a) Defining the concept of competitiveness at different levels of economic units:
 - firms (micro level),
 - sectors (meso level),
 - economy-wide (macro level).

In addition, the study will discuss the shift from one definition to another at the micro/meso and meso/macro intersections.

- b) For the purposes of the European Semester, establishing a set of indicators suitable for comparing the competitiveness of Member States over time and across Member States. These indicators will refer to the meso and macro levels only.
- c) Developing a systematic grid of available indicators of competitiveness which relates to the three levels (micro, meso and macro) and different policy objectives. Where appropriate, the hierarchy of indicators shall highlight interdependencies and dominant causal structures.
- d) Determining the strengths and, more importantly, weaknesses of a number of commonly used competitiveness indicators, including their associated measurement problems or biases.

The study rests upon a large body of literature that has been produced over the past decades on defining and measuring competitiveness. In addition, own empirical research is conducted to assess the relevance, quality and availability of different indicators for the specific needs of the EU report on integration and competitiveness and the country reports in the context of the European Semester. The empirical analysis focuses on three aspects. One aspect is the extent to which different competitiveness indicators cover similar or different dimensions of competitiveness. For this purpose, we analyse bivariate and multivariate correlation among indicators. A second aspect is the consistency of findings over time, for which country and sector rank analyses and analyses of the temporal variation of indicators are carried out. Thirdly, country-, size- and sector-specific issues are examined. To this end, we analyse indicators for each member state and at a more detailed sector level, including service sectors.

The report consists of three main parts. The following chapter 2 discusses the concept of competitiveness on a conceptual base for the three levels of analysis, firm, sector and economy-wide. Chapter 3 analyses three areas of competitiveness indicators that are of particular relevance to the European Semester exercise: cost competitiveness, innovation-related competitiveness, and export performance as a measure of competitiveness. The purpose of chapter 4 is to discuss in more detail issues of data quality and validity of a set of eight competitiveness indicators, including productivity measures, labour costs, energy costs, R&D and innovation indicators, and trade-related indicators. The final chapter of the report summarises the key findings and derives conclusions for measuring competitiveness at different levels of analysis.

2 Defining Competitiveness

This chapter discusses the concept of competitiveness and how competitiveness can be defined and measured at three levels of analysis: firm, sector, and total economy. For each level, a list of indicators that are commonly used in competitiveness analysis is presented. In addition, the chapter discusses the implications of a transition from one level to an adjacent level for different competitiveness indicators.

2.1 Firm Level

Florence Blandinières and Christian Rammer

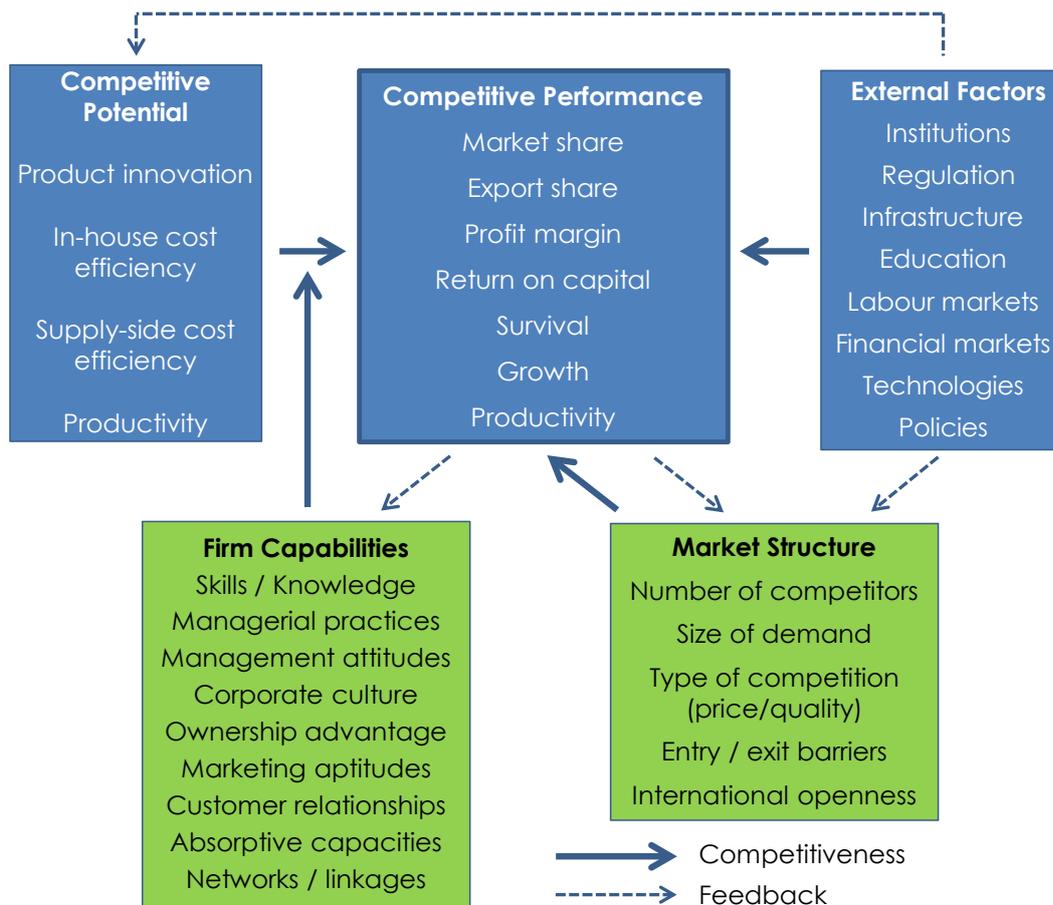
2.1.1 Introduction

Despite its popularity in the economics and management literature, there is no consensus about the actual meaning of the concept of firm competitiveness and how it should and could be measured. Several definitions co-evolved and led, in turn, to different measurement approaches. The IMD (2004) summarises 14 different definitions which exist within the literature. Just to name a few, the DTI (1994) defines firm competitiveness as “the ability to produce the right goods and services of the right quality, at the right price, at the right time. It means meeting customers’ needs more efficiently than other firms”. The OECD (1992) refers to firm competitiveness as the “capacity of firms to compete, to increase their profits and to grow. It is based on costs and prices, but more vitally on the capacity of the firms to use technology and quality and performance of the products”.

An enhanced definition of competitiveness has been developed by Buckley et al. (1998) who stress its multidimensional and dynamic aspects. The latter describes the current, and past, firm performances but also more dynamic elements, such as the managerial processes and the firm’s strategies to sustain its competitiveness. Buckley et al. (1998) and DC (2001) stress that competitiveness relates to “a combination of assets and processes, where assets are inherited (natural resources) or created (infrastructure) and processes transform assets to achieve economic gains from sales to customers” (DC, 2001). This stream of literature depicts competitiveness through the lens of the competency approach which can be put closer to the resource-based approach. They emphasise the role firms’ specific characteristics such as firm strategies, structures, competencies, capabilities to innovate, and other tangible and intangible resources for their competitive success (Bartlett and Ghoshal, 1989; Doz and Prahalad, 1987; Hamel and Prahalad, 1989, 1990; Peteraf, 1993; Ulrich, 1993). The ability of the firm to build, to develop and to deploy capabilities in a more effective way than its competitors is at the root of this view on competitiveness (Smith, 1995). Dynamic capabilities, flexibility, agility, speed, and adaptability have been increasingly stressed as crucial determinants of firms’ competitiveness (Barney, 2001; Sushil, 2000).

In line with Buckley et al. (1998), we split the concept of competitiveness along three main dimensions: competitive performance, competitive potential, and firm capabilities relevant to competitiveness. Competitive performance measures the firm's past and current performance in a market. The competitive potential of a firm relates to internal factors that may determine a firm's current or future competitive performance. Firm capabilities are key for translating the competitive potential into actual or future performance.

Figure 2-1: A conceptual model of firm competitiveness



Competitive performance is not only driven by firm-internal factors but also by external ones. Among the many external factors such as the institutional and regulatory framework, infrastructure provision, education, monetary environment (inflation, exchange rates) and factor markets, the structure of the markets in which a firm operates is of special importance. Market structure shapes competitive performance while in a dynamic perspective competitive performance of firms can alter market structure. Figure 2-1 summarises the main elements of a conceptual model of firm competitiveness.

2.1.2 Competitive Performance

The very meaning of competitiveness refers to the competition of products offered by different firms in the same market place. In this sense, competitiveness describes the ability of a firm to sell products. If products of different firms are homogeneous, price will be the only determinant of a product's competitiveness. In practice, products of different firms are rarely homogeneous owing to differences in quality features of products or in the way a firm offers and sells products (e.g. presenting a product, providing auxiliary services). Since the quality features of a product are determined by firms' actions, it is useful to relate competitiveness not just to products, but also to the firms offering a product.

A straightforward measure of competitiveness is a firm's **market share** for a given product in a given market. The more of a product a firm is able to sell, the higher the product's competitiveness. Market share can be measured either in physical terms (share in total number of items or in total quantity sold) or in monetary terms (share in total sales). The level of market share depends, among others, on the geographical boundaries of a product market. If a market is regionally bounded (e.g. due to high transaction costs), a high market share is not necessarily a good indicator of high competitiveness but rather reflects fragmented, small and potentially little competitive markets ('competitive' meaning competition among firms over potential buyers). A complementary measure of competitive performance is the share of sales generated in geographically open markets, i.e. markets in which firms from different regions offer their products. The **export share** is a frequently used indicator in this respect. It informs about a firm's ability to sell products in a market environment which is potentially more competitive than its home market and where the firm cannot profit from home-market advantages (e.g. in terms of reputation, ease of communication with potential buyers).

As firms may increase sales by offering products at zero or negative profits, a second key measure of competitiveness is the profit made per unit of product sold. The **profit margin** can be seen as complementary to the market share as some firms may yield high profit margins by selling only a few products and obtaining only a small market share. However, market share and profit margin can also be substitutive measures of competitiveness in case a firm has obtained a high market share and uses this dominant position in the market to sell products with a high mark-up (relying on some inflexibility of buyers to switch sellers owing to switching costs). In general, the relation of market share and profit margin depends on market structure (see Shepherd, 1972).

While the profit margin is a useful indicator for comparing firms in the same market and offering very similar products, this indicator is less suitable for comparing firms that produce different types of products as their production may require different amounts of capital. The **return on capital employed** is hence a competitiveness measure that is more neutral to sector specificities as long as all types of capital (both tangible and intangible assets) are considered at replacement costs. For

intangible assets, reliable capital data are often difficult to obtain, however. In addition, levels of return on capital employed tend to vary significantly and persistently across sectors and countries (Cable and Mueller, 2008).

Market share and profit margin are difficult to interpret when used across markets as variations in **market structure** matter. Market structure include as the size of a market (i.e. total demand), the number of competitors, the type of competition (i.e. the product characteristics that drive buyers decisions, particularly the role of price versus quality) and demand-supply relations (i.e. whether a market is a buyer's, a seller's or a balanced market) can yield to different mean values for market share and profit margins for different markets. As a result, a low market share in a large market with many competitors and intensive competition among sellers may represent a higher competitiveness as compared to a high market share in a small market with few competitors. As most firms offer different products and hence act on different markets, the average market share and profit margin of a firm will always reflect situations in different markets. In general, competitiveness at the firm-level need to be related to the specific product markets a firm serves.

A more generic indicator of competitiveness at the firm level that is less subject to the competitive situation in a market is **survival**. Survival represents a firm's ability to sell products in a market at cost-covering prices for a longer time. This would imply that firm age is an indicator for competitiveness. While age may indicate a high competitiveness in the past, it does not necessarily indicate current competitiveness. Older firms may rather be less competitive particularly if market conditions changed and the firm's competitive advantage, which helped the firm to stay in the market in the past, vanishes.

Another generic indicator of competitiveness at the firm level is **growth**. If a firm is successful in selling products it will be able to increase sales, hence grow (at least in terms of sales volume). This would imply that larger firms are more competitive. Similarly to age, size reflects past competitiveness but not necessarily current one. This is even more the case if size is not measured by sales but by accumulated assets. Growth in assets may be realised by attracting financial resources and factors of production, e.g. venture capital that expects future profits, or workers expecting sustainable jobs.

Productivity

Productivity is often used as a surrogate of competitiveness. At the firm level, however, productivity can be seen both as a potential for competitiveness and an outcome of competitiveness. A firm's productivity is supposed to reflect the overall efficiency of the firm through its capacity to transform inputs into outputs (both in terms of quantity and quality) (Fontagné et al., 2016). However, transferring a relative advantage in terms of efficiency over competitors into higher competitiveness in the market place is not necessarily straightforward (Buckley et al., 1998). First, productivity remains a partial performance measure and its interpretation

requires taking into account all production factors and technological change (e.g. substitution of input factors or their respective availability). Secondly, the qualitative dimension of the R&D efforts, or the type of innovation achieved, is poorly taken into account (Flanagan et al., 2007). Thirdly, comparing productivity of firms across industries and countries is difficult owing to variations in production functions and exchange rate effects (Cattell et al., 2004).

What is more, productivity may vary with a firm's 'buy or make' choice. If a firm focuses on a few high-productive in-house activities and purchases most inputs for its products externally, productivity measured in terms of value added by total factor input may be high. This high productivity does not necessarily translate in high competitiveness if inputs are purchased at high prices or in low quality.

2.1.3 *Competitive Potential*

Market share, profits, survival and growth are indicators of current or past competitiveness. Since markets are dynamic, a dynamic perspective on competitiveness has to take into account the potential for future competitiveness and the ability to adjust to changes in the market environment. While the latter often refers to firm capabilities, the former is linked to changes in the characteristics of a firm's products and processes. These changes are often referred to as **innovation**. Innovation represents a potential to increase competitiveness, though a firm needs to translate innovative advantages into competitive advantages. For example, buyers need to be convinced about likely superior features of a product innovation. In addition, innovations of competitors may undermine a firm's innovation.

Innovation includes product innovation (new characteristics or utilities of a product that differentiate a firm's product from those of other sellers) as well as process innovation (more efficient ways of producing products, including changes to quality features of the production process such as flexibility, reliability, speed). In addition, entering new sales markets or exploiting new (cheaper) supply markets can constitute innovations that potentially change a firm's competitiveness (see Schumpeter, 1934). A more detailed discussion of innovation indicators is presented in section 3.2.

Product innovation is a main approach to differentiate a firm's product from other products in the market. Product differentiation implies that the product price is not the only determinant for competitiveness. Indicators to measure product innovation range from qualitative indicators that measure the presence of an innovation to quantitative indicators that measure the number of innovations or their share in a firm's total sales. A main challenge is to capture the degree of novelty or change associated with a product innovation as higher levels of novelty or disruptiveness imply higher potential impacts on competitiveness. If a product innovation has a low level of novelty, e.g. if it is basically an imitation of an innovation introduced by other firms before, the product innovation will have little if any competitiveness enhancing potential but is rather an indicator for a firm's limited competitiveness.

Product innovation can result in the opening-up of new markets for the innovating firm in case the product innovation has no predecessor products in the firm. Entering a new geographical market with existing products is another type of market expansion which was stressed as a separate type of innovation by Schumpeter (1934). Market expansion can serve as a potential for higher competitiveness, for example if it allows firms to increase production volumes and exploit economies of scope or scale.

Process innovation is often associated with reducing unit cost of production, hence allowing to selling products at a lower price. Costs comparison enables to get the relative position of the firm in a given market from an input point of view. However, a firm can be very cost competitive without necessarily earning satisfactory returns, particularly if price competition is fierce. Under such a market structure, process innovation can be seen as a defensive reaction to keep a firm in the market rather than a competitiveness enhancing factor. It is therefore important both for product and process innovation to evaluate the market environment and a firm's competitive situation under which innovation takes place.

In addition to process innovation, firms may increase cost efficiency by identifying and exploiting **cheaper supply sources**. Schumpeter (1934) has stressed the role of opening-up new supply markets as a separate category of firm innovation. This may include outsourcing and off-shoring of activities and the establishment of subsidiaries in locations that offer cheaper production opportunities.

As product and process innovation is difficult to measure directly, indicators that measure the inputs into innovation have been used instead. A key indicator in this respect is **R&D expenditure** (Pavitt, 1984). Additional indicators are the number of **patents** or the number of **qualified scientists** (Patel and Pavitt, 1987). However, sectorial specificities reduce the capacity to directly compare such measures across firms. R&D (as defined in the Frascati Manual, see OECD, 2015) and patents are activities often found in manufacturing but are less relevant to firms in service sectors.

2.1.4 Firm Capabilities

Firm capabilities in the context of competitiveness comprise all routines and assets of a firm that help a firm to build up a competitive potential and to transfer its competitive potential into actual competitive performance. Literature has identified a large number of capabilities, ranging from human capital to organisational capital and including a number of assets that are often summarised as intangible assets (Corrado et al., 2005). A tentative list of firm capabilities include

- skills and competences of employees (Teece and Pisano, 1994)
- knowledge assets (Teece, 1998)
- managerial practices (see Bloom and van Reenen, 2007, 2010; Helfat and Martin, 2015; Helfat et al., 2007; Klingebiel and Rammer, 2014)

- management attitudes (e.g. commitment to internationalising business) (de Jong and den Hartog, 2007)
- corporate culture (and other aspects of organisational capital) (Graham et al., 2017)
- ownership advantages and outsourcing capacities
- marketing aptitudes and customer relationships (Grant, 2013)
- absorptive capacities (Cohen and Levinthal, 1990)
- networks and external linkages (Cassiman and Veugelers, 2006)

Various measures have been proposed to measure firm capabilities, often qualitative in nature and based on dedicated firm surveys. Only few measures have been established yet that are available for firms across sectors and countries over time, including measures on skills and absorptive capacities (conducting in-house R&D).

A further dimension of firm capabilities is economics of scale and scope. They have been put closer to the managerial processes because it is assumed that they are the result of investments and decision strategies made by the management. Economies of scale can be put closer to cost competitiveness and ease increasing the sales on a given market but highly differ across industries which are not affected in the same way by technological change. The same hold for economies of scope which follow distinct dynamics across markets and industries. However, economies of scale and scope reflect a capacity to learn about how to re-orientate the production to benefit from increase efficiency.

2.1.5 External Factors

When measuring competitiveness at the firm level, external factors need to be taken into account which may drive competitiveness but are out of control of a single firm. Some of these factors have been mentioned in previous sections when discussing limitations or qualifications of competitiveness indicators:

- efficiency and effectiveness of social and economic institutions
- government regulations
- inflation
- exchange rates
- availability and quality of infrastructure
- education system
- labour market (availability of skilled labour)
- financial markets (availability of credit and venture capital, interest rates)

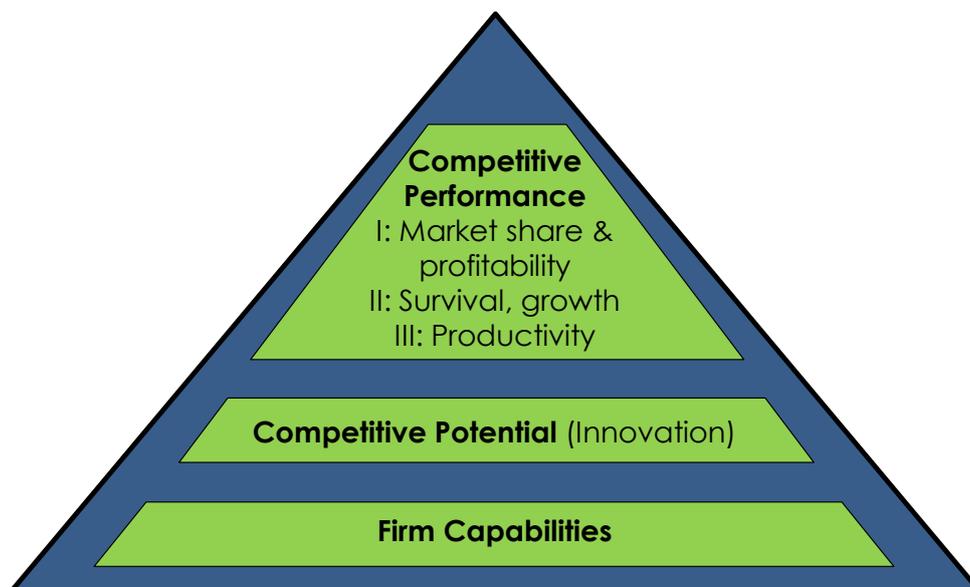
External factors can either facilitate or hinder a firm's attempts to successfully compete in the market. As some of these factors do not vary across firms within the

same country (e.g. exchange rates and some institutions such as the legal system), they are kind of country-fixed effects. Other external factors vary by region and sectors (e.g. labour market) and hence add another layer of differentiation to be considered when comparing competitiveness across firms.

2.1.6 A Hierarchical Model of Firm-level Competitiveness Indicators

In order to assess competitiveness at the firm level, all elements of the conceptual model should be taken into account. The core indicators are of course those that measure past or current competitiveness. For a balanced view, market shares and profitability should be used as key indicators. Survival and growth are also important indicators, though they may be affected to a greater degree by factors that are not related to a firm's competitiveness, e.g. changes in demand. Productivity is an indicator that captures both aspects of revealed competitiveness, and a firm's competitive potential.

Figure 2-2: A hierarchy of firm-level competitiveness indicators



The competitive potential, which is mainly related to innovation in a broader sense, is important to consider if competitiveness analysis should go beyond the current situation and also grasp likely changes of competitiveness in the future. However, the link between the competitive potential of a firm and future competitiveness is far from being straightforward. First, innovation is associated with uncertainty, i.e. it is difficult to foresee whether and to what extent an innovation can be transferred into superior market performance (in terms of market shares, profits or growth). Secondly, it is not only the innovative action of the focus firm that will determine its future competitiveness, but also the innovative actions of other firms. Thirdly, many factors mediate the translation of innovation into future competitiveness. An important

group are firm capabilities. They do not only link potentials to actual performance, but also determine a firm's ability to react to a dynamic environment.

Finally, competitiveness analysis at the firm level need to take into account market structures under which a firm operates, and various external factors. The former are particularly important if competitiveness of firms from different sectors is analysed. The latter is crucial for any international comparison of firm competitiveness.

2.2 Sector Level

Sven Heim and Christian Rammer

2.2.1 Introduction

This section discusses competitiveness at the level of economic sectors. Similarly to the firm level, there is no clear consensus on how to define competitiveness on the sector level, although it is clear that competitiveness on the sector level is strongly related to productivity and trade. In its 2015-2016 global competitiveness report, the World Economic Forum (Schwab, 2015) does not provide a definition for competitiveness at the sector level. However, Momaya (1998) notes that earlier versions of the global competitiveness report included a sector level definition, namely that sector-level competitiveness refers to the "extent to which a business sector offers potential for growth and attractive return on investment". D'Cruz (1992) defines competitiveness on the sector level as the collective ability of firms in a particular sector to compete internationally. Collignon and Esposito (2017) define the competitiveness of a sector as the relation of actual wages to equilibrium wages. They argue that their definition is superior to traditional measures like indices for real exchange rates, which are often based on relative prices of commodities and export baskets converted by given exchange rates, because equilibrium wages implicitly contain all important non-price elements of competitiveness.

Two types of sectoral competitiveness are distinguished. Intra-sector competitiveness relates the competitiveness of different countries within a sector. Inter-sector competitiveness relates to competitiveness of one sector as compared to other sectors within the same country. Before discussing both types in detail, we will first describe the most important indicators that are often used for both types. A detailed tabulation is provided by Castellani and Koch (2015), who collected more than 140 indicators, which can be divided into several groups which are presented in the following paragraphs.

2.2.2 Competitiveness Indicators

First, an important group of indicators refers to **productivity**. Generally, the more productive firms in a given sector are, the higher their ability to compete both internationally and against other sectors. *Labour productivity*, which is commonly defined as the ratio of output and input volume, is an indicator commonly used for country-level-analysis and thus suitable to measure productivity in the context of

intra-sector competitiveness. *Multi Factor Productivity and Total Factor productivity (MFP/TFP)*¹ relates to multiple inputs and is thus a more comprehensive measure than labour productivity with the drawback that data requirements are higher. It accounts for effects that are not caused by traditional inputs like labour or capital and is thus a very good measure in theory. Being computationally intensive to calculate, it may also suffer from an aggregation bias if applied on sector level. This is due to potential heterogeneity across firms².

Second, the group of indicators referring to **trade competitiveness** applies mostly to intra-sector competitiveness. Since intra-sector competitiveness is only a relevant concept if there is trade, trade-related indicators are most often used to assess the ability of a national economy's sector to compete with other national economies. In principal, a trade surplus indicates that a national economy can supply a greater amount of sector output to other countries than it purchases from other countries. A common and simple indicator is the *5-year change in export market shares* which aims to capture structural losses in competitiveness. The disadvantage is that export market shares may be influenced by global value chains. Therefore, export market share measures may not reflect competitiveness too well in sectors which are characterised by global value chains. The *relative trade balance* indicates the trade balance relative to total trade in a sector. It can be used to rank sectors and thus as an indicator for inter-sector competitiveness. Sector-interdependencies may however question whether a negative trade balance is a bad sign. For instance, imports might stimulate production in other sectors. The *revealed comparative advantage (RCA)* indicates the export share in a given sector and country compared to the export share in the same sector in a reference group of countries. A high RCA means that the industry in a given country performs well compared to the reference group. For EU member states, a natural reference group is the same sector in all (or a selection of) other EU countries. There are also trade quality indicators based on unit values or share of exports in high-price segments.

Third, indicators on **price and cost competitiveness** reflect the ability of firms in a given sector to sell at a competitive price in international markets. Price and cost competitiveness are often used synonymously (Fagerberg, 1988), though price competitiveness can be regarded as a broader concept which includes both competitiveness related to cheaper prices (reflecting cheaper production costs) and competitiveness related to the ability to enforce a certain price level in the market, e.g. by marketing efforts (Buckley et al., 1988). In this report, we will refer to cost competitiveness for denoting the ability to sell cheaper than competitors as a key for both intra- and inter-sector competitiveness. Non-cost aspects of price

¹ In some sources, like Castellani and Koch (2015), multi factor productivity (MFP) and total factor productivity (TFP) are distinguished. However, the OECD Glossary of statistical terms (OECD, 2001) states "Total Factor Productivity is a synonym for Multi-factor productivity (MFP). The OECD productivity manual uses the MFP acronym to signal a certain modesty with respect to the capacity of capturing all factors' contribution to output growth." We will thus also use the term MFP.

² See Biatour et al. (2011) for a detailed discussion.

competitiveness are included in quality aspects and subsumed under quality competitiveness.

Apart from using price-cost-margins, which are more common at the firm level and would have to be aggregated to sector level, indicators in this group use either Real Effective Exchange Rates (REERs) or *Unit Labour Costs* (ULC). The ULC indicator is easy to calculate and conveying the idea that an increase in labour costs reduces competitiveness while more efficient workers increase it. ULC is typically used for country level comparisons in intra-sector analysis. The *PPI-based REER index* uses a producer prices index (PPI) and is thus closer to the production side than indexes based on consumer prices. This indicator suffers from scarce and non-uniquely composed data on export oriented PPI. The *UCLM-based REER index* excludes (often untradeable) services by looking only at unit labour costs in the manufacturing (UCLM) sector.

Fourth, there is a large group of indicators covering **innovation and technology**. This is the key group to assess non-cost competitiveness. Depending on the sector, the ability to innovate better than rivals may be much more important than cost competitiveness. Indicators based on absolute or relative R&D expenses, like *R&D expenditure* in a sector, are related to technical change but do not measure it. They also neglect innovation sources such as learning by doing. Indicators which are based on patent applications (e.g. *number of patent applications in a given jurisdiction* but also quality-controlled measures) have a rationale in the sense that patents are strictly connected to innovation and thus to competitiveness, but they are not comprehensive. Another approach to measure the innovation ability of a sector is to look at SME-related indicators like *SMEs introducing product or process innovation*. A higher share of firms active in innovation is deemed to result in a higher level of innovation and hence higher competitiveness. *Intangible investments* as percentage of GDP is also a relevant indicator, as those investments are crucial for the creation of knowledge.

Fifth, a group of indicators refer to **firm dynamics**. Although this group may be of particular importance on the firm level, an aggregation over all firms could still tell important differences both between countries and if the competitiveness of different sectors within a country is compared. Bartelsman et al. (2009) identify the *average firm size³ relative to entry by age* as a useful indicator which tells about the gap in size between entrants and incumbents. A smaller relative size of entrants is considered as an indication for greater experimentation and thus higher competitiveness of a sector. Moreover, they mention the *share of gazelles*, which are firms that rapidly expand the number of their employees. If gazelles are important in an industry, this signals that the most innovative and productive companies are easily capturing resources and market shares which is good for competitiveness.

³ In Bartelsman et al. (2009) firm size is measured by number of employees, but other measures for firm size such as turnover might also be possible.

Finally, it is important to keep in mind that there is often a division of labour along the **global value chain**. Sometimes, an upstream part of a sector might be rather competitive, but the downstream part is to a lesser extent, or vice versa. Measuring competitiveness for the whole sector might yield misleading results in these cases with the remedy being again a separate analysis. However, there are also indicators which explain the importance of global value chains. The *intermediate import ratio* describes geographical fragmentation by relating intermediate import amount and total intermediate demand for each sector. The *value added export ratio* (the total foreign value added share of gross exports in percent) is a measure of the international fragmentation of production.

2.2.3 *Intra-sector vs. Inter-sector Competitiveness*

Overall, a sector-specific (for an analysis of intra-sector competitiveness) or country-specific (for an analysis of inter-sector competitiveness) selection of the mentioned indicators from all groups based is probably the best way to achieve a good measure of competitiveness. In practice, data availability will often restrict the choices. The remainder of this section points out the important differences between the analysis of intra-sector competitiveness and inter-sector competitiveness and general issues in the measurement of competitiveness at the sector level.

Intra-sector competitiveness relates to the competition between sectors from different national economies. Since intra-sector competitiveness is only a relevant concept if there is trade, trade-related indicators are most often used to assess the ability of a national economy's sector to compete with other national economies. In principal, a trade surplus indicates that a national economy can supply a greater amount of sector output to other countries than it purchases from other countries. For intra-sector competitiveness, basically the same factors apply as at the micro level, except for the indicators on restraining competition. In addition, domestic demand can also play an important role in either fostering or restricting competitiveness, depending on whether domestic demand is ahead of upcoming trends in the sector, or prefers idiosyncratic solutions that are reverse to international trends in demand.

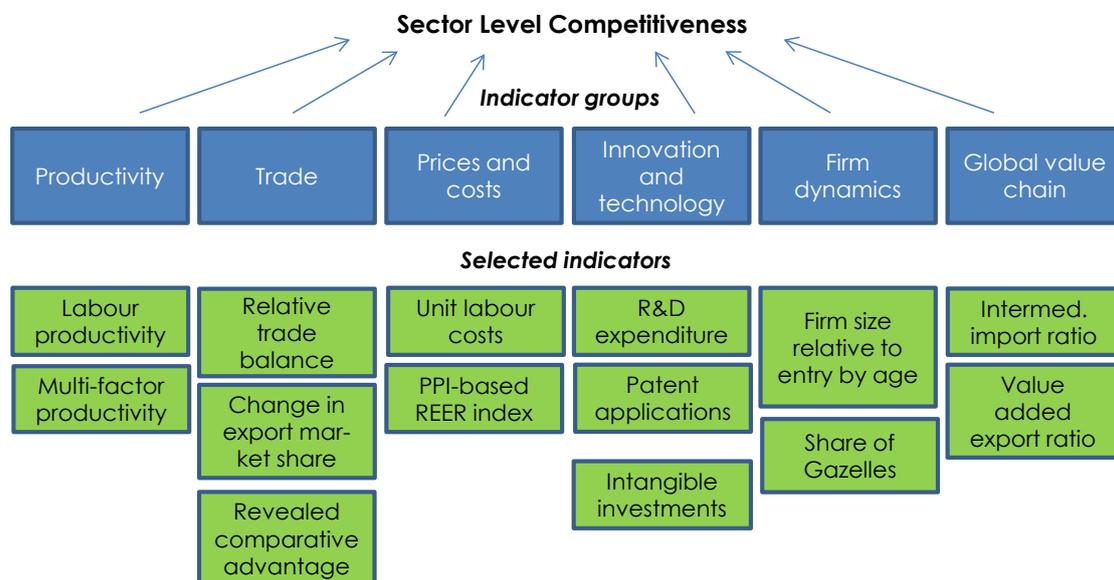
Inter-sector competitiveness is strongly related to the ability of a sector to attract (scarce) resources such as human capital and financial capital. The expected returns on investing in these types of capital are major factors driving competitiveness. In this respect, total factor productivity is perhaps the best direct output measure as it attracts or distracts factors of production to be reallocated from one sector to another. Factors that determine this type of competitiveness include economic structures such as competition, demand, corporate structure, infrastructure and the functioning of labour and capital markets.

A general challenge in measuring competitiveness at the sector level is that a sector usually comprises a number of heterogeneous products. It can well be that a nation's industry for some of these products is rather competitive, while it is not for

others. Whereas some indicators like ULC should be the same for each product in the sector, others could actually differ from product to product. In particular, innovation capabilities might be product-specific. As a consequence, when looking at large sectors, it might be worth measuring competitiveness also for different parts of the sector.

Figure 2-3 sums up the findings of this section: Competitiveness on the sector level is determined by several groups of indicators and the exact indicator selection depends on the particular policy need and/or the available data. Two or three of the most common indicators for each indicator group are mentioned in the figure. It is important to distinguish between inter-sector competitiveness and intra-sector competitiveness, but many of the indicators can be used for both types of analysis.

Figure 2-3: Indicators for measuring sector level competitiveness



2.3 Economy-wide

Michael Peneder

2.3.1 Introduction

In economic policy and business people regularly refer to “competitiveness” at the level of countries or regions, often not aware of the strong resentments this has courted among (part of) the academic profession. In the 1990s the debate culminated in Krugman's (1994) notorious verdict: “[L]et's start telling the truth: competitiveness is a meaningless word when applied to national economies. And the obsession with competitiveness is both wrong and dangerous.”

The future Nobel laureate's critique has been backed by many in the economics profession for a number of important concerns:⁴

- One is that the notion of competitiveness portrays international trade as a zero-sum game, ignoring the overall productivity gains from deepening international specialisation. This leads to a false impression of mutual conflict instead of gains.
- Another reason is that in large and integrated economies, such as the USA or the EU, growth and employment depend less on trade than on domestic demand.
- Finally, wages and productivity move together in the long run. Consequently, low wages are a sign of low competitiveness and vice versa.

The notion of competitiveness that Krugman did address was one that had traditionally focused on cost-based determinants, especially wages, and trade-related measures of performance. He concluded that productivity should instead be the primary target of economic policy. Partly in response to his criticism, concepts of competitiveness have soon advanced to a more refined perspective. For example, at the end of the 1990s the European Commission established the following definition: "*An economy is competitive if its population can enjoy high standards of living and high rates of employment while maintaining a sustainable external position*" (European Commission, 1998, p.9). To the present day it characterises competitiveness as a "*key determinant of growth and jobs in Europe*",⁵ thereby referring to a variety of factors, such as access to markets and resources (e.g., finance, energy, raw materials, skilled labour), the quality and efficiency of public administration, good infrastructure, or to being at the forefront of innovation and sustainable production.

The upshot is that the notion of competitiveness at the macro level acknowledges that locations compete for activities with high value added as the source of high per capita incomes and hence material well-being. Sometimes they compete directly, as is the case with the promotion of inward foreign direct investments, and may carry a considerable potential of mutual conflict, e.g. when negotiating the terms of international trade agreements. But often competition is indirect, trying to provide a favourable business environment in general, or fostering e.g. innovation and productivity growth with a focus on the particular needs of individual sectors. Overall, competitiveness at the aggregate level has become a sometimes blurred but generally accepted notion.

2.3.2 The "Iceberg" Model

Once we accept competitiveness to be a meaningful notion at the aggregate level of countries, we need to be more specific about its targets and drivers. Acknowledging that many relationships will be endogenous, non-linear and

⁴ For opposite views see, e.g., Cohen (1994), Prestowitz (1994), Thurow (1994) and Fagerberg (1988, 1996). Krugman (1996) renewed his critique.

⁵ As retrieved from its official homepage (2017-03-23):
https://ec.europa.eu/growth/industry/competitiveness_en

discontinuous, a general representation ought to be flexible and schematic. For that purpose, the *iceberg* model of competitiveness in Figure 2-4 organises targets and drivers along stylised analytic layers (Peneder, 2017). Different from schematic representations that typically line-up various “pillars” or groups of determinants horizontally, it highlights a certain vertical structure of presumed causal relationships that exhibit two important features: First, the vertical structure reveals many indicators to simultaneously measure specific dimensions of competitive performance relative to the deeper layers as well as its determinants relative to higher layers. Second, the tip of the iceberg represents the most visible outcomes, whereas the specific drivers and impacts generally become more difficult to detect as we move down the levels. Further down the layers, variables more and more represent latent characteristics that are of importance to the overall performance but of which many require additional diagnostic tools and data that are difficult to obtain. In other words, the tip of the iceberg helps us to spot a nation’s overall performance, but does not necessarily reveal much about the size and the form of its underlying factors. For studying the drivers of competitiveness one must also search below the “water line”.

Starting from the top, we first align with Krugman, Porter (1990) and others, and position productivity (in its various forms) as the primary target at the aggregate level. Without denying the well-known limitations and pitfalls as a measure of welfare, thinking of **GDP per capita** as a measure of average living standards in terms of material well-being corresponds well to the European Commission’s emphasis on growth and employment. Moreover, for two reasons it is particularly good at aggregating the impact of many other drivers of economic performance. First, one will hardly find any meaningful measure of economic performance that does not have a positive association with and impact on GDP per capita. Those with potential negative trade-offs, such as low labour cost or balanced public budgets, are better interpreted not as measures of competitiveness *per se*, but depict constraints of a country’s long term economic sustainability.⁶

The second reason is that the value added of economic activities provides for a meaningful statistical concept of aggregation. To see the point, one must compare it to synthetic indicators such as the various ranks and indices of world competitiveness and other popular scoreboards. They sum up the scores of numerous variables considered relevant. No matter whether they are explicit or implicit (i.e. by the choice of variables), the weightings are exogenously assumed. This contrasts sharply with GDP, which adds the value of economic activities as revealed by the buyer’s willingness to pay – at least for the ideal setting of pure market transactions. In less ideal situations, statistical offices have much experience and exert considerable effort to approximate that value (e.g. via the cost of inputs in non-market activities). Apart from the manifold difficulties of accurate

⁶ Their task is to indicate imbalances, e.g. if wages rise ahead or fall behind the growth of labour productivity relative to a country’s trade partners. In the end, it is still productivity growth which determines what wages an economy can afford to pay.

measurement and the shortcomings with respect to a society's non-economic objectives ("Beyond GDP"), the key point is that the National Accounts rely on a clear concept of how the value of different economic activities add up. This is an important advantage for the study of competitiveness at the aggregate level.

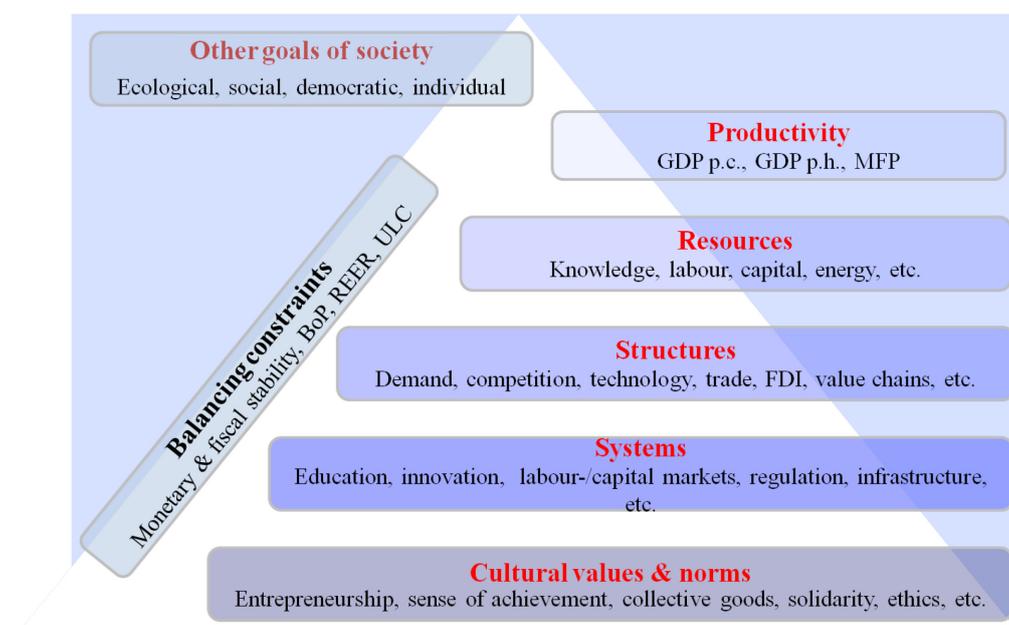
To illustrate the argument, consider any determinant reasonably assumed to have a positive impact on competitiveness, but for which one knows little about the precise magnitude of effects. In addition, the actual impacts may often depend on other factors that render the determinant effective in some circumstances and ineffective in others. Scoring schemes to produce a synthetic aggregate index must make general assumptions, at best conditioning them on one or a few other factors.⁷ But this is a far cry from the flexibility of the conventional National Accounts. For example, a change in labour regulations, the number of scientific publications, or the many other variables considered relevant, will increase GDP per capita only if and to the extent that they actually enhance the value added as revealed in concrete economic transactions. In contrast, synthetic indices of competitiveness can only assume, or at best estimate, an average impact that equally applies across different countries.

Moving down from the tip of the *iceberg* closer to the "waterline", **growth accounting** is the established method to decompose changes in gross output, value added or per capita income into the contributions of various inputs. If one assumes, among others and as a first empirical approximation, that one can represent the economy by an aggregate production function, this approach has the advantage of offering a unified analytical framework. Growth accounting nevertheless remains close to the surface of competitiveness and cannot tell us, e.g. what caused the growth of multi-factor productivity or the changes in the quantity or quality of a particular input. For that purpose one has to go further below the imaginary "water line".

The primary objective of **structural analyses** is to detect characteristic patterns of production and markets to identify a country's relative strengths and weaknesses from a comparative international perspective. By identifying potential needs for public interventions and reform, it primarily supports the prioritization and strategic orientation of policy. Examples are the study of international differences in demand, technological capabilities, openness to trade and foreign direct investments (FDI), trade performance or global value chains. In section 3.3 we will specifically focus on various measures of trade performance (trade balances, export shares, revealed comparative advantage, etc.) and test the sensitivity of rankings among EU Member States to the choice among different data sources or indicators.

⁷ For example, weighting schemes can, and sometimes do, differentiate by an economy's degree of development (per capita income).

Figure 2-4: The iceberg model of competitiveness (Peneder, 2017)



At an even deeper level, institutions are where most policies become operational. Examples are public security, the legal system, educational and innovation systems, public infrastructure, and manifold regulations affecting finance, product or the labour markets. Furthermore, an economy's overall competitiveness may depend on the prevalent cultural values and norms that shape human behaviour. Examples are the people's predisposition for entrepreneurial initiative, sense of achievement as well as trust, the provision of collective goods, solidarity and ethics. The latter factors are typically not within the reach of direct policy intervention, but institutional reforms may indirectly affect them in the long run. There exist a variety of country-wide indicators on specific institutional characteristics. Many of them originate in periodic surveys and reflect the opinion of e.g. a country's business leaders.⁸ On the one hand, their dependence on subjective assessments is a major shortcoming, but on the other hand we benefit from their immediate connect to our concern for competitiveness. Contrasting GDP p.c. with the broader welfare objectives of society, Jones and Klenow (2016) have recently provided summary statistics of economic well-being. Calculating a consumption-equivalent welfare of countries from data on consumption, leisure, and mortality by age⁹, their main conclusions are as follows:

"First, the correlation between our welfare index and income per capita is very high. This is because average consumption differs so much across countries and is strongly correlated with income. Second, living standards in Western Europe are much closer to those in the United States than it would appear from

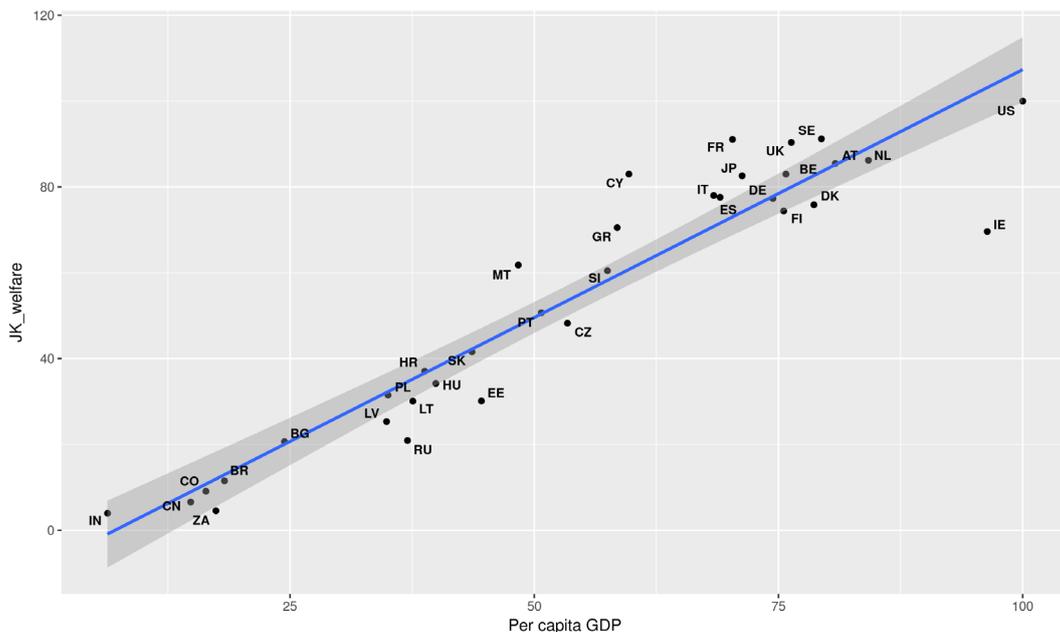
⁸ To put it casually, one can always try and ask people about their opinion, if there is no better data available.

⁹ That is without accounting, e.g., for environmental sustainability or indicators of personal "happiness".

GDP per capita. Longer lives with more leisure time and more equal consumption in Western Europe largely offset their lower average consumption vis-à-vis the United States. Third, in most developing economies, welfare is markedly lower than income, due primarily to shorter lives but also to more inequality" (Jones and Klenow, 2016, p. 2454).

Figure 2-5 presents an extraction of the data provided by Jones and Klenow, focusing only on the EU Member States as well as the USA, Japan, South Korea and the BRICS and adding the simple linear prediction of a bivariate regression. All values are relative to the benchmark of the USA = 100. Also for this reduced sample the correlation between GDP per capita and the Jones-Klenow measure of living standards is shown to be very high. Furthermore, Figure 2-6 presents the ratio of welfare to GDP per capita, better highlighting the differences for individual countries. While the USA exhibits the highest value for both per capita income and welfare, the figure also confirms that many European countries display a substantially better ratio of welfare to income. In contrast, the welfare to income ratio is markedly lower for most emerging and transition economies.

Figure 2-5: Welfare and GDP p.c. (2007)



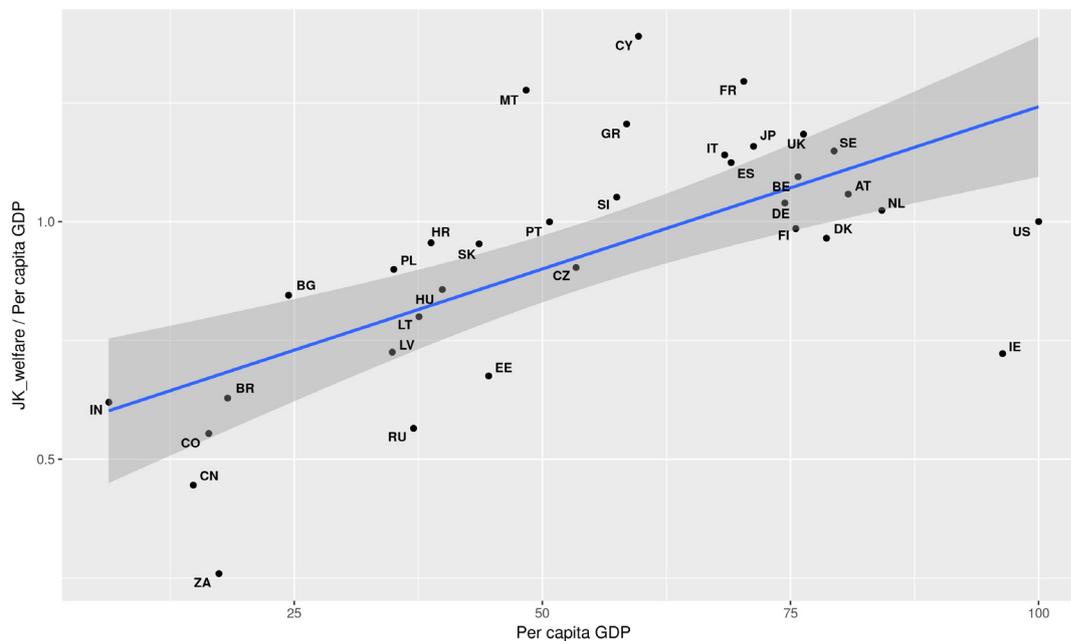
Note: Per capita GDP and the Jones-Klenow welfare index are expressed relative to the USA = 100.

Source: Extraction from database of Jones and Klenow (2016), WIFO calculations.

Finally, addressing certain limitations of their analysis, Jones and Klenow (2016) point at three caveats. One is the assumption of a global set of preferences, another that life expectancy is the only indicator of health conditions, and finally that ecological concerns are not accounted for in their specific set-up. More generally, however, one must also be aware that in this kind of welfare comparisons, for instance, a higher investment rate *ceteris paribus* implies lower consumption and hence welfare. Consequently, one ought to be cautious about the long-term implications

of a higher consumption equivalent in the current data (that may, e.g., relate to low investment opportunities) versus the economy's ability to earn income for future consumption in the long-run.

Figure 2-6: The ratio of welfare to GDP p.c. (2007)



Note: Per capita GDP and the Jones-Klenow welfare index are expressed relative to the USA = 100.

Source: Extraction from database of Jones and Klenow (2016), WIFO calculations.

2.4 Relation between Different Levels

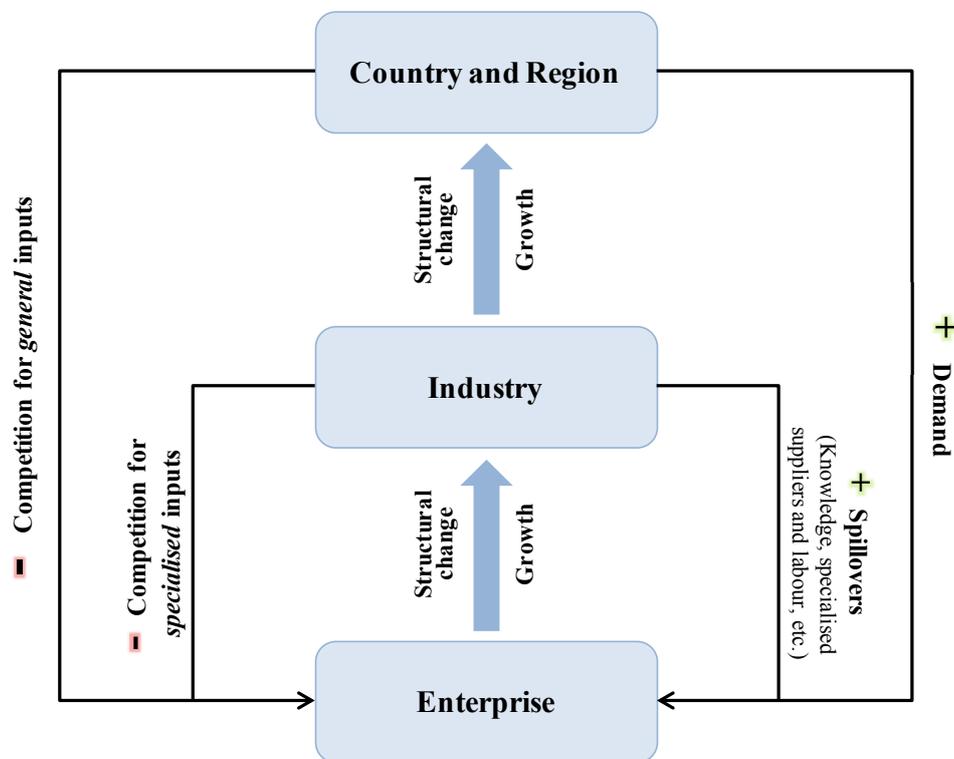
Michael Peneder

According to Krugman (1994, 1996) the concept of competitiveness applies only to individual firms. In contrast, nations or regions would not compete in any meaningful sense. But this perspective ignores the fundamental relatedness between the micro, meso and macro levels of economic activity (Peneder, 2017). Competition arises from scarcity, which, among other factors, can affect natural resources, capital, labour, human skills or technological knowledge.¹⁰ The crucial question is whether such scarcities only affect individual enterprises, households or workers. This can hardly be the case, since the relative abundance of the various factors of production (including knowledge) clearly influences firms' locational choices and their differential performance. The theory of comparative advantage tells us that relative scarcities at the aggregate level affect industrial location and specialization at the meso level. And when industries systematically vary in their productivity performance, differences in industrial specialization also affect a region's overall per capita income.

¹⁰ Also, the access to certain markets can be scarce, giving a natural advantage to firms in a location that is better integrated than others.

In short, despite their fundamental differences, the micro, meso and macro levels of economic activity are inextricably interwoven, i.e. interdependent parts of the same reality. Figure 2-7 illustrates this connectedness with a schematic representation of how the rise in competitiveness at one level systematically affects also the competitiveness at each of the other levels. For example, let's assume that all firms in a particular sector become more competitive either in terms of increased profitability, faster growth or improved odds of survival or entry of a new firm. *Ceteris paribus* and by mere aggregation, this will also raise the competitive performance at the meso level of its according industry in that location. Typical measures of performance would be the average profitability of the sector, the growth in sector output and the growth in the number of active firms or an increase in the sector's *revealed comparative advantage* (RCA).

Figure 2-7: Mutual interactions between the micro, meso and macro level



By the same reasoning, the better performance of that industry positively affects the aggregate performance at the level of individual countries or regions. Consistent with the previous discussion, the improved competitiveness may affect aggregate MFP growth, employment and hours worked and/or GDP per hour. Each of those changes will end up in an increase of GDP per capita and hence average income.

But the causal effects do not only move from the micro to the meso and then the macro level through simple aggregation. For example, higher overall income feeds back to the individual firm via increased demand for final and/or intermediate goods, which can positively affect either of the aforementioned measures of competitiveness at the firm level. In addition to this positive feedback from the macro to the micro level, the stronger industry performance also raises the potential

for positive spillovers (e.g. via knowledge diffusion, specialised suppliers and/or labour), thus establishing also a positive feedback from the meso to the micro level.

Differences between indicators at the various levels become more apparent through negative feedbacks, or trade-offs. For example, higher incomes at the macro level increase the demand and competition for *general* inputs of production such as labour, capital or natural resources, and thereby raise their prices. Similarly, the faster growth of a particular industry increases the demand of and hence competition for *specialised* inputs.

These feedbacks from the macro and the meso level negatively affect the individual firm at the micro level, but not necessarily the competitiveness of the industry as such. The reason is that higher input prices also foster structural change, driving the less competitive firms out of the market and thereby increasing the share of those with a higher profitability, capacity to grow, etc. At least in the medium-to-long run, this change in the composition of firms may improve the performance of the industry at the meso level. Relatedly, the competition for general inputs may foster structural change at the meso level and shift the composition of production towards the more productive sectors that create more value per inputs and hence can afford to pay higher prices.

3 Competitiveness Indicators for the European Semester

Building on the results of chapter 2, this chapter aims to identify relevant competitiveness indicators at the meso level and the economy-wide level which can be used for assessing competitiveness of member states in the context of the European Semester. The purpose of this chapter is to discuss indicators conceptually and in terms of their policy relevance on the one hand, and to validate the usefulness, reliability and validity of the indicators empirically, notably in order to see to what extent the choice of alternative indicators affects the relative position of sectors or member states. The indicators discussed in this chapter relate to three areas of competitiveness: cost competitiveness, competitiveness related to generating and exploiting new knowledge (R&D, innovation), and export competitiveness. The analyses are performed at the meso and macro level.¹¹

The selection of the indicators rests on three criteria:

- Meaningful economic concept, i.e. direct link to the economic concept of competitiveness as discussed in chapter 2;
- Empirical validity, i.e. whether indicators accurately measure what the concepts require or assume;
- Data quality in terms of completeness (country and sector coverage), timeliness, scope of revisions and other quality characteristics (e.g. outliers, consistency over time).

The presentation is organised by the three areas of cost competitiveness, innovation-related competitiveness and export competitiveness. Each section starts with the motivation for selecting a certain set of indicators and performs a series of empirical analysis. Key competitiveness indicators are summarised in 'fact sheets' which can be found in the Appendix (chapter 7) at the end of this report.

Issues of data quality are not discussed in detail in this chapter but are subject to chapter 4 which contains a detailed analysis of data quality aspects for a series of indicators on the three areas of competitiveness that are presented in the present chapter.

¹¹ An application to the micro level is shown in the Appendix (chapter 8) based on data from the German Innovation Survey as this micro-level data base contains a number of relevant competitiveness indicators. Micro data that are available at the European level turned out to be not suited for a detailed analysis of competitiveness indicators.

3.1 Cost-related Competitiveness

Niklas Dürr and Stefan Frübing

3.1.1 Motivation

We have discussed several potential indicators of measuring cost competitiveness at the sector level in Section 2.2.2 and emphasised their strengths and weaknesses. In practical use, Unit Labour Costs (ULC) is the most established measure of cost competitiveness. ULC “measure the average cost of labour per unit of output and are calculated as the ratio of total labour costs to real output “(OECD)¹² or in an alternative definition “defined as the ratio of labour costs to labour productivity” (Eurostat).¹³ However, using this simple measure has at least two major drawbacks.

- A major drawback of ULC indices is that they ignore **intra-sectoral quality heterogeneity**, i.e. differences in quality of the products across countries. However, in reality for most products the concept of monopolistic competition between countries is more appropriate.
- A further problem when inferring competitiveness trends from ULC indices is that the choice of the benchmark year may affect the interpretation substantially as it assumes that in an **arbitrary chosen base year** all countries start from supposedly equal conditions. Thus, it is ignored that substantial disequilibria may exist at the moment when the index starts, so that the future evolution might reflect the adjustment of levels toward the equilibrium.

We will therefore also construct more complex measures to assess cost competitiveness and complement them with non-cost competitiveness measures to address the above concerns from using ULC indices to evaluate competitiveness at the sector level.

The empirical approach we apply is as follows. We first rank the countries' sectors according to their relative competitiveness for the different measures, and secondly correlate the resulting ranks of measures over time and sectors to assess their interrelatedness. Finally, we conclude by recommending measures.

3.1.2 Data

In our application we use 2-digit NACE Rev.2 to define sectors. The main data sources utilised are Eurostat COMEXT and AMECO which we use to construct the respective competitiveness indices.

For the regressions described above as step 4 of the empirical application we collect data from the following sources:

¹² OECD definition, see <https://stats.oecd.org/glossary/detail.asp?ID=2809> (last accessed 20 July 2017).

¹³ Eurostat definition, see <http://ec.europa.eu/eurostat/web/macroeconomic-imbances-procedure/nominal-unit-labour-cost> (last accessed 20 July 2017).

- Transparency International for the Corruption Index
- World Economic Forum to collect variables on the efficacy of national competition authorities
- The Price and Cost Competitiveness Report by the European Commission for data on Real Effective Exchange Rates
- The World Economic Outlook Database (WEO) provided by the International Monetary Fund (IMF) for data on the inflation rate (GDP deflator)
- The World Bank's World Development Indicators (WDI) for interest rates the total market capitalization of listed firms as a share of the GDP (to control for the size of the stock market) and domestic credit to private sector as a share of the GDP.
- The Eurostat COMEXT Database for Export and Import Quantity and Value and Production Quantity and Value
- The AMECO by the European Commission for macro variables in different sectors
- The ZEW cartel database for the number of cartels
- The OECD Stan Database for capital stock needed for Equilibrium wages

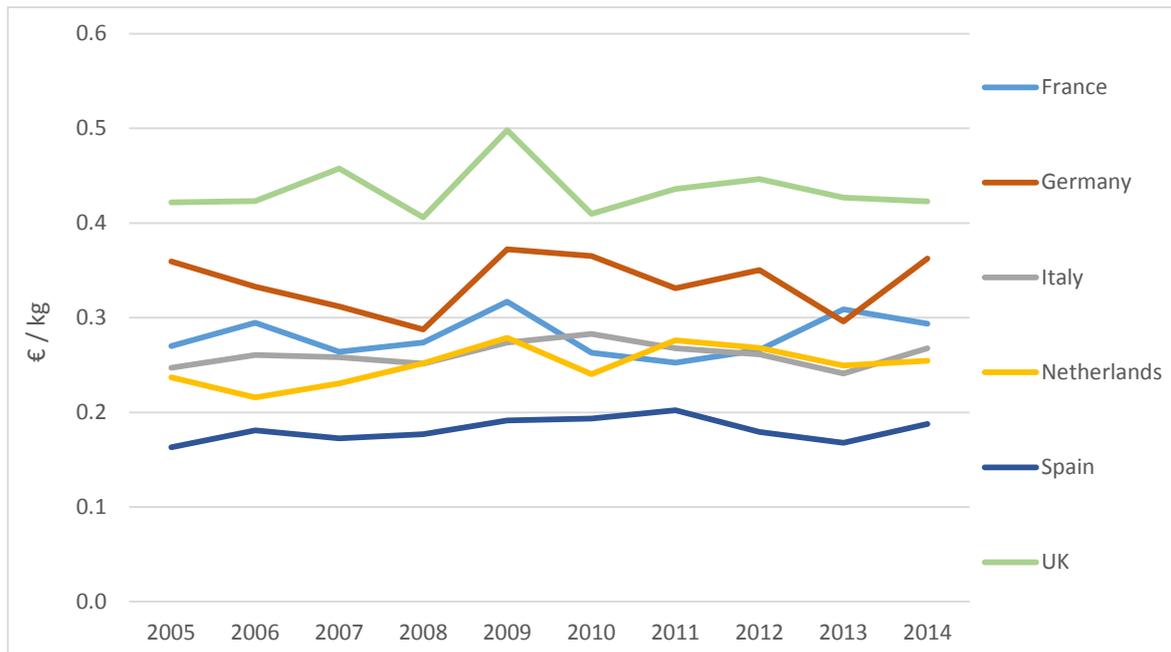
3.1.3 Empirical Analysis of Indicators

As already mentioned above, unit labour cost is a standard measure for cost competitiveness. It is derived by dividing the total labour costs by real output. As both, numerator and nominator are given in Euro, the ULC is a unit-less measure. ULC, hence relates costs of labour to productivity making it an insightful indicator for competitiveness. Figure 3-1 therefore shows the development of ULC for selected countries for one particular industry (C10 - manufacture of food products). Generally over the years, the United Kingdom shows the highest ULC while Spain shows the lowest values.

To calculate the physical unit labour cost (PULC), the ULC are multiplied with the export prices, which in turn deliver a price per kilo exported. As the ULC are unit-less and the export prices are given in Euro per kilo, the PULC are measured in Euro per kilo, too. In this respect, the PULC come with the advantage of a unit attached to it that can be more directly interpreted. However, it is not quite clear how the composition of different heavy and lighter products affect the measure. The PULC in turn are needed to calculate the selling capacity and quality index.

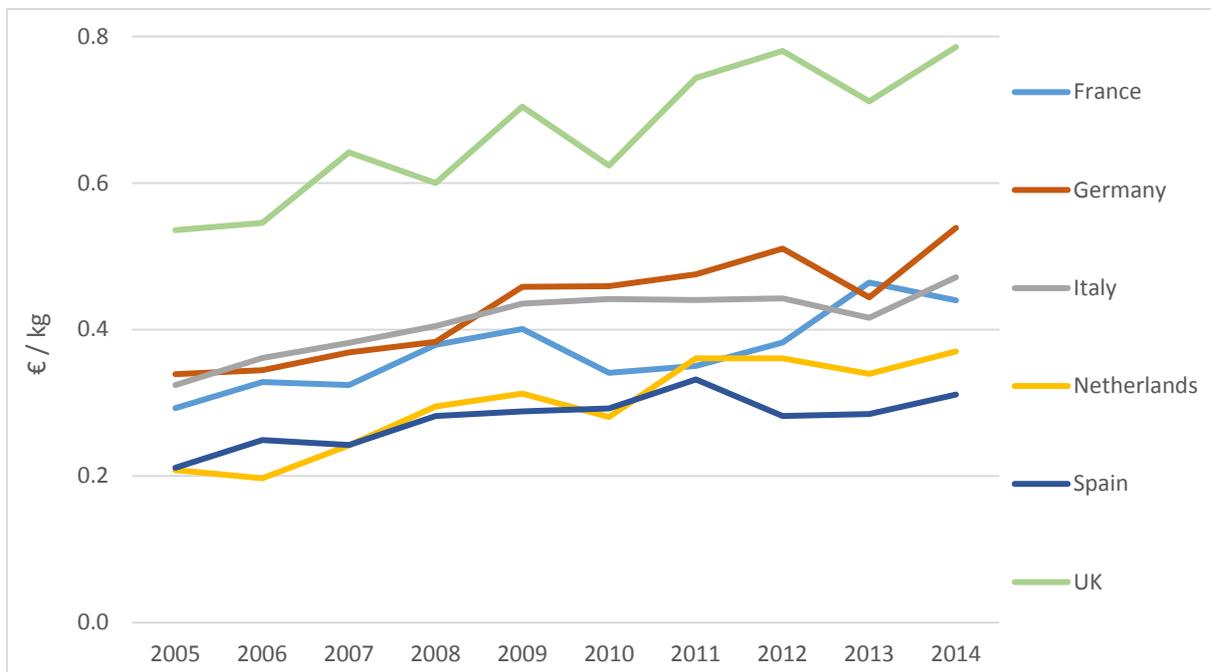
Figure 3-2 depicts the PULC for the aforementioned set of countries and the same industry. Generally, all PULC increase over time, while the United Kingdom shows by far the highest value with the remaining countries showing relatively comparable values.

Figure 3-1: Unit labour cost of selected countries in C10 (manufacture of food products), 2005-2014



Source: Own calculations based on Eurostat Comext and Ameco data

Figure 3-2: Physical unit labour cost of selected countries in C10 (manufacture of food products), 2005-2014



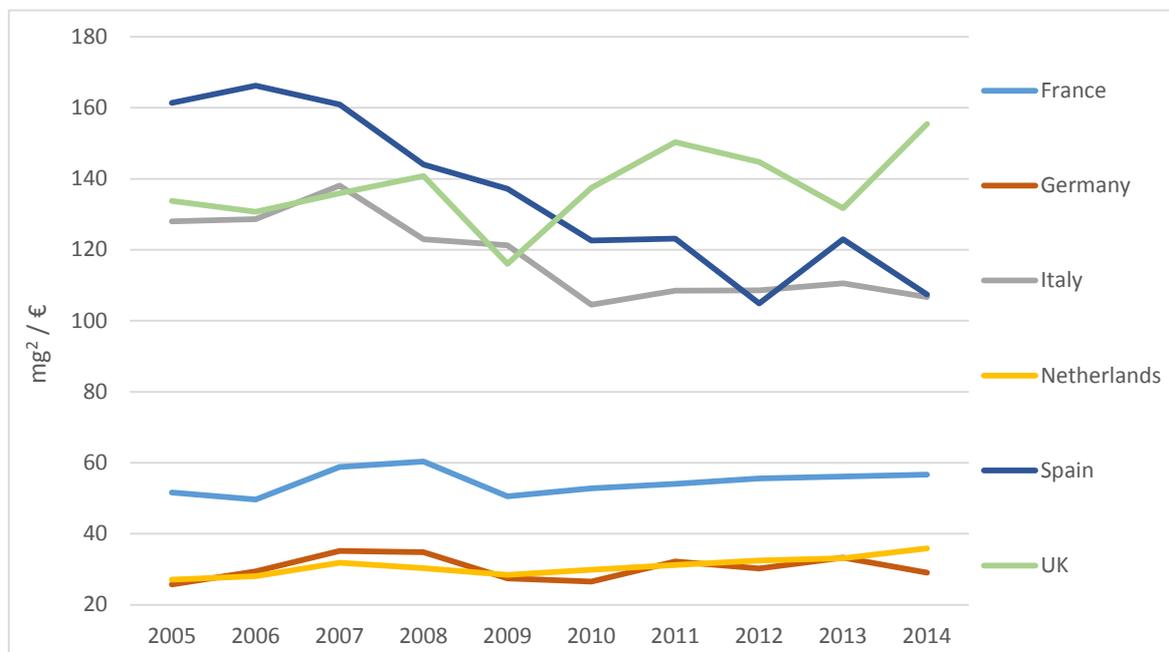
Source: Own calculations based on Eurostat Comext and Ameco data

To address the first drawback discussed above, we build the **selling capacity** and a **quality index** both based on the identification strategy suggested by Di Comite (2016). The main intuition is that by observing costs, prices and quantities sold over time it is possible to estimate key demand parameters at the country-sector level. Assuming exogenous labour costs the identification of overall demand effects can be determined and aggregate market effects can be disentangled from quality-specific demand effects.

The **selling capacity** is an approach to measure the amount of goods a country was able to export to other countries at a profit maximising level of markups. In this respect, the measure captures all the characteristics of a product attributed to the capacity of exporting except the price and quality. This could include the distribution networks as well as the awareness of importers or general reputation. Hence, the selling capacity is a suitable complement to the various cost competitive measures.

To illustrate the measure, Figure 3-3 plots the selling capacity over time for selected countries exemplarily for the NACE Code 10 – Manufacturing of food products. The selling capacity is given in $\text{mg}^2 / \text{€}$ as it measures the amount of goods that can be exported for a given level of markups. In this case, the Netherlands, and Germany show a higher selling capacity than France which in turn performs better than the United Kingdom, Italy and Spain.

Figure 3-3: Selling capacity of selected countries in C10 (manufacture of food products), 2005-2014

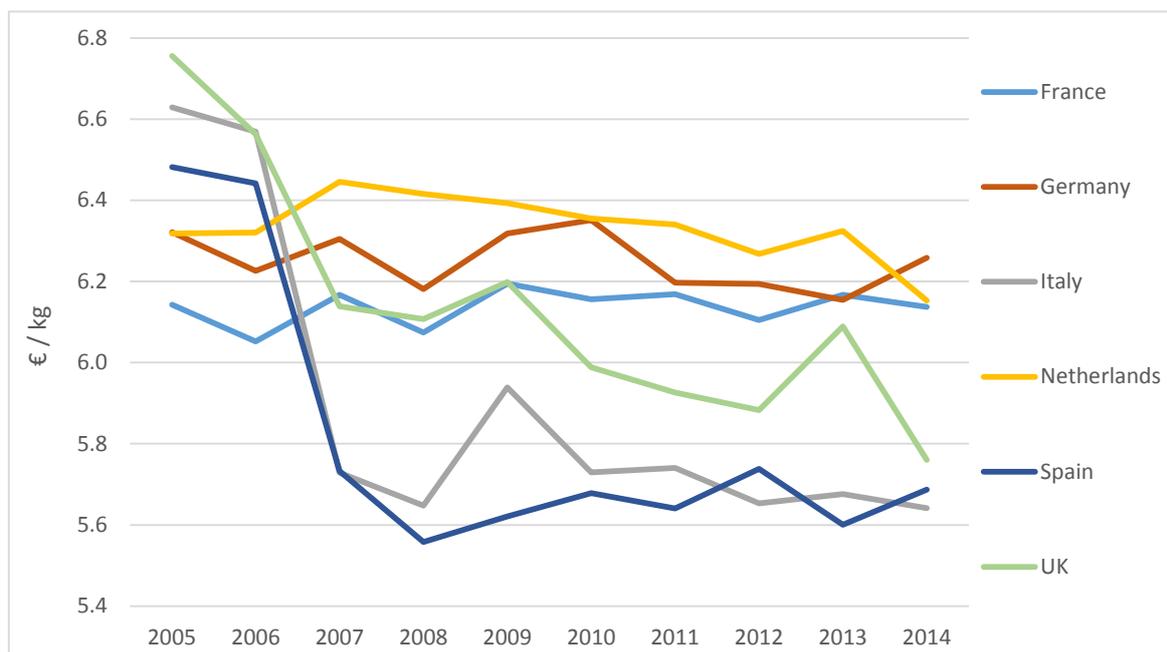


Source: Own calculations based on Eurostat Comext and Ameco data

The **product quality index** as Di Comite introduced it, captures the respective quality and completes the attributes of a product. The quality index is built upon two assumptions. Firstly, the degree of substitutability between different varieties (sectors) must not vary over time. At least for short time-periods and well-defined product categories this is plausible. Secondly, the weighted average quality within a market (country) must also not vary over time. In other words, the quality improvement in every sector has to follow the general country's trend in product improvement. Finally, the quality index is based on a reference market. Following Di Comite, we chose the EU 28 market as the reference which can be interpreted as the weighted average of all member states. Additionally, the quality index is built upon a regression with only ten data points (one for each year). This is due to the fact that monthly trade statistics are not very reliable. Yet, the respective estimates in the regressions even with only very little observations are significant in many cases.

Figure 3-4 shows the quality index for the same selection of countries and NACE code. While the quality index remained stable for the Netherlands, Germany, and France, it declined for the United Kingdom, Italy, and Spain after the year 2007 and remained on a lower level afterwards.

Figure 3-4: Product quality index of selected countries in C10 (manufacture of food products), 2005-2014



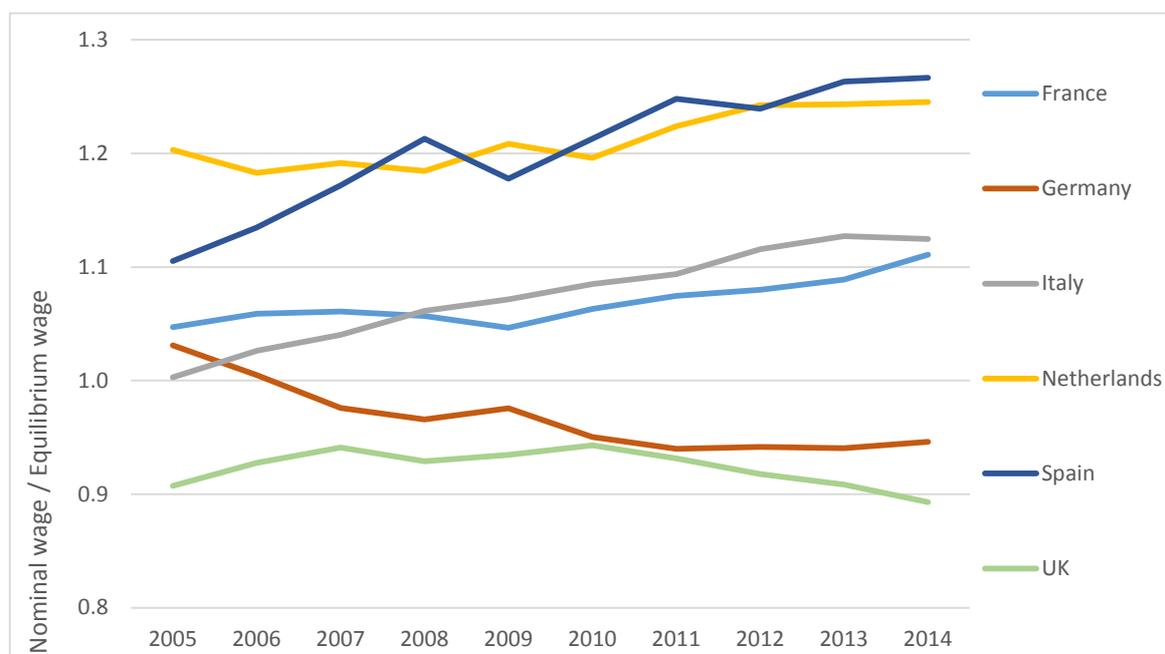
Source: Own calculations based on Eurostat Comext and Ameco data

To overcome the second drawback we compute an **equilibrium wage based measure** of competitiveness as suggested by Collignon and Esposito (2017). The idea of this concept is to measure competitiveness as the deviation of actual wage costs from nominal equilibrium wage levels of a sector. Therefore, following the argumentation of Collignon and Esposito (2017), wages above the equilibrium are

'overvalued' and may cause competitive disadvantages while wages below equilibrium are competitive and accelerate growth. In an ideal world, the equilibrium wage would match the nominal wage in every country over the years. We therefore use the measure equilibrium wage index by relating the equilibrium wage to the nominal wage in each country.

Figure 3-5 illustrates the development of the Equilibrium wage index over the years across all industries. For example Germany managed to decrease its equilibrium wages on a level below the nominal wages resulting in an index value below 1, while for the remaining countries (except the United Kingdom) the index stays above 1 and increases over time. This may be partly explained by the backwardness of German worker unions in collective bargaining and may in turn explain the strong role Germany has started to play over the recent decade.

Figure 3-5: Equilibrium wage index of selected countries at the economy level, 2005-2014



Source: Own calculations based on Eurostat Comext and Ameco data

However, these more sophisticated measures of competitiveness come at the cost of relatively higher data requirements and a more complex calculation as they are based on structural estimation approaches. In this section we therefore aim to analyse how precisely the traditional measures such as ULC, PULC (Physical Unit Labour Cost) or Export Price Indices, (i.e. indices based on the price paid to purchase a certain amount of a (manufacturing) good in the international market, measured for instance in €/kg) proxy the more complex measures.

The following tables (Table 3-1 to Table 3-6) display each country's individual rank for each measure over the years. In case of equilibrium wages not all data has been

available in all sectors and for all countries. In most of the cases the value cumulative stock, needed for the calculation, was missing. Therefore, we see missing values for the equilibrium wage index in some cells.

The top ten countries in each measure are shaded in bright blue while the countries ranked eleven to 20 are shaded medium blue and the remaining eight ranks are in dark blue. For the maps we calculated an overall rank over the seven measures and plotted the outcome for the year 2014, the last year in our panel. The shading of the countries on the map follows the shading scheme in the tables, where again the top ten countries are in bright blue, the middle group in medium blue and the last eight countries in darker blue.

In sector C10 (food products), Romania ranks first in ULC. In PULC and Export Prices, Slovenia is on the first place while Ireland ranks first in Labour Productivity. In Quality index and Selling Capacity these two countries are ranked rather lower while Malta and Germany respectively make the first places. The column for equilibrium wages is empty as for this section, the values for cumulative stock, needed to calculate the equilibrium wage was not available.

In sector C20 (chemicals and chemical products), Greece ranks first in terms of PULC and Export price. This is also reflected in equilibrium wage, where the country is second. However, its LP does not rank is the first group as well. In terms of quality index and selling capacity, Ireland and Belgium rank first places respectively.

In the industry C21 (pharmaceuticals), the Netherlands make the first place in PULC, export price and selling capacity. In ULC Ireland is first and in quality index it is Germany. The first place in equilibrium wage index takes the Czech Republic.

In industry C26 (computer, electronic and optical products), Romania ranks very well in the cost competitiveness indicators and a little weaker in the non-cost competitiveness indicators. In Non-cost competitiveness indicators, Ireland, France, and Austria perform best. Interestingly, Ireland is also first in ULC.

In industry C28 (machinery and equipment), Slovakia ranks first in Export Price and Ireland is again on number one for ULC. The best selling capacity value is shown by Germany, while Estonia has the best quality and the UK the best in equilibrium wages.

In industry C29 (motor vehicles), Greece is first in PULC and Export price. Again, Ireland shows the best value for ULC, the UK for Equilibrium prices, and Germany for selling capacity. Here, again we miss values for equilibrium wages (i.e. Belgium, France, Italy the Netherlands and Portugal) as we do not observe values for cumulative stock.

Table 3-1: Country rank for cost competitiveness indicators in industry C10 (manufacture of food products), 2014

	ULC	PULC	Export price	LP	Quality index	Selling capacity	Equilibrium wage index
Austria	4	6	13	10	21	11	.
Belgium	7	9	12	3	18	4	.
Bulgaria	9	4	3	27	6	13	.
Croatia	8	7	8	23	12	24	.
Cyprus	14	27	27	16	2	27	.
Czech Rep.	24	14	7	20	10	10	.
Denmark	23	23	25	4	14	12	.
Estonia	20	11	9	18	11	23	.
Finland	10	18	21	8	28	25	.
France	19	19	16	9	20	3	.
Germany	25	21	15	13	17	1	.
Greece	2	5	18	14	25	22	.
Hungary	15	8	6	21	9	9	.
Ireland	18	25	26	1	3	20	.
Italy	16	20	20	7	26	5	.
Latvia	28	15	4	25	5	19	.
Lithuania	21	16	10	24	13	18	.
Luxembourg	22	22	22	12	27	26	.
Malta	13	28	28	.	1	28	.
Netherlands	12	12	14	2	19	2	.
Poland	11	17	17	19	22	7	.
Portugal	17	13	11	17	16	15	.
Romania	1	2	2	26	7	14	.
Slovakia	6	3	5	21	8	16	.
Slovenia	3	1	1	15	4	17	.
Spain	5	10	19	11	24	6	.
Sweden	26	26	24	5	15	21	.
UK	27	24	23	6	23	8	.

Source: Own calculations based on Eurostat Comext and Ameco data

Table 3-2: Country rank for cost competitiveness indicators in industry C20 (manufacture of chemicals and chemical products), 2014

	ULC	PULC	Export price	LP	Quality index	Selling capacity	Equilibrium wage index
Austria	18	17	16	5	19	11	8
Belgium	26	19	17	2	16	1	3
Bulgaria	13	4	2	25	4	15	
Croatia	23	5	3	27	3	19	
Cyprus	27	20	18	23	20	27	
Czech Rep.	6	15	19	18	22	16	11
Denmark	11	24	26	7	23	23	4
Estonia	17	13	10	19	11	22	
Finland	16	10	7	6	9	12	5
France	24	25	24	10	28	5	6
Germany	25	22	22	9	26	3	7
Greece	3	1	1	15	2	13	2
Hungary	8	9	11	14	13	9	
Ireland	1	28	28	1	1	28	
Italy	19	23	23	11	27	7	10
Latvia	10	7	9	28	12	24	
Lithuania	4	3	4	22	6	10	
Luxembourg	28	27	27	13	7	26	
Malta	20	6	5	21	5	25	
Netherlands	12	14	12	3	14	2	1
Poland	9	12	13	20	15	6	
Portugal	14	8	8	17	10	14	12
Romania	2	2	6	26	8	18	
Slovakia	5	11	14	24	18	20	
Slovenia	22	21	20	16	21	21	
Spain	15	16	15	12	17	4	
Sweden	7	18	21	4	25	17	
UK	21	26	25	8	24	8	9

Source: Own calculations based on Eurostat Comext and Ameco data

Table 3-3: Country rank for cost competitiveness indicators in industry C21 (manufacture of pharmaceutical products and pharmaceutical preparations), 2014

	ULC	PULC	Export price	LP	Quality index	Selling capacity	Equilibrium wage index
Austria	18	11	8	6	27	9	9
Belgium	26	15	13	2	18	5	8
Bulgaria	13	23	22		11	21	
Croatia	23	22	19	16	14	20	
Cyprus	27	27	27	17	6	27	
Czech Rep.	6	25	25	19	8	24	1
Denmark	11	12	12	5	20	10	5
Estonia	17	7	6	21	4	22	
Finland	16	8	7	3	3	12	3
France	24	16	16	11	17	6	11
Germany	25	6	4	9	1	2	12
Greece	3	9	14	15	21	15	10
Hungary	8	24	24	13	9	19	
Ireland	1	4	10	1	26	7	
Italy	19	5	5	8	2	3	6
Latvia	10	21	21		12	25	
Lithuania	4	2	3	12	28	11	
Luxembourg	28	28	28		5	28	
Malta	20	13	9		23	18	
Netherlands	12	1	1	7	22	1	2
Poland	9	17	18	18	15	14	
Portugal	14	14	15	14	19	16	4
Romania	2	19	23	20	10	23	
Slovakia	5	10	11	22	24	17	
Slovenia	22	26	26		7	26	
Spain	15	3	2	10	25	4	
Sweden	7	20	20		13	13	
UK	21	18	17	4	16	8	7

Source: Own calculations based on Eurostat Comext and Ameco data

Table 3-4: Country rank for cost competitiveness indicators in industry C26 (manufacture of computer, electronic and optical products), 2014

	ULC	PULC	Export price	LP	Quality index	Selling capacity	Equilibrium wage index
Austria	18	14	13	5	1	12	10
Belgium	26	18	16	4	18	14	7
Bulgaria	13	8	9	24	3	19	
Croatia	23	1	1	19	17	8	
Cyprus	27	27	27		7	28	
Czech Rep.	6	15	15	20	21	13	12
Denmark	11	23	22	6	12	20	6
Estonia	17	26	26	21	8	26	
Finland	16	19	18	11	16	18	1
France	24	5	2	7	19	1	11
Germany	25	9	8	8	28	2	8
Greece	3	11	14	12	24	23	2
Hungary	8	22	21	16	13	16	
Ireland	1	17	25	1	9	21	
Italy	19	7	6	10	26	3	9
Latvia	10	21	20	15	14	25	
Lithuania	4	12	17	23	22	22	
Luxembourg	28	16	10		2	15	
Malta	20	28	28		6	27	
Netherlands	12	20	19	3	15	7	4
Poland	9	10	11	22	5	10	
Portugal	14	24	23	18	11	24	5
Romania	2	2	5	25	25	9	
Slovakia	5	6	7	14	27	6	
Slovenia	22	4	3	17	20	11	
Spain	15	3	4	12	23	4	
Sweden	7	25	24	2	10	17	
UK	21	13	12	9	4	5	3

Source: Own calculations based on Eurostat Comext and Ameco data

Table 3-5: Country rank for cost competitiveness indicators in industry C28 (manufacture of machinery and equipment), 2014

	ULC	PULC	Export price	LP	Quality index	Selling capacity	Equilibrium wage index
Austria	18	20	20	7	9	14	9
Belgium	26	24	22	1	5	12	3
Bulgaria	13	10	10	27	24	20	
Croatia	23	15	13	22	26	22	
Cyprus	27	28	28	15	11	28	
Czech Rep.	6	11	12	19	27	9	11
Denmark	11	13	15	12	3	13	10
Estonia	17	22	24	18	1	25	
Finland	16	19	18	10	8	18	5
France	24	16	14	11	28	4	7
Germany	25	18	16	8	2	1	8
Greece	3	1	2	26	16	19	12
Hungary	8	5	6	14	19	7	
Ireland	1	26	27	3	12	26	
Italy	19	14	11	9	25	2	6
Latvia	10	7	7	25	20	21	
Lithuania	4	12	17	23	6	23	
Luxembourg	28	25	21	4	4	24	
Malta	20	27	26		13	27	
Netherlands	12	23	25	2	23	15	4
Poland	9	8	8	21	21	6	
Portugal	14	9	9	16	22	17	2
Romania	2	3	5	24	18	11	
Slovakia	5	2	1	20	14	5	
Slovenia	22	6	3	17	15	10	
Spain	15	4	4	13	17	3	
Sweden	7	17	23	6	10	16	
UK	21	21	19	5	7	8	1

Source: Own calculations based on Eurostat Comext and Ameco data

Table 3-6: Country rank for cost competitiveness indicators in industry C29 (manufacture of motor vehicles, trailers and semi-trailers), 2014

	ULC	PULC	Export price	LP	Quality index	Selling capacity	Equilibrium wage index
Austria	18	22	21	3	1	15	7
Belgium	26	25	24	6	4	12	
Bulgaria	13	6	5	25	12	18	
Croatia	23	11	8	23	15	21	
Cyprus	27	28	28	20	7	28	
Czech Rep.	6	9	11	13	20	5	5
Denmark	11	3	3	9	10	10	4
Estonia	17	14	14	19	22	22	
Finland	16	27	27	11	8	25	3
France	24	17	15	8	21	4	
Germany	25	23	20	2	28	1	2
Greece	3	1	2	21	11	23	6
Hungary	8	8	10	12	18	6	
Ireland	1	19	25		6	27	
Italy	19	10	9	10	16	2	
Latvia	10	12	13	18	23	24	
Lithuania	4	4	4	24	13	20	
Luxembourg	28	2	1		9	9	
Malta	20	13	12		19	26	
Netherlands	12	24	23	4	5	19	
Poland	9	7	6	17	14	3	
Portugal	14	16	18	16	26	17	
Romania	2	5	7	22	17	7	
Slovakia	5	21	22	14	2	14	
Slovenia	22	18	16	15	24	16	
Spain	15	20	19	7	27	8	
Sweden	7	15	17	5	25	11	
UK	21	26	26	1	3	13	1

Source: Own calculations based on Eurostat Comext and Ameco data

Having analysed these six sectors, some reoccurring patterns can be identified. Ireland seems to be leading in ULC while performing rather weak in the remaining measures. Slovenia and Slovakia show very good ranks for PULC and Export price, which in the end ensures them very good overall rankings. Germany seems to have very good distribution channels as it ranks very well in selling capacity in most industries. Finally, the UK has undervalued wages as it often ranks first in the equilibrium wage index.

Next, we compare the different measures by computing rank correlations over time and sectors sector. In Table 3-7 we report the respective outcomes where the first entry is the rank correlation coefficient and the second entry shows the respective observations. The shading of the cell indicates the confidence interval. A shade of bright blue represents the ten per cent confidence interval, the medium blue the five per cent confidence interval, and the dark blue the one per cent confidence interval.

Table 3-7: Rank correlations of cost competitiveness indicators across the introduced sectors

	ULC	PULC	Export price	LP	Quality index	Selling capacity
ULC	1 1680					
PULC	0.3527 1680	1 1680				
Export Price	0.1121 1680	0.9256 1680	1 1680			
LP	-0.1795 1072	-0.3914 1072	-0.4236 1072	1 1072		
Quality index	-0.0087 1680	-0.1447 1680	-0.0973 1680	-0.0796 1072	1 1680	
Selling Capacity	-0.0699 1680	0.3857 1680	0.4139 1680	0.3391 1072	-0.297 1680	1 1680

10% conf. interval
 5% conf. interval
 1% conf. interval

Source: Own calculations based on Eurostat Comext and Ameco data

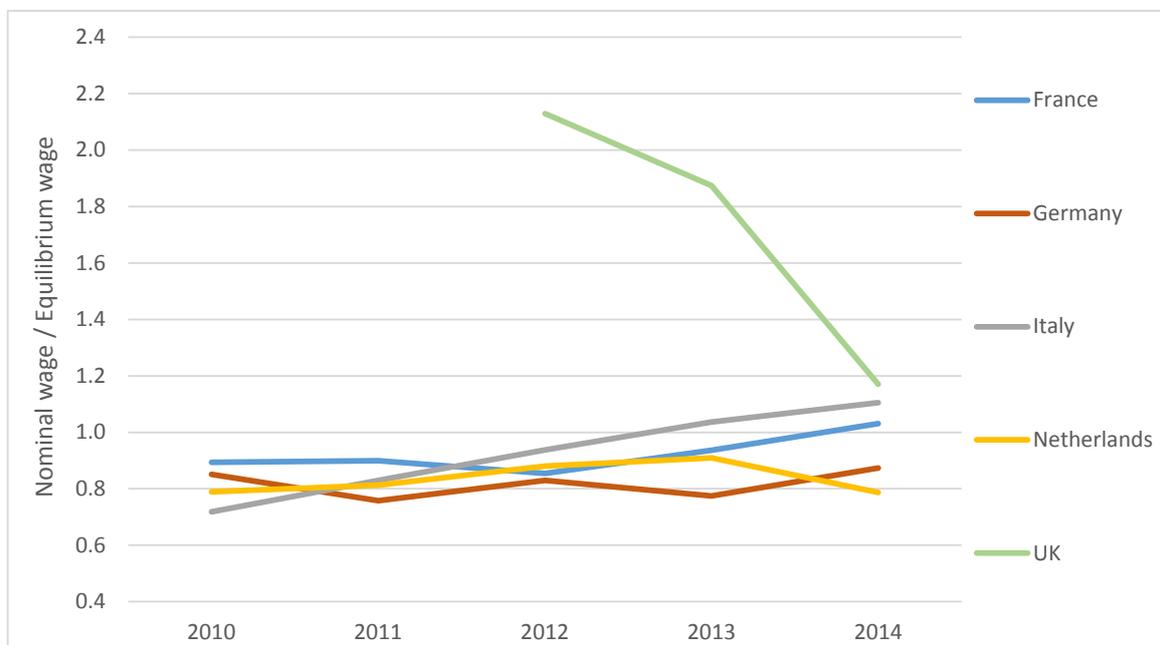
The cost competitiveness indicators ULC, PULC and Export prices are often strongly and significantly correlated with each other. This indicates that these indicators can be used interchangeably and can also act as a proxy for each other. The Labour Productivity also correlates positively with these mentioned cost competitiveness measures, however to a lower extent. The most interesting part of this analysis is however that the quality index is mostly correlated negatively with the cost competitiveness indicators. In this respect it is an inevitable aspect of competitiveness as without this measure the picture would be incomplete as countries with low labour costs would always perform very well and would therefore be seen as very competitive. In contrast countries with rather higher wages such as France, the Netherlands and Sweden manage to produce products of higher quality and by doing so compensate the relative inferiority in cost competitive measures. The selling capacity in turn adds a very interesting further aspect by

measuring all the other aspects apart from labour costs and quality like distribution channels and can therefore be interpreted as a proxy for managerial skills. Interestingly, Germany performs very well in this dimension of competitiveness. So, selling capacity reflects very well the recent relative economic strength of Germany and can therefore be seen as an insightful measure.

To close the section we explore some selected service sectors in terms of their competitiveness. As there is no data available for GVA and other variables and therefore the cost and non- cost competitiveness indicators as described by Di Comite cannot be constructed, we focus on equilibrium wages. So, Figure 3-6 to Figure 3-10 show the equilibrium wage index for engineering, underground engineering, accommodation, telecommunication, and research for selected countries. Spain had to be dropped as there was no information available for this country.

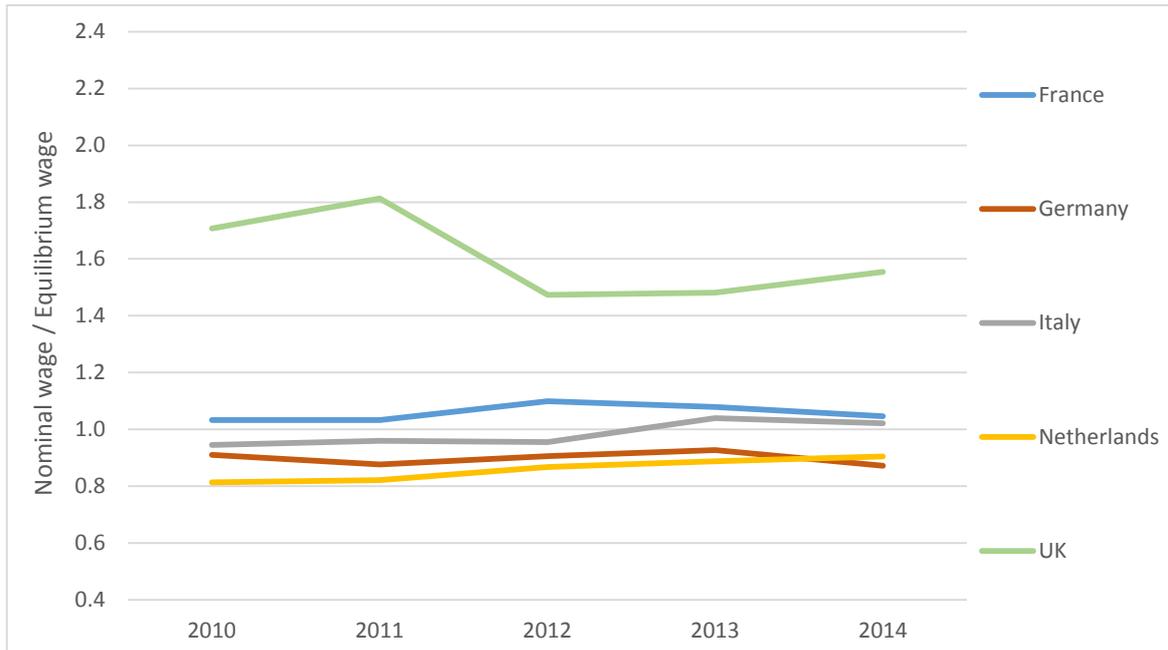
In contrast to the industrial sectors, where the UK was in the top group, the country shows a worse equilibrium wage index. Yet, the country's development shows a convergence to unity closing the gap to the other countries. In the sector I55 – Accommodation, Italy shows the highest and therefore worst index and it is also increasing at the end of the observation period. The remaining countries are all very comparable around 1 or between 0.5 and 1.

Figure 3-6: Equilibrium wage index of selected countries in sector F41 (construction of buildings), 2010-2014



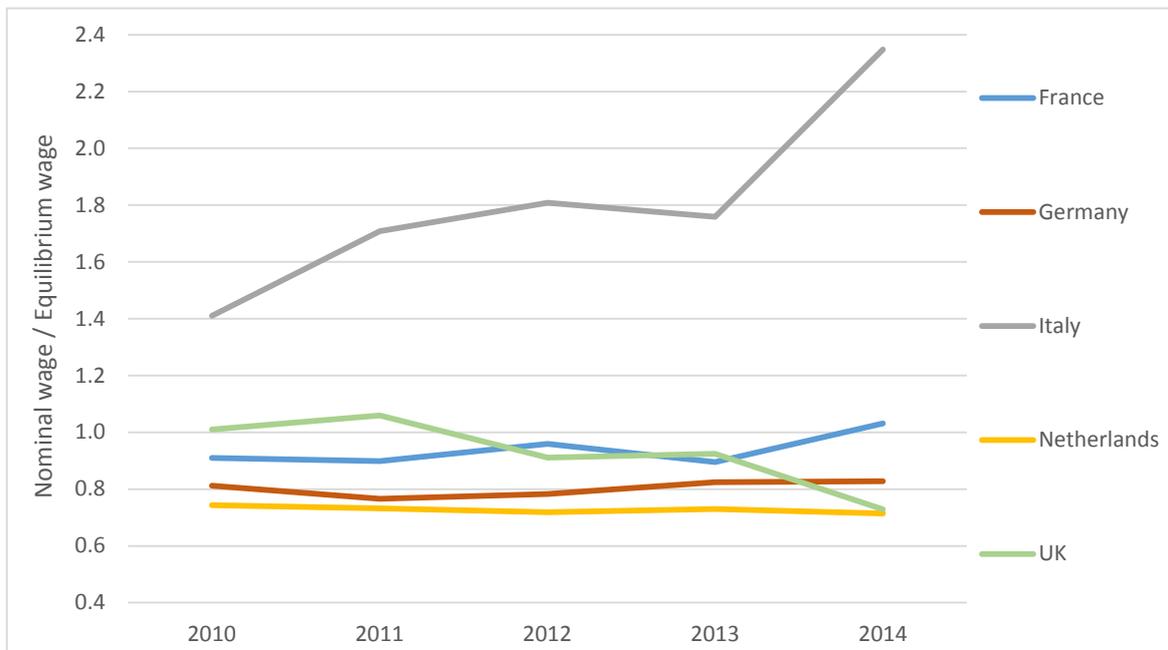
Source: Own calculations based on Eurostat Comext and Ameco data

Figure 3-7: Equilibrium wage index of selected countries in sector F42 (civil engineering), 2010-2014



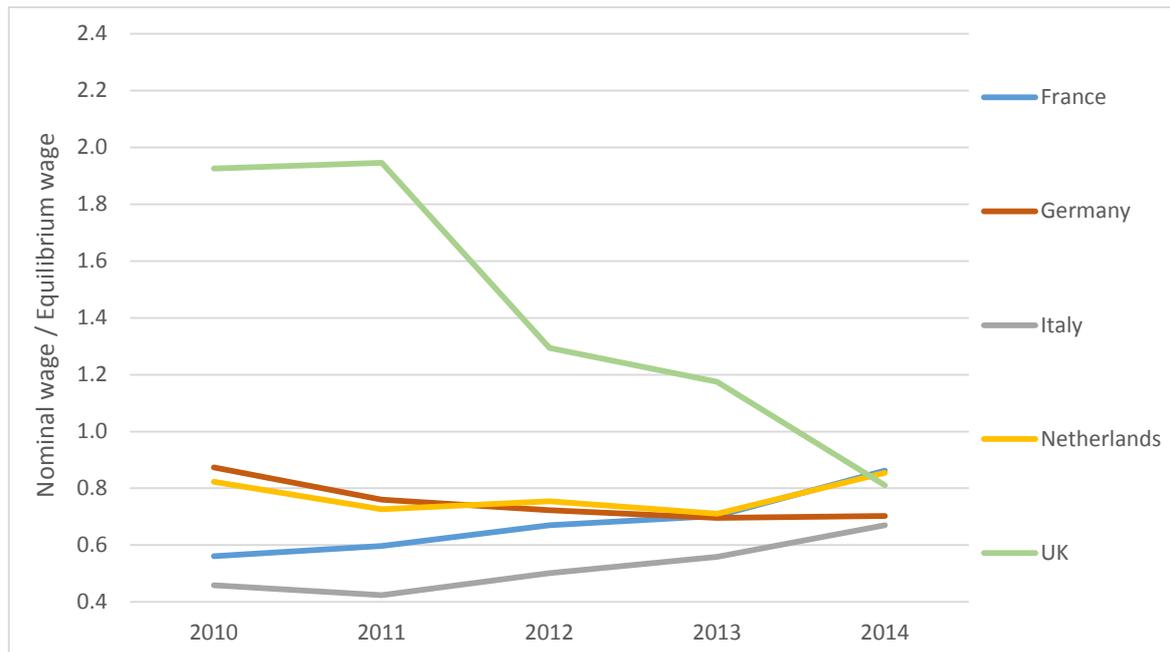
Source: Own calculations based on Eurostat Comext and Ameco data

Figure 3-8: Equilibrium wage index of selected countries in sector I55 (accommodation), 2010-2014



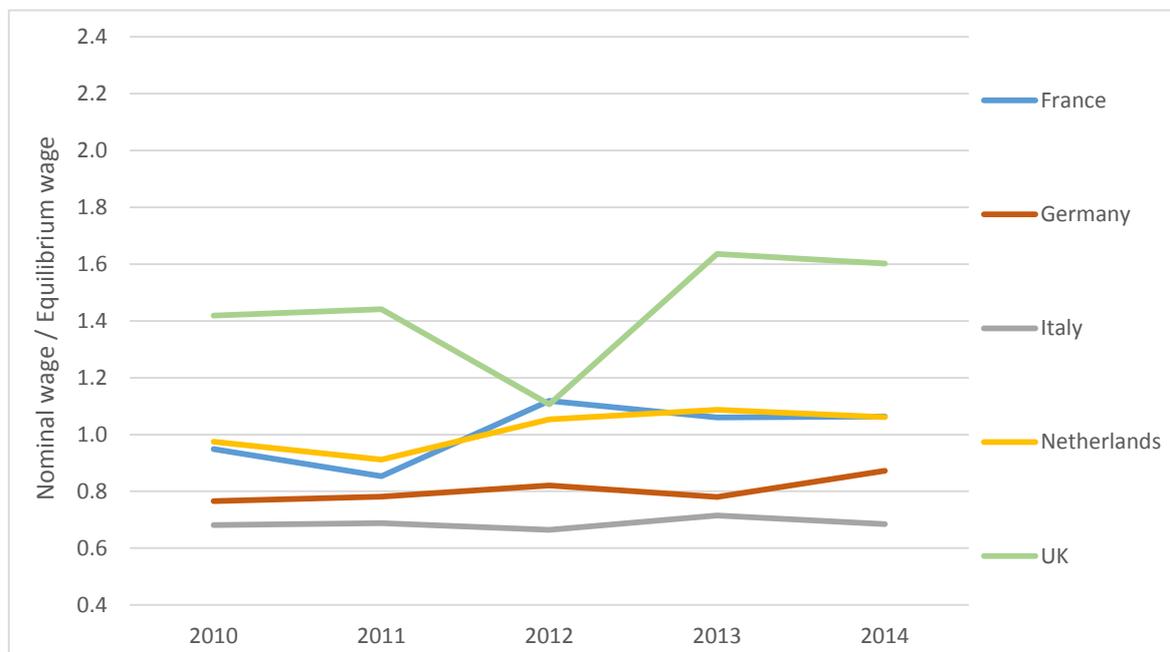
Source: Own calculations based on Eurostat Comext and Ameco data

Figure 3-9: Equilibrium wage index of selected countries in sector J61 (telecommunications), 2010-2014



Source: Own calculations based on Eurostat Comext and Ameco data

Figure 3-10: Equilibrium wage index of selected countries in sector M72 (scientific research and development), 2010-2014



Source: Own calculations based on Eurostat Comext and Ameco data

3.1.4 Conclusions

To conclude, we recommend the use of ULC complemented by the quality index and the selling capacity to evaluate a country's or industry's cost competitiveness. These three measures provide an integrated overview of the cost competitiveness because each measure looks at a specific aspect of cost competitiveness. Even though ULC comes with the drawback that a substantial disequilibria can exist depending on the starting year and that ULC only cover labour earnings not considering the other components that generate added value, ULC is the benchmark that evaluates the cost level in relation to GDP. The quality index captures the quality of a product. ULC might be high in certain cases but the quality produced might be as well. Evaluating only the costs might be misleading in such cases. Additionally, these two are complemented by the selling capacity, capturing everything else but quality and costs like export channels or reputation. As these aspects are very important as well the selling capacity cannot be neglected. Also, the selling capacity is rather easy to assess and has turned out to be a very stable measure.

Finally, the equilibrium wage index can be an insightful additional measure also to give advice in collective bargaining or to evaluate the outcome of recent negotiations on wages. The advantage of the equilibrium wage index is that it can also be used for service sectors with the downside that it holds several missing values.

3.2 Innovation-related Competitiveness

Bettina Peters and Christian Rammer

3.2.1 Motivation

In Section 2.1, we argued that innovation is a key determinant for the competitive potential of firms. Product innovation allows for differentiating a firm's product from competitor's product, avoiding price competition and allowing for providing the firm with unique selling propositions in the market. Process innovation often results in lower unit costs of products, providing the innovator with a price advantage. Process innovation may also contribute to product differentiation, particularly in services, if new or improved processes allow for higher levels of customisation, flexibility or user-friendliness of products. Marketing innovation typically act in a similar way as product innovation as they contribute to product differentiation while organisational innovation has similar competitive impacts as process innovation.

At the sector level, the role of innovation for competitiveness is even more prominent than at the firm level for two reasons:

- First, spillovers of innovative ideas complicate the appropriability of returns from innovation. If an innovative solution developed by a firm is quickly copied or adopted by other firms in the same market, the innovator will gain little if any competitive advantage. For the entire sector however, rapid spillovers of innovative ideas will strengthen the competitiveness of the sector since many firms use more sophisticated products or processes and may be able to serve the needs of buyers in a better way. If innovation spillovers are regionally bounded (which they often are due to the tacit nature of knowledge, requiring personal contact for exchanging the knowledge), a sector with high spillovers will gain competitiveness over sectors in other regions.
- Second, firms frequently compete over innovative solutions, and often only one firm finally succeeds and is able to appropriate the innovator's rent, either by being the fastest (described as 'patent races' in the literature, see Shapiro, 1985; Denicolò, 1996) or by developing an innovation design that becomes the dominant design in the market (see Beise, 2004; Bartlett and Ghoshal, 1990). The other firms end up with high costs for developing innovative solutions but with no improvement of their competitive situation. At the sector level however, the enlarged pool of knowledge produced by unsuccessful innovators may stimulate future innovation. In addition, some innovation designs that did not succeed in the firms' target market may be successful in other regional markets. Hence a sector with a fierce competition for the innovative solutions is likely to gain more in terms of competitiveness than a sector with a lower level of innovative efforts, even if many of the innovative firms are unsuccessful with their efforts.

The European Commission and the EU Member States have acknowledged the special importance of innovation for competitiveness by considering innovation as a key pillar of both the Lisbon Strategy and its successor, the Europe 2020 Strategy. In addition, the European Commission is publishing a monitoring system of the innovative capacity and performance of EU Member States, the European Innovation Scoreboard (EIS).

The purpose of this section is to discuss the availability and validity of indicators for innovation-related competitiveness at the sector level. Analysing innovation-related competitiveness at the sector level adds important information as compared to an analysis on the country level only. Since resources for innovation tend to be particularly scarce (e.g. talented people, highly skilled researchers, venture capital, capacity for co-operation in public research), many national economies tend to focus their innovative capacities and a smaller number of sectors in order to achieve a critical mass for innovation. If such a sector specialisation in innovation is in place, it tends to be reinforced by adjustment in institutions to the specific needs of these innovative sectors (including the education and science systems, financial markets, regulation, policy support). An analysis at the country level may overlook innovative hotspots in a few (often small) sectors and hence underestimate the role of innovation for competitiveness of countries in particular sectors.

3.2.2 Data Sources

For measuring innovation-related competitiveness and establishing indicators that are comparable across countries and time, several data sources are available. We focus on indicators that have been discussed in section 2.1.3 as determining the competitive potential through innovation. These include the development and introduction of product and process innovation, the investment into these activities (especially R&D), and the use of protection mechanisms to protect the innovative outcome (IPRs). Three data sources are of particular relevance in this respect:

- Data on research and development (R&D) activities
- Data on the use of intellectual property rights (IPRs)
- Data on innovation activities collected through the Community Innovation Surveys (CIS)

In contrast to the EIS, we refrain from considering indicators on 'enablers of innovation' such as human resources, science, and financing of innovation (venture capital) as these are no direct indicators of innovation-related competitiveness. For the same reason, we also do not consider indicators on outcomes and impacts of innovation such as the growth of high-tech sectors or knowledge-intensive services.

All data sources are discussed with respect to providing data at the sector level for the business enterprise sector. Innovation indicators not related to the competitiveness of economic sectors within the business enterprise sector are therefore excluded (e.g. diffusion of certain technologies in the household sector).

R&D Activities

Data on R&D activities are collected by Eurostat based on R&D surveys conducted by Member States. R&D data include **in-house expenditure for R&D** (broken down by source of funds and by type of expenditure) as well as the **number of R&D employees** (broken down by sex and by professional position (researchers, other R&D personnel)).

R&D data are available for all NACE rev. 2 sectors starting in 2005. For previous years (starting in 1993), sector breakdown by NACE rev. 1 is available. For manufacturing, sector data are available at the division and, for some divisions, at the group level. For other economic sectors, breakdowns are less detailed, except for section J (information and communication).

When linking R&D data with other sector level data (e.g. total employment, value added, gross production) one has to take into account that R&D data may be collected not at the enterprise level, resulting in inconsistencies between R&D and other economic data at the sector level.

Data on R&D activities by sector are also available for non-EU countries. Eurostat includes some non-EU countries in its reporting tables (e.g. US, Japan, Korea, China, Brazil, Russia, Switzerland, Norway, Turkey). Data for other OECD countries are available through the OECD database ANBERD (Analytical Business Enterprise R&D database).

R&D data are generally viewed as highly reliable. International comparability is also regarded as very good. R&D data at sector level suffer from non-disclosure due to confidentiality regulations. This is particularly true for smaller countries with only a few R&D performing firms per sector.

Comparability of R&D data across sectors is hampered by variations in the way the R&D process is organised in an industry. If the share of outsources (contracted-out) R&D is high, R&D data underestimate the actual R&D activity in a sector. In addition, the nature of R&D varies substantially across sectors. In some sectors like automotive and other vehicles, a large fraction of R&D costs refer to testing and engineering design while in other sectors such as chemicals, the main part of R&D is close to scientific research.

A major drawback of R&D as an indicator for innovation-related competitiveness is its input character. R&D is an activity usually targeted at innovations, but it is not an indicator for having arrived at innovation. R&D therefore is a proxy for the amount of (technological) knowledge that may be produced and that could be used for developing and introducing innovation.

Data on IPRs

The use of intellectual property rights (IPRs) is generally viewed as a throughput indicator between the generation of new knowledge (R&D) and its transfer into innovation (see Griliches, 1990). The most commonly used IPR indicator is patents. Recently, also trade mark and design applications have been used as innovation indicators (see Schmoch and Gauch, 2009; Jensen and Webster, 2004). The main advantages of patent, trade mark and design data is their nature as register data. All applications are registered and published by authorities (usually patent and trade mark offices). The difficulty in using these data is mainly related to the choice of offices to be considered. As national regulations for applying for patents, trademarks and designs vary, the number of applications cannot be directly compared between offices nor simply added across offices.

For **Patent data**, different data sources can be used. Patents can be applied at national patent offices and at international patent offices (the European Patent Office (EPO) which offers patent protection for European countries, and the World Intellectual Property Organisation (WIPO), offering protection in all its member states through the so-called Patent Co-operation Treaty (PCT) procedure). Since national applicants tend to apply patents primarily at their national offices, application data from national offices usually have a home country bias. There are different procedures to avoid this bias. First, one could only consider applications only at the two international offices or only one of them. Secondly, one can consider only patents applied in all major parts of the world (either through national or international applications). A common approach is the so-called Triadic patent which counts patents that have been applied at the EPO, the US patent office and the Japanese patent office. Another approach is to count every single patent application at any office but avoid double counting by aggregating patent applications to patent families, each family is representing patents that rely on the same underlying invention.

For analysis of patent applications in Europe, considering only applications to the European Patent Office (EPO) is a straightforward choice which involves little biases across EU Member States, but underestimates patent activity of non-European applicants. Patent application data from the EPO are available from Eurostat broken down by NACE rev. 2 division. Patent applications are assigned to sectors based on a correspondence table that links codes of the International Patent Classification (IPC) to NACE division. The correspondence table basically rests on technological proximity between an IPC code and a NACE division (see Schmoch et al., 2003 for the underlying methodology). Patents are assigned to all manufacturing (section C) divisions except 33, to divisions 42 and 43 of section F (construction) and to division 62 (computer programming). Patent data are hence not available for almost all service sectors. Using IPC, patent data can also be assigned to fields of technology, e.g. ICT, nanotechnology, biotechnology or energy technologies.

Patent data are only available with a time lag of two to three years owing to the fact that patent applications are disclosed not earlier than 18 months after the application date or the earliest priority date.

Trademark data and **design** are available from Eurostat based on applications at the European Union Intellectual Property Office (the former Office for the Harmonisation of the Internal Market) and represent Community Trademarks and Community Designs. As for patent applications, these data are useful for comparing sectors of European countries but are not useful for comparisons with sectors from countries outside Europe.

Neither trademark nor design data are available for NACE sectors. For both IPRs, classification schemes exist that can be broadly linked to economic sectors based on the NACE scheme:

- For trademarks, the so-called Nice classification contains 45 classes which are reported in the Eurostat database. The classes refer both to manufacturing products and service products, though the degree of detail is much greater for manufacturing products (34 classes) than for services (11 classes).
- For designs, the so-called Locarno classification offers 32 different classes which are reported in the Eurostat database. The classes mainly comprise consumer goods as well as some generic categories (e.g. graphic symbols).

A main drawback of all IPR-related indicators is their loose link to innovation. While many innovations are not protected by any IPR, many IPRs do not protect innovation (see Griliches, 1990). Another drawback is that the innovative content of a single IPR varies substantially. For example, while some patents are essential for a breakthrough innovation, many others have no economic value while others are only used strategically, e.g. to block inventive activities of other firms. There is no established way of weighting patents or other IPRs by their innovative or economic importance, though many attempts have been made (Hall and Harhoff, 2012; Gambardella et al., 2008).

Innovation Activities (CIS)

The best data source for obtaining indicators on innovation-related competitiveness in sectors across Europe is the Community Innovation Survey (CIS). The CIS is a data collection exercise co-ordinated by Eurostat and conducted in all member states and a number of other European countries (in 2014: Iceland, Norway, Switzerland, Turkey). It started in 1992, with follow-up surveys in 1996, 2000 and 2004. Since then, the CIS is conducted biennial based on a EU regulation. The main purpose of the survey is to collect data on innovation activities of firms, covering both inputs and outputs, and the way innovation activities are organised. The CIS targets enterprises with 10 or more employees in NACE sections B to E, H, J and K and in divisions 46, 71, 72 and 73. Survey data are weighted to represent the total population of firms in the respective sectors and size class.

The CIS contains a variety of indicators on innovation-related competitiveness:

- Number of **firms having introduced innovations** (differentiated by the type of innovation: product, process, marketing, organisational)
- **Expenditure for innovation** (differentiated by type of expenditure: in-house R&D, external R&D, machinery/equipment/software, other external knowledge, other)
- **Volume of sales from product innovation** (differentiating by the degree of novelty: new-to-the-market, only new-to-the-firm)
- Characteristics of the **organisation of product or process innovation activities**:
 - o number of firms conducting certain types of innovation activities
 - o number of firms pursuing certain objectives of innovation
 - o number of innovative firms engaged in innovation cooperation
 - o number of innovative firms using certain types of information sources for their innovation activities
 - o number of innovative firms having received public funding for innovation
 - o number of innovative firms with product or process innovations that have been developed alone, jointly with others, or completely by others
- Information on **other innovation-related activities**:
 - o number of firms using certain protection methods for their IP
 - o number of firms reporting certain hampering factors for innovation as important

Some of these indicators vary by survey year or are excluded in certain survey years. In addition to these indicators, additional indicators are included in a single survey year ("one-off modules"). In the past, these additional indicators covered environmental innovation, skills and creativity for innovation, goals and strategies of firms.

CIS data are reported for NACE rev. 2 divisions from 2008 on. In previous years, data were reported for NACE rev. 1 divisions.

CIS-based indicators share a number of drawbacks that have restricted their use in policy analysis, including the European Semester:

- Many indicators refer to the number of firms and are hence driven by the activities of small firms since small firms represent the vast majority of all firms. Since their economic significance in terms of employment or value added is often limited, indicator results may be misleading.
- The definition of innovation, which is based on the Oslo Manual recommendations, is subjective in nature. As a result, the same event (e.g. the introduction of a product that is different from previously offered products) may be considered as an innovation in one firm, but not in another. What is more, the perception of what an innovation is may differ among managers within the same

firm, potentially resulting in divergent responses for the same firm if respondents in the firm change.

- Some key indicators such as the sales volume from product innovation (i.e. sales from product innovations not older than 3 years) strongly depend on market structure and other characteristics of the product market. For example, if product life cycles are short, the indicator will be high. The novelty measure for product innovation, new-to-the-market, heavily depends on the geographical demarcation of markets. Firms only active in local markets are more likely to report higher figures than firms serving the world market. Also the number of competitors, the volume of demand, the type of competition and the competitive strategy of the firm affect this indicator.
- The indicator on innovation expenditure suffers from the fact that many firms have no accounting or reporting system for innovation in place. As a consequence, innovation expenditure figures often represent rough estimates or cover only a fraction of all expenditure. This may be particularly the case for firms with significant R&D expenditure. They may only report R&D expenditure as innovation expenditure, but not expenditure for intangible investment, marketing or other non-R&D activities related to innovation.
- Some important aspects of innovation performance are not covered in CIS data, including output indicators on process innovation. While some countries collect such indicators, e.g. the cost reduction that has been achieved from process innovation (Belgium, Germany, Switzerland), they are not part of the harmonised CIS questionnaire.
- There are only few non-European countries that collect innovation data that would be directly comparable to the CIS-based data, including Japan. Other non-European countries collect innovation data based on divergent definitions (e.g. Canada, Australia). The United States have not engaged in a comparable data collection effort yet, though the 2010 R&D survey contained some innovation data. It is planned, however, that a CIS-like innovation collection activity will be carried out in 2018 in the USA.

Further data quality issues of CIS indicators refer to the sample design of the survey. Particularly at the level of individual sectors, sample sizes in some countries are small, resulting in a lower level in statistical accuracy of the reported data. As a consequence, for many sectors in many countries, no indicators are available. More details on quality issues of CIS data are discussed in section 4.6.3.

3.2.3 *Empirical Analysis of Indicators*

In this section, we examine a set of innovation indicators that are potentially relevant for competitiveness analyses at the sector level in the context of the European Semester. The selected indicators cover all three areas discussed above. We focus on those indicators that have been frequently used in the past to assess the innovative performance of countries, regions or sectors, including exercises such as

the European Innovation Scoreboard. We consider only indicators for which data at the NACE division (2-digit) level are available. In the area of IPRs, this implies that no indicators on trademarks or industrial designs can be used since these indicators cannot be readily broken down by NACE classifications while indicators on patenting are available for manufacturing sectors only (plus computer programming). The following eight indicators are considered:

R&D

- R&D expenditure as a share of value added in the sector
- R&D personnel as a share of total employment in the sector

Use of IPRs

- EPO patent applications per employed persons¹⁴

Innovation input and output, organisation of innovation activities

- Innovation expenditure as a share of total sales
- Share of firms conducting R&D in-house continuously
- Share of firms having introduced any type of innovation
- Share of sales from total product innovations
- Share of product/process innovative firms with innovation cooperation

The indicator analysis focuses on three main aspects: (a) descriptive results for each indicator for selected sectors, (b) the robustness of the measures with respect to the stability of results over time (in terms of ranking of Member States by sector), and (c) the similarity (or dissimilarity) of results for different indicators by examining the correlation between indicators.

The analysis is conducted at the level of sectors and countries for the time period 2008 to 2014. We focus on the following subset of NACE divisions: C13, C20, C21, C22, C25, C26, C27, C28, C29, C30, H, J58, J62, M71 and M72. The choice of these sectors has been motivated by two considerations. First, data for these sectors are rather complete across countries and time for most indicators. Second, innovation is a relevant (or even dominating) factor of competitiveness.

For each indicator, an indicator fact sheet is produced that contains a brief assessment of the validity of the indicator in terms of measuring competitiveness, data availability and quality,¹⁵ and specific features of the indicator that should be considered when using the indicator for the European Semester (or other) analysis. The fact sheets are shown in the Appendix.

¹⁴ Alternatively, the number of patent applications may be related to value added. Using the number employed persons as reference is motivated by the fact that the main input to producing patents is (qualified) labour. Using value added would result in relatively lower patent intensity of sectors and countries with high labour productivity.

¹⁵ A more detailed analysis of data quality is carried out in section 4.6.2 for R&D and for CIS-based innovation indicators.

A. Descriptive Results

R&D expenditure as a share of value added in the sector

The indicator is defined as in-house R&D expenditure as a percentage of gross value added. It hence shows the R&D intensity of production. The higher the share, the more a sector's value added rests on new knowledge (assuming that R&D expenditures are effective in the way that they result in new knowledge).

Data on in-house R&D expenditure are taken from the R&D statistics while value added data are provided by structural business statistics (SBS). As the unit of observation may vary between R&D statistics and SBS, and as firms may be assigned to different sectors in the two statistics, the relation of the two data sources may produce inconsistent results. This is for example the case for C26 in Finland. For this sector (electronics), the share of R&D expenditure in value added exceeds 100% for the 2008 to 2014 period, probably because for some firms, R&D expenditures are assigned to C26, while their value added is assigned to a different sector.

The results by country and sector show that most countries report either high values or low values for most sectors, implying that differences in R&D intensity is rather a country-specific phenomenon (Table 3-8). At the same time, sector differences in R&D intensity are huge, with C21 (pharmaceuticals) and C26 (electronics) showing the highest R&D intensity in manufacturing. In some countries, also C30 (other vehicles incl. aircraft) and C29 (automotive) show very high R&D intensities. Some very high values in some sectors and countries (e.g. C29 in Germany or C27 in the Netherlands) may be caused to some extent by a difference in sector assignment in R&D statistics and SBS for some key R&D performers.

The M72 sector (scientific research and development) often shows R&D intensities above 100%. The reasons for this may again be differences in sector assignment of firms in R&D statistics and SBS. In addition, many firms in these sectors produce little market output and fund their R&D activities from attracting external financial funds, e.g. venture capital or public grants.

The coefficient of variation is highest for C26, implying that R&D intensities vary strongly across member states. While in some countries, the C26 sector is strongly focused on an R&D-based production, in other member states it is a sector with a low R&D intensity. The lowest coefficients of variation are found for C21 and J62 (computer programming), implying that member states have rather similar R&D intensities in these two sectors (though there are clearly some outliers).

Table 3-8: R&D expenditure as a share of value added by sector and member state (average 2008 to 2014)

	C13	C20	C21	C22	C25	C26	C27	C28	C29	C30	H	J58	J62	M71	M72
AT	2.6	9.2	14.9	7.3	3.1	28.1	20.5	11.3	15.2	17.3	0.1	2.3	7.1	n.a.	130
BE	3.6	5.1	33.2	4.6	2.3	32.7	12.5	7.5	3.8	21.1	0.1	2.5	5.4	n.a.	61
BG	n.a.	0.3	3.7	0.2	0.6	2.1	0.7	1.5	n.a.	1.3	0.0	0.1	1.1	n.a.	181
CY	n.a.	1.5	3.9	1.5	0.2	5.5	0.3	1.0	n.a.	2.6	0.0	0.2	3.8	n.a.	n.a.
CZ	1.7	3.3	10.0	1.2	0.9	5.6	2.8	4.0	3.4	10.7	0.0	1.9	5.5	n.a.	94
DE	1.9	9.6	24.4	4.1	1.7	29.0	4.6	6.6	24.0	24.1	0.1	n.a.	5.0	n.a.	21
DK	1.0	15.5	24.8	3.9	n.a.	21.4	7.9	13.2	4.4	3.2	0.1	6.5	10.9	n.a.	121
EE	0.6	3.4	12.8	1.4	0.2	2.3	1.8	1.6	1.7	n.a.	0.2	n.a.	14.5	n.a.	112
EL	0.4	2.2	12.3	0.4	1.4	14.1	2.8	1.8	n.a.	2.1	0.0	0.7	10.7	n.a.	22
ES	2.2	3.5	15.0	2.0	1.2	12.6	5.2	3.7	4.2	15.8	0.2	1.4	5.6	n.a.	125
FI	n.a.	8.2	13.4	3.8	1.9	153	17.4	11.2	5.9	8.5	0.2	3.5	10.2	n.a.	79
FR	4.2	6.8	9.3	6.7	3.3	33.3	8.6	7.6	14.5	25.9	0.1	7.5	5.6	n.a.	117
HR	0.0	1.4	13.0	0.2	0.2	1.3	1.0	0.4	46.4	1.0	0.0	0.3	1.7	n.a.	61
HU	0.9	1.8	17.7	0.7	0.9	3.1	2.6	1.6	2.7	1.4	0.0	1.4	6.2	n.a.	2
IE	n.a.	4.6	1.5	2.9	4.9	5.7	8.1	5.1	1.6	n.a.	0.0	n.a.	n.a.	n.a.	83
IT	1.8	4.0	6.9	2.6	1.2	19.9	4.5	4.1	14.4	19.7	0.1	0.2	2.5	n.a.	64
LT	0.1	2.8	13.6	0.3	1.5	7.6	2.0	2.3	3.1	0.4	0.0	n.a.	3.0	n.a.	85
LU	n.a.	4.6	n.a.	n.a.	1.2	n.a.	7.9	4.6	n.a.	n.a.	0.4	1.6	0.8	n.a.	n.a.
LV	6.0	1.8	8.5	n.a.	0.2	4.1	5.4	3.8	n.a.	n.a.	0.0	n.a.	1.6	n.a.	79
MT	n.a.	1.6	n.a.	n.a.	0.4	n.a.	2.0	n.a.	n.a.	n.a.	0.1	n.a.	4.1	n.a.	37
NL	1.7	8.5	14.6	2.8	1.3	18.9	28.5	11.8	7.3	5.4	0.3	n.a.	4.6	n.a.	20
PL	0.7	0.9	4.4	0.5	0.8	2.3	2.4	1.6	1.6	3.1	0.0	1.3	4.1	n.a.	57
PT	1.7	3.5	20.7	2.2	1.4	7.8	4.9	2.5	4.0	3.7	0.4	3.5	8.3	n.a.	42
RO	0.2	1.8	2.6	0.2	0.2	2.3	1.5	0.7	2.6	1.1	0.1	4.1	1.8	n.a.	20
SE	2.7	n.a.	19.6	1.9	3.0	42.6	13.3	11.1	n.a.	n.a.	0.2	n.a.	n.a.	n.a.	n.a.
SI	4.1	5.6	22.2	2.2	3.0	24.3	8.7	4.2	9.1	13.3	0.1	2.7	6.1	n.a.	62
SK	n.a.	1.6	7.7	1.4	0.5	0.5	3.2	1.4	2.4	10.8	n.a.	n.a.	2.3	n.a.	95
UK	0.8	3.3	5.9	1.2	4.2	12.4	3.4	8.7	11.2	12.7	0.0	0.6	3.5	n.a.	132
UAV	1.8	4.3	13.0	2.2	1.5	18.9	6.6	5.0	8.7	9.3	0.1	2.2	5.2	n.a.	76.1
CoV	85	80	61	86	84	158	100	79	120	89	110	93	65	n.a.	58

n.a.: not available; UAV: unweighted average across member states; CoV: Coefficient of variation.
Source: Own calculations based on Eurostat R&D and SBS statistics.

R&D personnel as a share of total employment in the sector

The share of R&D personnel in total employment is another measure of R&D intensity. In contrast to R&D intensity based on expenditure, it is not affected by variations in value added due to fluctuations in output prices. In addition, R&D expenditure related to investment in tangible assets (e.g. new laboratories) and the purchase of materials needed for R&D does not affect this indicator. The results in terms of sector rankings are similar to the R&D intensity based on expenditure. The most R&D intensive manufacturing sector based on R&D personnel data is again C26, followed by C21 and C30 (Table 3-9). A main difference is when comparing service and manufacturing sectors. J62 shows a significantly higher R&D intensity than C29 and C30, whereas for the expenditure based R&D intensity, C29 and C30 would appear as much more R&D intensive than J62.

There are no intensities above 100 percent, and there are also lower coefficients of variation. All in all it seems that R&D intensity based on personnel data provides somewhat more stable and consistent results than R&D intensity based on expenditure.

Table 3-9: R&D personnel as a share of total employment by sector and member state (average 2008 to 2014)

	C13	C20	C21	C22	C25	C26	C27	C28	C29	C30	H	J58	J62	M71	M72
AT	1.1	7.8	8.0	4.5	1.9	18.0	11.8	6.9	9.0	12.7	0.0	2.1	6.1	n.a.	64.5
BE	2.0	4.8	19.7	2.8	1.4	22.0	8.3	5.2	2.1	10.1	0.1	1.4	4.6	n.a.	36.4
BG	n.a.	0.6	2.6	0.1	0.4	1.7	0.5	0.7	n.a.	0.5	n.a.	0.0	1.1	n.a.	77.4
CY	n.a.	1.1	3.9	0.9	0.1	9.3	0.1	0.8	n.a.	1.3	0.0	0.6	4.6	n.a.	n.a.
CZ	0.6	2.8	5.9	0.8	0.4	3.6	1.6	2.3	2.4	3.7	0.0	2.0	5.8	n.a.	60.4
DE	0.9	6.8	16.1	2.0	0.9	17.4	3.2	3.8	11.6	10.3	0.0	n.a.	3.2	n.a.	11.4
DK	0.7	12.6	23.7	2.4	0.3	17.4	5.6	5.9	2.4	1.2	0.1	4.1	8.7	n.a.	34.3
EE	0.2	2.4	4.2	0.4	0.1	1.5	1.0	0.7	0.9	n.a.	0.0	n.a.	7.5	n.a.	43.0
EL	0.2	2.2	6.6	0.2	0.8	13.3	1.2	0.7	n.a.	2.6	0.0	0.2	6.2	n.a.	5.5
ES	1.2	4.1	11.8	1.4	0.7	11.0	4.1	3.2	2.6	8.9	0.1	1.4	5.2	n.a.	71.5
FI	n.a.	8.4	18.0	2.2	0.7	33.1	9.6	5.9	2.8	2.7	0.1	2.1	8.1	n.a.	33.4
FR	1.8	5.4	7.0	3.9	1.7	20.9	5.5	5.5	5.4	14.2	0.0	6.4	5.4	n.a.	49.4
HR	0.0	1.4	7.7	0.1	0.1	1.2	0.7	0.3	4.9	0.3	0.0	0.2	1.8	n.a.	14.7
HU	0.3	2.7	15.9	0.7	0.4	2.5	1.1	1.7	2.0	1.0	0.0	1.3	4.7	n.a.	0.9
IE	n.a.	4.1	3.8	1.2	1.6	7.1	4.6	3.3	1.4	n.a.	0.0	n.a.	n.a.	n.a.	46.9
IT	1.2	3.6	6.2	1.5	0.7	10.4	3.5	3.2	6.8	7.1	0.0	0.4	2.8	n.a.	30.1
LT	0.1	2.4	4.2	0.2	0.8	5.3	1.0	1.7	3.1	0.3	0.0	n.a.	3.0	n.a.	32.6
LU	n.a.	6.2	n.a.	n.a.	1.1	n.a.	4.6	4.9	n.a.	n.a.	0.4	3.2	1.9	n.a.	n.a.
LV	0.2	2.3	10.0	0.2	0.2	4.7	1.8	1.2	1.4	0.1	0.0	0.0	1.4	n.a.	29.3
MT	n.a.	1.4	n.a.	n.a.	0.4	n.a.	3.1	n.a.	n.a.	n.a.	0.1	6.9	10.5	n.a.	13.4
NL	1.3	10.9	13.7	2.7	1.3	17.4	18.5	9.1	6.0	6.0	0.2	n.a.	5.5	n.a.	11.3
PL	0.3	1.1	3.8	0.2	0.3	1.4	1.3	0.8	0.8	2.4	0.0	0.9	3.1	n.a.	33.2
PT	0.6	2.8	8.5	1.5	0.5	4.8	2.4	1.9	2.5	1.4	0.1	2.9	6.4	n.a.	17.5
RO	0.1	1.4	3.4	0.1	0.2	1.1	0.8	0.7	0.9	0.8	0.0	1.4	2.3	n.a.	18.0
SE	0.8	7.9	n.a.	0.7	1.3	25.9	5.7	5.4	9.1	25.2	0.0	n.a.	n.a.	n.a.	40.2
SI	1.8	5.7	17.2	1.3	1.1	15.3	4.4	2.6	3.5	6.6	0.0	1.7	6.0	n.a.	38.5
SK	n.a.	1.1	2.8	0.4	0.2	0.5	1.1	0.9	0.4	2.1	n.a.	n.a.	1.7	n.a.	47.6
UK	0.7	3.7	6.3	0.9	1.9	9.1	2.7	5.2	6.5	7.0	0.0	0.4	3.8	n.a.	33.4
UAV	0.8	4.2	9.2	1.3	0.8	10.6	3.9	3.1	3.9	5.4	0.1	1.9	4.7	n.a.	34.4
CoV	79	74	65	94	73	83	103	76	79	111	143	102	52	n.a.	58

n.a.: not available; UAV: unweighted average across member states; CoV: Coefficient of variation.
Source: Own calculations based on Eurostat R&D and SBS statistics.

EPO patent applications per employed persons

The number of patent applications filed at the EPO related to the number of employed person is a measure of patent intensity, i.e. to what extent the economic activities in a sector are linked to new technological knowledge that has a clear industrial application perspective. Since granted patents give the patent holder an exclusive right to use this knowledge, products protected by patents may have a kind of monopoly position on the market as long as the patent right is active and can be effectively enforced by the patent holder. There is hence a link between patent intensity and competitiveness.

Patent data are assigned to sectors using a correspondence table between IPC codes and NACE codes. As this correspondence table is derived from the general proximity between certain fields of technology (e.g. transport technology) and certain NACE sectors (e.g. automotive, other vehicles) and of observed correlations between the sector assignment of patent applicants and the IPC codes of their patent applications, the correspondence table may not represent the actual patent activity of a specific sector in a specific country. In addition, the propensity to patent an invention may vary across sectors. What is more, in some sectors the same

amount of effort to generate new technological knowledge may result in a smaller number of patent applications than in another sector, owing to technology-specific features of patentable new technological knowledge.

The sector with the highest patent intensity is C26, followed by C21 (Table 3-10). The automotive sector (C29) reports a low patent intensity which is in sharp contrast to its high R&D intensity. A main reason for this result is the fact that many R&D activities in the automotive sector target technologies that are assigned to other sectors (e.g. R&D on electronics, new materials or mechanical engineering). The computer programming sector (J62) has a very low patent intensity since new software can be patented only in very special circumstances.

Table 3-10: EPO patent applications per employed persons by sector and member state (average 2008 to 2013)

	C13	C20	C21	C22	C25	C26	C27	C28	C29	C30	H	J58	J62	M71	M72
AT	0.6	6.8	9.0	1.6	1.3	13.6	4.3	5.8	2.6	7.1	n.a.	n.a.	0.2	n.a.	n.a.
BE	0.2	5.0	6.8	2.2	0.7	25.4	4.1	6.8	0.7	2.0	n.a.	n.a.	0.2	n.a.	n.a.
BG	0.0	0.1	0.3	0.0	0.0	0.5	0.1	0.2	0.1	0.1	n.a.	n.a.	0.0	n.a.	n.a.
CY	0.1	1.3	2.2	0.4	0.3	21.0	3.1	2.5	1.6	n.a.	n.a.	n.a.	0.7	n.a.	n.a.
CZ	0.1	0.5	2.0	0.0	0.0	1.0	0.2	0.4	0.1	0.1	n.a.	n.a.	0.0	n.a.	n.a.
DE	0.7	6.0	9.1	1.5	1.1	13.4	5.0	5.5	2.1	3.1	n.a.	n.a.	0.2	n.a.	n.a.
DK	1.0	4.5	7.7	2.3	1.0	12.0	8.8	5.4	3.7	3.7	n.a.	n.a.	0.1	n.a.	n.a.
EE	0.0	0.7	15.2	0.1	0.1	2.3	0.1	1.3	0.4	2.4	n.a.	n.a.	0.2	n.a.	n.a.
EL	0.0	0.5	2.1	0.1	0.1	4.8	0.5	1.2	0.5	0.6	n.a.	n.a.	0.1	n.a.	n.a.
ES	0.1	1.1	5.8	0.3	0.2	7.8	2.2	2.7	0.3	1.0	n.a.	n.a.	0.1	n.a.	n.a.
FI	0.5	5.7	9.2	0.9	0.6	16.8	4.4	5.9	5.0	1.7	n.a.	n.a.	0.5	n.a.	n.a.
FR	0.4	4.7	7.7	1.4	0.7	17.0	6.4	8.1	2.3	1.7	n.a.	n.a.	0.2	n.a.	n.a.
HR	0.1	0.2	0.9	0.1	0.0	0.7	0.3	0.4	0.0	0.1	n.a.	n.a.	n.a.	n.a.	n.a.
HU	0.0	0.6	1.7	0.1	0.1	1.2	0.3	0.5	0.2	0.4	n.a.	n.a.	0.0	n.a.	n.a.
IE	0.6	2.5	2.0	0.6	0.4	7.2	5.0	4.7	1.0	1.2	n.a.	n.a.	0.3	n.a.	n.a.
IT	0.1	2.4	4.6	0.8	0.4	4.6	3.4	2.5	1.3	1.0	n.a.	n.a.	0.1	n.a.	n.a.
LT	0.0	0.3	6.1	0.0	0.1	1.3	0.2	0.7	0.2	n.a.	n.a.	n.a.	0.1	n.a.	n.a.
LU	n.a.	12.5	n.a.	n.a.	0.8	n.a.	6.1	2.4	n.a.	n.a.	n.a.	n.a.	0.1	n.a.	n.a.
LV	n.a.	1.7	3.5	0.4	0.1	3.0	0.5	1.4	0.2	0.9	n.a.	n.a.	n.a.	n.a.	n.a.
MT	n.a.	2.3	n.a.	n.a.	0.6	n.a.	3.1	n.a.	n.a.	17.2	n.a.	n.a.	0.1	n.a.	n.a.
NL	0.5	5.8	13.2	1.7	0.6	35.4	16.0	7.0	3.0	2.4	n.a.	n.a.	0.1	n.a.	n.a.
PL	0.0	0.4	1.4	0.0	0.1	1.3	0.3	0.5	0.1	0.1	n.a.	n.a.	0.0	n.a.	n.a.
PT	0.0	0.6	2.7	0.1	0.0	2.1	0.4	0.9	0.1	0.4	n.a.	n.a.	0.0	n.a.	n.a.
RO	0.0	0.1	0.2	0.0	0.0	0.8	0.1	0.1	0.0	0.0	n.a.	n.a.	0.0	n.a.	n.a.
SE	0.5	3.7	6.1	1.1	0.8	25.5	5.9	6.4	2.5	1.7	n.a.	n.a.	0.2	n.a.	n.a.
SI	0.1	1.3	6.5	0.0	0.2	2.4	1.0	1.2	0.2	1.5	n.a.	n.a.	0.1	n.a.	n.a.
SK	0.0	0.3	1.3	0.1	0.0	0.4	0.1	0.3	0.1	0.6	n.a.	n.a.	0.1	n.a.	n.a.
UK	0.2	3.7	11.0	0.6	0.4	11.6	4.2	4.9	1.2	0.8	n.a.	n.a.	0.1	n.a.	n.a.
UAV	0.2	2.7	5.3	0.6	0.4	9.0	3.1	2.9	1.1	2.1	n.a.	n.a.	0.2	n.a.	n.a.
CoV	117	107	77	114	98	107	115	88	118	169	n.a.	n.a.	100	n.a.	n.a.

n.a.: not available; UAV: unweighted average across member states; CoV: Coefficient of variation.
Source: Own calculations based on Eurostat IPR and SBS statistics.

Innovation expenditure as a share of total sales

The relation of innovation expenditure to total sales ('innovation intensity') is an indicator that is conceptually close to the indicator on R&D expenditure as a share of value added. There are however major differences. Innovation expenditure include all R&D expenditure (both in-house and extramural) and a number of other innovation-related expenditure such as expenditure for new tangible assets required

for innovations, expenditure for design and testing, and expenditure for marketing, training and other preparatory activities related to product or process innovation. What is more, the indicator is related to total sales instead of value added. The main reason for this choice is the fact that data on innovation expenditure is collected only for firms with 10 or more employees. Since no value added data broken down by this size class for each sector is available, one cannot calculate an innovation intensity based on value added. By using total sales, which is taken from the same data source as innovation expenditure, one avoids problems of different sector assignment of firms in different statistics.

Table 3-11: Innovation expenditure as a share of total sales by sector and member state (average 2008 to 2014)

	C13	C20	C21	C22	C25	C26	C27	C28	C29	C30	H	J58	J62	M71	M72
AT	1.4	3.6	n.a.	3.1	2.0	14.4	8.3	4.9	3.8	6.7	0.5	1.0	7.2	9.3	95.7
BE	2.1	1.4	32.1	2.0	1.8	10.2	5.4	3.7	1.0	7.9	1.6	2.9	6.1	8.2	67.4
BG	0.5	2.2	n.a.	1.7	1.2	1.8	1.5	1.6	0.4	0.6	0.6	0.7	1.6	0.4	70.4
CY	0.1	2.1	3.4	3.0	3.5	n.a.	1.3	1.9	n.a.	1.4	0.6	0.8	5.8	2.6	n.a.
CZ	2.1	2.1	5.9	2.3	2.2	1.8	1.7	3.0	3.0	5.6	0.9	1.9	4.6	1.8	17.0
DE	1.8	3.7	12.8	2.1	2.2	9.5	5.4	4.8	8.5	7.7	2.0	1.2	6.7	1.7	41.6
DK	0.7	8.7	25.2	2.8	0.9	12.1	3.9	5.3	2.5	1.3	0.4	4.7	7.4	2.4	62.9
EE	1.2	1.3	4.1	2.1	2.0	1.9	1.4	1.7	1.9	4.0	2.4	0.7	14.3	5.7	111.6
EL	1.7	2.1	3.8	1.5	3.0	2.9	2.1	2.6	2.3	5.1	0.7	2.6	4.1	1.6	37.3
ES	1.1	1.1	5.1	1.1	1.0	5.0	1.8	1.6	2.5	6.2	1.0	0.9	2.6	3.0	84.3
FI	1.4	2.6	n.a.	1.7	2.2	12.1	6.6	3.5	2.6	2.9	0.6	2.7	7.6	4.2	40.4
FR	1.9	2.2	4.9	2.9	2.8	11.4	5.2	2.8	3.9	9.4	0.6	4.1	5.0	4.6	42.4
HR	1.3	1.3	10.9	3.2	2.1	2.3	1.8	2.7	2.5	0.8	1.4	1.0	6.1	0.8	4.1
HU	0.6	0.7	9.5	0.6	1.3	1.4	6.1	1.6	2.3	0.6	1.0	1.0	4.4	1.6	14.6
IE	1.8	2.1	3.3	4.1	2.5	2.8	3.1	2.9	1.8	2.2	1.2	n.a.	1.8	2.1	19.3
IT	1.6	1.5	3.4	1.6	1.7	6.7	2.3	2.0	2.5	5.5	0.7	0.6	4.1	2.7	40.1
LT	0.5	1.0	15.1	2.7	2.0	3.4	1.8	1.9	1.8	0.6	2.4	2.6	6.8	2.5	111.8
LU	n.a.	2.2	n.a.	n.a.	1.2	n.a.	n.a.	4.2	0.4	n.a.	0.5	1.6	n.a.	n.a.	n.a.
LV	0.5	1.3	4.1	1.1	1.5	2.0	1.3	1.3	1.2	0.2	0.4	0.1	1.0	1.4	30.1
MT	n.a.	0.8	2.7	4.7	2.2	0.5	1.2	3.2	n.a.	n.a.	0.8	10.5	5.7	0.9	n.a.
NL	1.4	2.1	13.4	1.5	1.4	8.6	15.2	5.1	2.3	2.0	0.5	1.0	5.2	2.8	55.1
PL	0.8	1.7	4.9	1.7	1.6	1.4	1.7	2.3	2.6	2.8	1.3	1.5	2.8	1.4	39.1
PT	1.6	0.9	9.2	2.0	2.2	1.8	1.6	1.7	1.8	2.3	0.9	3.0	6.8	3.6	35.7
RO	0.3	2.7	1.3	1.2	0.9	0.7	1.0	1.8	3.1	1.1	0.6	0.7	1.7	1.2	44.7
SE	1.9	2.6	61.2	n.a.	1.7	24.7	5.9	4.5	7.4	22.2	0.5	5.1	4.0	4.7	27.8
SI	n.a.	n.a.	n.a.	1.5	2.3	n.a.	3.0	n.a.	1.5	n.a.	n.a.	n.a.	n.a.	1.0	n.a.
SK	1.9	1.9	3.7	1.7	0.8	0.4	2.3	2.1	1.5	3.1	1.1	0.9	1.4	1.1	7.5
UK	0.9	1.1	3.6	1.3	2.7	2.3	1.5	1.6	3.8	2.0	1.5	0.9	1.9	1.9	20.6
UAV	1.2	2.1	10.6	2.1	1.9	5.7	3.5	2.8	2.7	4.2	1.0	2.1	4.9	2.8	46.7
CoV	49	73	126	45	35	104	88	44	68	110	59	103	58	78	65

n.a.: not available; UAV: unweighted average across member states; CoV: Coefficient of variation.
Source: Own calculations based on Eurostat innovation statistics.

The results show that C21 has the highest innovation intensity, followed by C26, J62 and C30 (Table 3-11). Similarly to the two R&D indicators, most countries tend to show either high or either low values for most sectors. However, variation in a country's ranking across sectors is higher for innovation intensity (average standard deviation of country ranks is 6.4) than for R&D intensity (5.5 based on expenditure, 5.3 based on personnel). There seems to be more specialisation in innovation across sectors within a country than for R&D. Another significant difference between

innovation and R&D intensity is the lower coefficients of variation for innovation intensity. Some sectors such as C13 (textiles), C28 (machinery and equipment) and C22 (rubber and plastic products) report very low values, i.e. innovation intensity in these sectors is rather homogenous across member states. High coefficients of variation are reported for C21, C30 and C26.

Share of firms conducting R&D in-house continuously

Another R&D-related indicator is the share of firms that conduct R&D in-house on a continuous base. This indicator is derived from the CIS and refers to firms with 10 or more employees. It shows to what extent the firm population in a sector engages in R&D. This can be seen as an indicator of how broad a competitive strategy based on new knowledge generation is prevalent in a sector.

Table 3-12: Share of firms with continuous in-house R&D activity by sector and member state (average 2008 to 2014)

	C13	C20	C21	C22	C25	C26	C27	C28	C29	C30	H	J58	J62	M71	M72
AT	13	56	n.a.	25	10	73	43	39	33	72	1	12	37	14	92
BE	33	54	66	32	14	66	41	31	28	33	3	15	39	30	76
BG	n.a.	4	13	1	2	8	3	5	n.a.	n.a.	n.a.	n.a.	3	1	93
CY	n.a.	24	41	10	2	n.a.	3	8	n.a.	n.a.	1	6	27	8	n.a.
CZ	8	36	34	9	6	26	16	18	15	31	1	16	30	7	58
DE	26	64	64	24	13	59	42	40	33	44	2	11	48	19	81
DK	n.a.														
EE	8	34	53	7	4	22	17	16	13	7	3	6	27	7	88
EL	3	22	33	8	4	33	16	7	21	n.a.	3	8	41	10	40
ES	10	35	58	11	5	43	23	18	18	24	1	8	31	16	95
FI	19	55	n.a.	24	13	63	44	39	35	21	2	19	43	19	40
FR	21	47	51	23	10	53	36	36	24	35	2	38	38	17	67
HR	2	18	49	4	3	15	17	9	16	6	0	3	25	3	25
HU	2	18	36	5	2	14	12	8	11	8	1	8	20	4	44
IE	n.a.														
IT	14	31	41	13	6	40	24	24	24	20	2	6	30	13	55
LT	2	20	29	3	4	34	13	8	23	7	0	4	28	4	50
LU	8	64	n.a.	39	5	n.a.	21	61	44	n.a.	4	21	24	n.a.	n.a.
LV	8	11	32	2	6	16	13	9	6	8	0	2	7	3	48
MT	n.a.	12	64	8	5	33	29	20	n.a.	n.a.	2	14	27	5	33
NL	32	51	56	38	16	56	35	39	32	29	3	25	43	23	58
PL	2	15	28	3	2	15	11	8	7	9	0	4	10	1	54
PT	7	30	31	14	7	50	25	17	18	13	4	17	47	15	61
RO	6	6	25	3	2	5	8	7	6	4	1	2	11	5	59
SE	16	36	47	10	6	48	18	30	17	33	1	24	22	15	n.a.
SI	19	42	n.a.	11	8	37	35	26	23	56	2	13	40	13	n.a.
SK	6	22	26	3	2	9	18	12	8	15	1	5	13	6	47
UK	n.a.														
UAV	12	32	42	13	6	36	23	21	21	24	2	12	29	11	60
CoV	79	55	36	86	68	57	55	69	50	77	72	72	44	70	34

n.a.: not available; UAV: unweighted average across member states; CoV: Coefficient of variation.
Source: Own calculations based on Eurostat innovation statistics.

The results show that M72 (scientific research and development) is the sector with the highest share, which comes with no surprise (Table 3-13). Interestingly, there are many firms in this sector not conducting R&D on a permanent base though providing R&D services is the constitutive feature of this sector. Among

manufacturing sectors, C21 reports the highest share, followed by C26 and C20 (chemicals). In the service sector, J62 has a high share of continuously R&D performing firms. Comparing the results for this indicator with the R&D intensity results, C20 is a sector with a high R&D orientation of firms while R&D intensity is not particularly high.

As for R&D intensity, most countries either show high values in most sectors or low values in most sectors. A country's ranking does not vary strongly across sectors for most member states (the average standard deviation of country rankings across sectors is 4.3 which is lower than for R&D intensity). The coefficient of variation by sector is substantially lower than for R&D or innovation intensity. A low coefficient of variation is found for C21 and J62. There is no sector with a very high value for this measure of cross-country heterogeneity.

Share of firms having introduced any type of innovation

The share of firms that have introduced any type of innovation (product, process, marketing or organisational) is an indicator for the incidence of innovation among a sector's firms. The value is based on CIS results and refers to firms with 10 or more employees. The results are strongly driven by small firms as these firms represent the majority of all firm in each sector and each country.

The sectors with the highest indicator values include M72, C21, C26, J62 and C20 (Table 3-13 Table 3-14). The coefficients of variation are much lower than for other indicators, implying a low level of heterogeneity across countries within each sector. The most homogenous sectors in this respect are M72, C21, C29 and J62. A country's rankings across sectors is also quite homogenous. The average standard deviation of a country's ranking across sectors is 4.6 which is slightly higher than for the share of continuously R&D performing firms.

Table 3-13: Share of firms having introduced any type of innovation by sector and member state (average 2008 to 2014)

	C13	C20	C21	C22	C25	C26	C27	C28	C29	C30	H	J58	J62	M71	M72
AT	67	76	n.a.	70	55	97	78	81	69	99	36	65	86	57	95
BE	76	81	87	76	58	87	70	68	67	65	41	69	77	71	87
BG	30	55	n.a.	35	35	54	52	50	46	47	14	28	43	25	100
CY	38	68	72	48	41	n.a.	28	54	n.a.	33	32	59	71	48	n.a.
CZ	46	77	74	58	49	61	55	57	56	65	29	58	70	41	77
DE	88	94	93	82	73	95	85	89	85	91	53	81	93	73	93
DK	49	76	70	52	48	76	69	62	48	62	41	64	60	48	72
EE	49	68	100	46	40	55	53	56	51	63	35	54	63	35	91
EL	52	68	n.a.	57	51	n.a.	73	64	n.a.	n.a.	36	62	81	49	82
ES	40	71	83	50	34	72	54	52	56	61	26	45	68	53	100
FI	62	80	n.a.	69	54	89	73	72	56	55	30	56	79	57	73
FR	58	77	86	64	50	80	66	73	58	70	39	73	74	59	83
HR	50	61	70	57	39	71	58	54	72	31	31	42	74	35	55
HU	21	50	68	35	21	42	39	34	45	36	17	42	54	29	68
IE	66	85	n.a.	72	59	78	72	69	n.a.	n.a.	42	n.a.	78	57	83
IT	51	78	87	64	53	78	69	64	66	66	37	61	78	59	80
LT	24	48	n.a.	42	38	72	63	55	60	43	24	39	78	40	70
LU	58	96	n.a.	82	56	100	84	91	89	n.a.	51	85	81	n.a.	n.a.
LV	40	45	72	28	36	57	36	59	53	12	17	20	41	32	77
MT	n.a.	44	74	49	36	64	68	65	n.a.	n.a.	37	54	63	39	67
NL	59	77	89	72	48	80	71	65	63	62	33	68	72	57	72
PL	22	47	59	32	26	45	45	37	41	34	14	31	42	20	67
PT	52	79	79	70	59	89	73	67	68	n.a.	57	70	83	69	79
RO	33	31	61	27	28	28	32	32	41	37	19	40	38	29	92
SE	59	70	84	71	51	81	67	74	63	77	34	71	71	56	80
SI	n.a.	n.a.	n.a.	53	43	n.a.	70	63	69	n.a.	28	n.a.	77	47	n.a.
SK	32	45	49	40	28	39	44	38	48	28	21	36	50	34	77
UK	35	60	53	54	53	69	72	62	52	66	39	51	59	51	66
UAV	48	67	76	56	45	70	61	61	59	55	33	55	68	47	79
CoV	35	25	18	29	27	27	25	24	21	39	34	30	22	30	14

n.a.: not available; UAV: unweighted average across member states; CoV: Coefficient of variation.
Source: Own calculations based on Eurostat innovation statistics.

Share of sales from total product innovations

The share of sales in total sales that is generated by product innovations is one of the rare quantitative output indicators of innovation. Its limitations are discussed in more detail in section 4.6. The indicator is based on CIS results. The highest values are reported by the sectors C26, M72 and C29 (Table 3-14). Differences across sectors are lower than for other innovation indicators. Country rankings are less consistent across sectors for this indicator. The average standard deviation of these rankings is 6.3. This value is close to that found for innovation intensity. Variation across countries within a sector is much lower, however, than for innovation intensity. There is no sector with a coefficient of variation exceeding 100 percent. Highest heterogeneity is found for C20 while C25 (metal products), C22 and C26 report very low values.

Table 3-14: Share of sales from total product innovations by sector and member state (average 2008 to 2014)

	C13	C20	C21	C22	C25	C26	C27	C28	C29	C30	H	J58	J62	M71	M72
AT	18	13	n.a.	17	11	36	37	25	25	29	8	6	25	17	54
BE	16	7	12	13	8	29	20	25	26	8	11	12	12	11	35
BG	10	8	36	12	11	19	17	32	22	20	2	8	14	12	25
CY	7	16	19	11	11	n.a.	4	8	2	3	10	13	18	11	n.a.
CZ	22	13	13	16	11	31	23	22	39	27	8	16	24	6	19
DE	12	16	17	13	9	40	32	26	51	37	8	8	27	10	25
DK	14	49	23	13	7	31	19	23	16	17	2	11	20	15	32
EE	17	11	9	8	8	44	9	15	11	32	8	9	26	7	31
EL	n.a.	14	n.a.	8	8	17	44	20	25	31	8	9	47	13	26
ES	20	18	22	15	12	37	29	25	47	34	9	5	28	12	39
FI	8	11	n.a.	14	10	29	23	17	15	43	2	6	16	8	59
FR	14	16	13	19	10	33	19	21	40	27	7	13	21	13	30
HR	7	11	21	18	9	21	22	13	6	44	6	8	20	4	14
HU	3	5	9	5	3	29	19	13	45	20	6	5	12	5	21
IE	8	5	19	13	12	27	25	18	30	3	13	n.a.	22	10	71
IT	17	15	11	15	10	27	24	24	25	23	8	9	23	13	27
LT	2	2	39	12	10	35	19	20	25	7	8	6	24	8	27
LU	n.a.	7	n.a.	n.a.	5	n.a.	16	27	28	n.a.	5	10	n.a.	n.a.	n.a.
LV	4	15	13	6	10	37	10	11	33	52	2	1	8	3	9
MT	n.a.	2	19	11	8	20	18	30	n.a.	n.a.	4	5	10	3	n.a.
NL	11	14	12	11	8	30	35	25	15	30	5	12	14	13	27
PL	8	11	12	8	9	15	23	17	24	25	4	6	9	2	16
PT	12	12	7	18	10	40	19	13	36	17	6	11	17	12	19
RO	10	9	9	7	6	25	18	8	19	12	6	3	12	6	26
SE	10	n.a.	n.a.	n.a.	8	11	n.a.	16	17	20	6	9	12	7	20
SI	14	n.a.	n.a.	9	13	23	40	16	29	n.a.	n.a.	5	13	8	n.a.
SK	5	35	53	13	7	55	22	13	41	51	4	2	10	7	27
UK	31	31	n.a.	19	18	33	32	33	24	19	6	15	25	21	28
UAV	12	14	18	13	9	30	23	20	27	25	6	8	19	9	29
CoV	55	73	62	32	30	32	40	35	46	54	43	46	45	48	48

n.a.: not available; UAV: unweighted average across member states; CoV: Coefficient of variation.
Source: Own calculations based on Eurostat innovation statistics.

Share of product/process innovative firms with innovation cooperation

The share of innovation active firms with cooperation as part of their innovation activities is an indicator that is frequently used to capture the openness of innovation processes in firms. Openness is often viewed as a prerequisite for successful innovation. The indicator refers to firms with 10 or more employees that conducted product or process innovation activities. Innovation cooperation also refers to these two types of innovations.

The results are quite in line with those for other innovation indicators. The sectors with the highest values include M72, C21, C26, C20 and C30 (Table 3-15). Countries tend to show either high or low values for most sectors, suggesting that the cooperation behaviour is partly driven by country-specific environments. The average standard deviation of a country's ranking for this indicator across the 15 sectors analysed is 4.9, which is lower than for R&D intensity, but higher compared to the share of innovating firms and to the share of firms with continuous in-house R&D activities.

The coefficient of variation is rather low and does not vary much across sectors. The sectors with the highest coefficients of variation are C13 and H (transport), the most homogenous cooperation behaviour across countries is found for sectors C21, C27 (electrical equipment) and J62.

Table 3-15: Share product/process innovative firms with innovation cooperation by sector and member state (average 2008 to 2014)

	C13	C20	C21	C22	C25	C26	C27	C28	C29	C30	H	J58	J62	M71	M72
AT	24	43	n.a.	34	16	69	45	38	32	66	8	21	45	23	88
BE	39	51	52	38	22	59	37	30	35	39	15	32	37	39	74
BG	3	8	16	6	5	14	11	9	7	8	1	6	11	4	37
CY	n.a.	33	47	21	13	n.a.	14	25	n.a.	33	13	27	33	20	n.a.
CZ	15	35	40	16	12	25	23	18	24	32	4	12	21	10	63
DE	26	40	55	22	12	43	26	25	24	34	3	5	31	16	66
DK	19	42	47	19	15	40	30	23	17	23	12	23	16	21	41
EE	21	47	59	20	14	38	30	22	34	30	8	20	30	15	86
EL	9	30	40	19	12	21	24	12	36	25	14	15	41	21	46
ES	8	18	38	10	5	24	15	11	15	22	2	8	20	15	66
FI	24	39	n.a.	25	17	47	25	29	23	24	4	18	31	23	34
FR	20	34	46	22	11	39	24	25	17	33	5	22	24	19	59
HR	10	16	33	16	10	16	24	17	23	10	6	11	25	8	25
HU	4	15	36	9	4	18	15	11	20	21	4	11	20	8	42
IE	14	33	44	15	8	35	19	21	21	n.a.	7	n.a.	24	11	46
IT	5	13	17	6	4	24	9	8	10	10	3	7	22	13	47
LT	5	27	45	16	9	29	22	16	39	20	7	8	37	15	50
LU	42	15	n.a.	39	8	80	33	40	44	n.a.	9	35	17	n.a.	n.a.
LV	10	7	28	6	6	14	8	11	9	9	3	3	13	4	52
MT	n.a.	4	26	9	6	29	20	10	n.a.	n.a.	2	n.a.	11	3	n.a.
NL	22	35	39	30	14	40	26	22	23	28	7	24	22	24	43
PL	4	18	31	8	7	16	17	13	17	18	2	7	11	5	38
PT	9	22	26	16	10	47	24	16	20	17	8	19	34	19	57
RO	5	6	17	4	2	5	7	5	6	5	1	6	9	4	40
SE	n.a.	27	54	22	14	35	30	31	28	38	6	22	23	18	54
SI	36	44	n.a.	21	14	47	38	24	35	50	5	25	34	16	n.a.
SK	8	26	29	11	5	13	21	14	15	14	3	12	16	10	33
UK	21	48	59	26	21	45	35	36	32	31	13	21	40	25	45
UAV	16	28	38	18	11	34	23	20	23	26	6	16	25	15	51
CoV	70	50	33	53	49	53	40	47	44	55	65	54	41	55	31

n.a.: not available; UAV: unweighted average across member states; CoV: Coefficient of variation.
Source: Own calculations based on Eurostat innovation statistics.

B. Robustness over Time

An important dimension of data quality of innovation-related competitiveness indicators is the robustness of results over time. On the one hand, innovation is a dynamic phenomenon, and whether a certain activity or object is classified as innovative depends on the point in time it is conducted or introduced to the market. On the other hand, innovation is a more subjective concept compared to other measures of competitiveness. Innovation needs to be defined against a certain reference which is subject to the market to which an innovation refers, and to the firm which introduces an innovation. Changes over time in innovation indicators may hence be more common than for other indicator areas, but they also challenge the interpretation of results.

A simple measure for the stability of results is the variation of a country's indicator values (or its ranking) over time for a given indicator in a certain sector. Calculating the mean of these sector-specific variations over time for each indicator provides a measure of how consistent the results are for the different years of the observation period (considering the relatively short period from 2008 to 2014). This analysis assumes that high temporal fluctuations in a country's rank rather indicate unreliable results than actual dynamics in innovation activities. This assumption is very plausible since innovation is usually an activity based on a strategic decision, requiring investment in specific skills, capabilities and capital goods (implying high sunk costs in case of short-term changes in innovation activities) and lasting over a multi-year period.

For most indicators and most member states, innovation indicator values are quite consistent over time. Using the coefficient of variation as a measure of variation (as its values are independent from the unit of measurement and can hence be easily compared across indicators), the average coefficient across all indicators and countries is 29 (Table 3-16). Higher variation over time is observed for the share of sales from product innovation (43), patent intensity (42) and innovation expenditure (41) while temporal variation is on average relatively low for the share of innovating firms (14). Variation over time is also somewhat lower for the other two indicators that give shares in the total number of firms (share of firms with continuous R&D, share of firms with innovation cooperation).

When looking at individual indicators and countries, very low variation over time is found for the share of innovating firms in Sweden, Portugal and Ireland. For the R&D intensity based on personnel data, Germany and France report little variation within the observation period 2008-2014. These two countries also show the lowest coefficient of variation for R&D intensity based on expenditure data. For innovation intensity, Germany, Spain and Italy report rather similar sector-specific values over time. The smallest temporal variation for patent intensity is found for France, Germany, the Netherlands and the UK.

The sales share from product innovations shows a high variation over time for most countries. Spain, Germany and Sweden report the lowest variation. These three countries plus Belgium also have the lowest variation for the share of continuously R&D performing firms. The share of firms with innovation cooperation varies comparably little over time in Sweden, Spain, France and the UK.

Table 3-16: Average coefficient of variation of a country's indicator value over time (for the 2008 to 2014 period) across 15 sectors, by innovation indicator

	RDI exp	RDI pers	Patent	InnExp	RD cont	InnShare	InnSales	InnCoop
AT	18	12	17	32	21	8	25	25
BE	20	20	24	35	14	8	32	18
BG	41	29	57	55	31	12	45	26
CY	67	77	74	65	53	24	60	49
CZ	22	19	37	31	23	13	29	17
DE	12	8	13	19	14	8	20	20
DK	25	22	27	32	n.a.	14	49	37
EE	50	32	63	56	42	33	55	31
EL	50	35	52	42	42	9	44	40
ES	13	10	17	20	10	8	18	13
FI	27	16	24	27	26	11	40	22
FR	13	8	13	29	16	7	18	14
HR	65	52	68	51	34	12	61	34
HU	50	39	42	51	31	13	34	23
IE	25	23	41	49	n.a.	6	45	29
IT	20	18	15	22	33	12	28	30
LT	68	50	71	58	36	21	61	39
LU	50	55	30	46	30	11	73	46
LV	58	69	70	73	49	27	53	60
MT	44	38	77	69	51	22	72	42
NL	26	25	14	26	22	12	32	22
PL	40	40	37	31	22	14	28	27
PT	22	20	43	26	21	6	33	28
RO	64	51	83	53	43	29	69	50
SE	28	21	23	32	12	5	21	11
SSI	34	31	54	21	17	7	33	16
SK	38	34	63	51	57	26	51	36
UK	29	27	14	50	n.a.	15	69	14
Mean	37	31	42	41	30	14	43	29

n.a.: not available;

RDI exp: R&D expenditure as a share of value added in the sector

RDI pers: R&D employees as a share of total employment in the sector

Patent: EPO patent applications per employed persons

InnExp: Innovation expenditure as a share of total sales

RD cont: Share of firms conducting R&D in-house continuously

InnShare: Share of firms having introduced any type of innovation

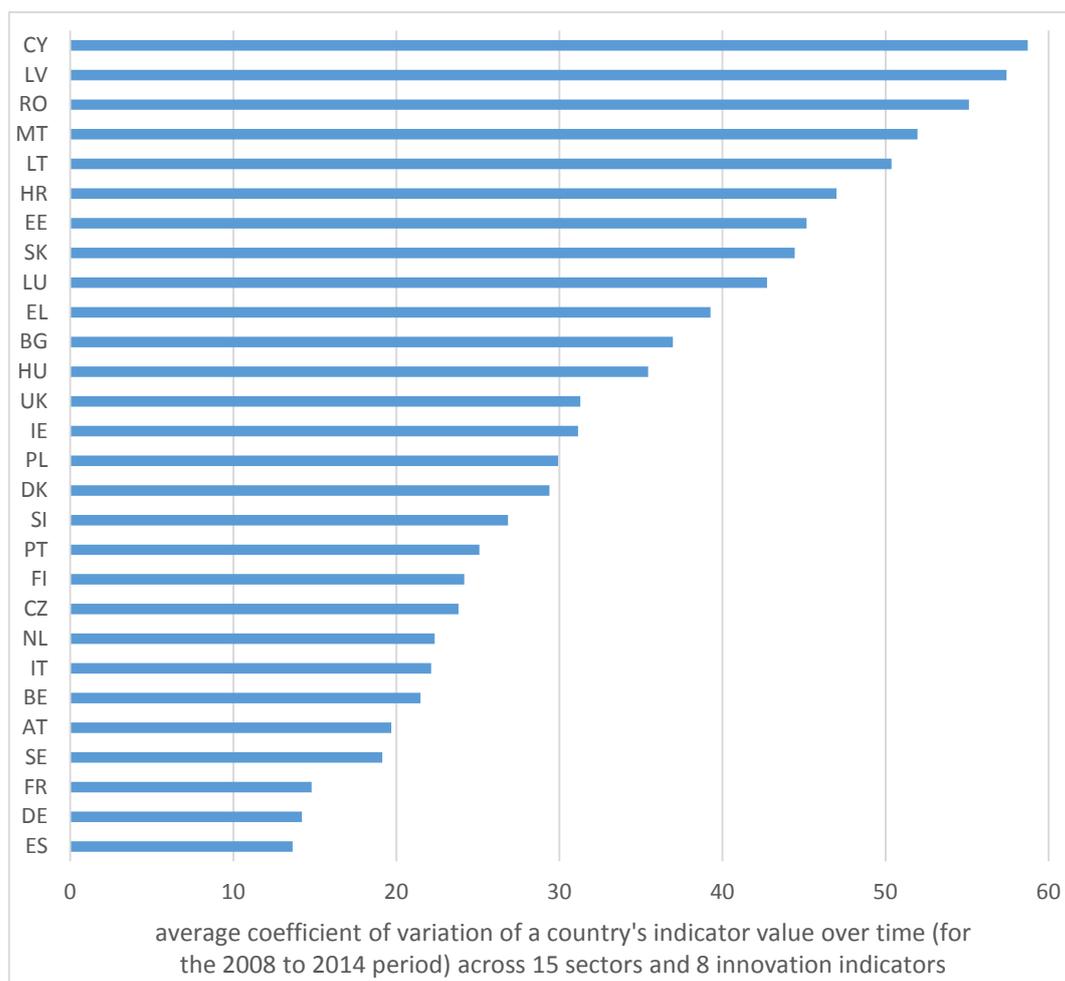
InnSales: Share of sales from total product innovations

InnCoop: Share of product/process innovative firms with innovation cooperation.

Source: Own calculations based on Eurostat R&D, IPR, innovation and structural business statistics.

Countries with relatively low temporal variation of indicator values include Spain, Germany and France, i.e. large member states. Very high variation over time is observed for small member states (Cyprus, Latvia, Malta, Lithuania), but also for Romania (see Figure 3-11 for the average coefficient of variation across sectors and indicators).

Figure 3-11: Average coefficient of variation of a country's indicator value over time (for the 2008 to 2014 period) across 15 sectors and 8 innovation indicators



Source: Own calculations based on Eurostat R&D, IPR, innovation and structural business statistics.

Very similar results are found when examining the stability of a country's ranking over time for a certain indicator in a specific sector. The most stable country rankings at the sector level are found for patent intensity (Table 3-17). Rankings are also quite stable over time for both R&D intensity indicators and the share of firms performing R&D continuously. These results demonstrate that R&D is a rather.

Country rankings are least stable for the sales share from product innovation and for innovation intensity. For both indicators, substantial changes in a country's ranking over time are usually observed for smaller countries, but also for the UK. For the sales share from product innovation, the UK's coefficient of variation averaged across the 15 sectors is 8.1. In 2008 and 2010, the UK ranked very low in most sectors while in 2012 and 2014, UK ranked among the top-4 in eight sectors.

Table 3-17: Average standard deviation of a country's ranking over time (for the 2008 to 2014 period) across 15 sectors, by innovation indicator

	RDI exp	RDI pers	Patent	InnExp	RD cont	InnShare	InnSales	InnCoop
AT	1.2	1.0	1.1	2.8	1.9	2.4	3.9	3.1
BE	1.5	1.4	1.5	3.4	1.5	2.3	4.2	2.1
BG	3.1	2.9	1.9	3.8	1.6	1.9	4.7	2.0
CY	3.8	3.8	4.1	6.7	4.5	4.0	5.6	7.0
CZ	2.5	2.3	1.9	3.6	2.3	3.2	3.6	2.8
DE	1.8	1.7	1.2	1.9	1.3	0.8	2.7	3.0
DK	2.0	2.0	1.6	3.1	n.a.	2.9	4.5	4.2
EE	3.4	2.8	3.1	5.3	3.6	5.9	5.6	4.2
EL	2.8	2.3	2.1	5.1	3.0	2.4	4.5	5.7
ES	2.0	1.8	1.2	2.1	1.9	2.0	2.7	2.4
FI	1.4	1.5	1.5	3.3	2.1	2.8	3.9	2.7
FR	1.4	1.4	1.1	2.8	1.9	2.2	3.1	2.7
HR	2.2	2.8	2.5	4.4	2.3	2.4	5.6	3.3
HU	2.9	2.6	1.9	3.8	2.4	2.0	4.0	2.7
IE	2.1	2.5	2.3	5.4	n.a.	2.2	5.8	3.7
IT	2.2	2.1	1.4	2.4	3.2	3.4	4.1	2.3
LT	4.2	3.8	3.1	4.5	2.1	3.8	5.6	4.6
LU	2.5	0.9	2.2	2.9	2.6	2.1	4.9	3.6
LV	5.7	3.5	4.3	4.6	2.2	3.5	4.8	4.2
MT	3.2	2.6	5.2	5.2	3.9	4.9	6.4	3.5
NL	2.1	1.6	1.1	2.9	2.7	3.5	4.7	3.0
PL	3.2	2.9	2.0	2.8	2.0	2.0	2.5	2.3
PT	2.2	2.2	1.9	2.7	1.9	1.7	4.7	3.0
RO	3.5	3.5	1.8	4.6	2.9	1.9	6.5	1.6
SE	3.3	1.7	1.6	3.2	1.8	1.3	1.5	1.8
SI	2.1	2.3	2.3	3.8	1.9	2.1	4.6	2.2
SK	3.2	2.6	2.5	3.8	2.9	3.1	4.7	4.0
UK	2.4	2.5	1.1	6.0	n.a.	4.5	8.1	1.6
Mean	2.6	2.3	2.1	3.8	2.4	2.8	4.5	3.2

n.a.: not available;

RDI exp: R&D expenditure as a share of value added in the sector

RDI pers: R&D employees as a share of total employment in the sector

Patent: EPO patent applications per employed persons

InnExp: Innovation expenditure as a share of total sales

RD cont: Share of firms conducting R&D in-house continuously

InnShare: Share of firms having introduced any type of innovation

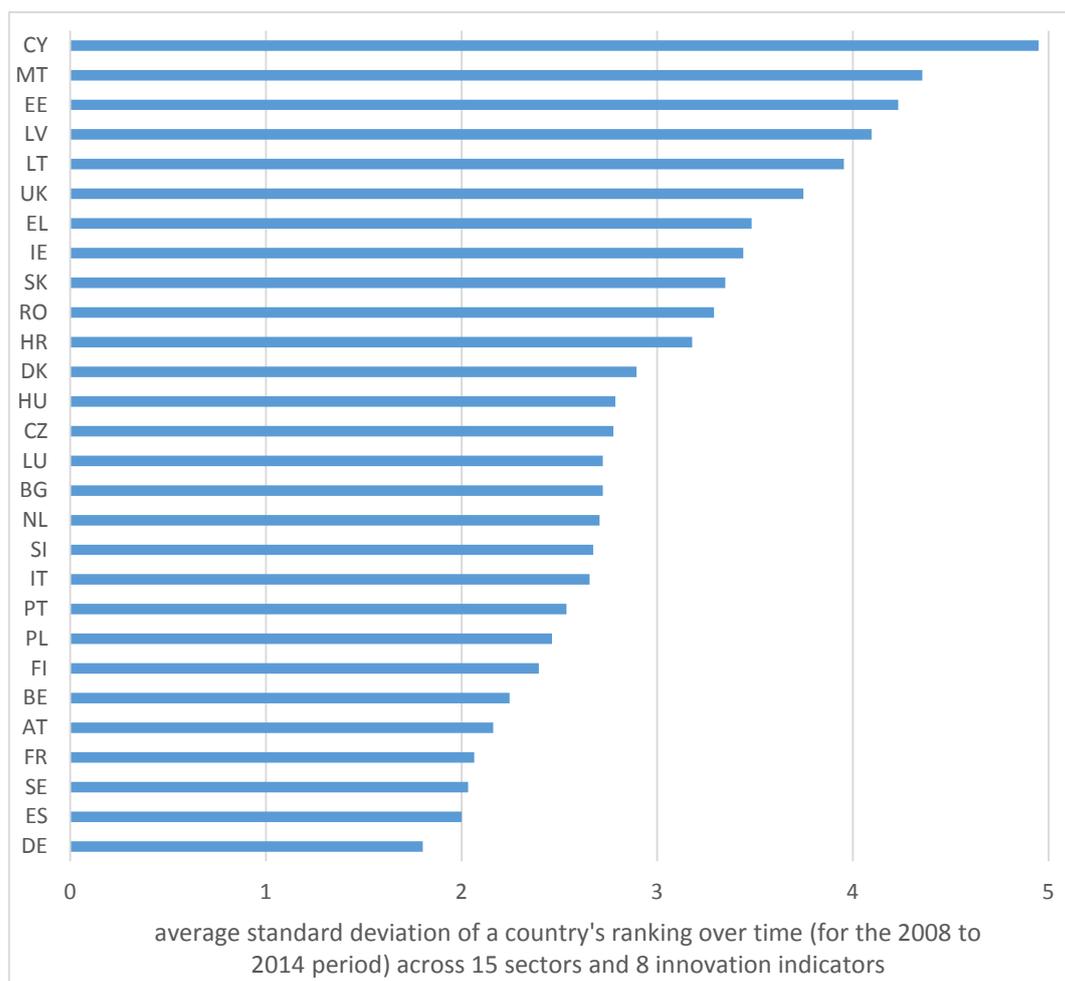
InnSales: Share of sales from total product innovations

InnCoop: Share of product/process innovative firms with innovation cooperation.

Source: Own calculations based on Eurostat R&D, IPR, innovation and structural business statistics.

Averaging the standard deviation of a country's ranking over time across all 15 sectors and eight indicators reveals that rankings do vary least for Germany, Spain, Sweden and France. Small member states (Cyprus, Malta, Estonia, Latvia, Lithuania) report the highest temporal variation of ranks in sector-specific innovation indicators (Figure 3-12). The UK is the only large member state that shows a high variation of rankings.

Figure 3-12: Average standard deviation of a country's ranking over time (for the 2008 to 2014 period) across 15 sectors and 8 innovation indicators



Source: Own calculations based on Eurostat R&D, IPR, innovation and structural business statistics.

C. Correlation between Indicators

For choosing among the different innovation indicators, correlation between indicators is an important information. On the one hand, highly and positively correlated indicators tend to measure the underlying phenomenon in a very similar way, suggesting that only one out of a group of highly correlated indicators need to be used. On the other hand, low or even negative correlations between indicators may hint at conceptual or measurement problems for some indicators. The correlation analysis is performed for each of the 15 sectors separately by calculating pairwise correlation coefficients across member states and observation years (covering 2008-2014). The results are presented in Table 3-18.

We find significant positive correlation between R&D intensity (both expenditure and personnel based) and the share of continuously R&D performing firms for all 15 sectors. The share of innovating firms is also positively related with these three indicators in all sectors. The share of innovating firms is also significantly positively correlated with these three indicators as well as with patent intensity and innovation

intensity for all 15 sectors except for C21 (pharmaceuticals) for which no significant correlation is found with personnel-based R&D intensity.

For most sectors, R&D intensity indicators and patent intensity are positively correlated, except for C13 (textiles) and C30 (other vehicles incl. aircraft).

Innovation intensity is positively correlated with R&D intensity and the share of continuously R&D performing firms in most sectors except for C22 (rubber and plastic products), C25 (metal products) and H (transport). In these three sectors, innovation intensity seems to be loosely related to R&D-based indicators.

The sales share of product innovation is an indicator that shows rather weak correlations with other innovation indicators. In some sectors (C20, C25, C27, C28), there is a significant correlation with R&D intensity. Only two sectors show a significant positive correlation between patent intensity and the sales share of product innovations (C27, C28) while there is a negative correlation in case of C29. More often one finds a positive correlation between the sales share of product innovations and innovation intensity, though not in C21, C26 and C30 which are sectors that particularly rely on R&D in their innovation strategies. The sales share of product innovation is positively correlated to the share of innovating firms and the share of firms with continuous in-house R&D in most sectors except for C26, C29 and C30.

The indicator on innovation cooperation is correlated with most other innovation indicators for most sectors. One exception is C29 where no correlation with R&D intensity, patent intensity, innovation intensity and the share of firms with innovation cooperation is found. In H, J58 and M72, cooperation is not correlated with R&D intensity but with all other indicators (except innovation intensity in case of J58). In J62, the correlation between cooperation and R&D is rather weak.

Table 3-18: Ctd.

	a	b	c	d	e	f	g	a	b	c	d	e	f	g	a	b	c	d	e	f	g	
	J62							M71							M72							
b	0.78							.							0.26							
	(155)							(0)							(147)							
c	0.23	0.21											
	(97)	(98)						(0)	(0)						(0)	(0)						
d	0.67	0.41	0.21					.	.	.					0.38	0.25						
	(76)	(77)	(48)					(0)	(0)	(0)					(54)	(53)	(0)					
e	0.42	0.45	0.42	0.45				.	.	.	0.47				0.34	0.45		0.56				
	(75)	(76)	(48)	(83)				(0)	(0)	(0)	(75)				(54)	(54)	(0)	(59)				
f	0.22	0.27	0.41	0.34	0.84			.	.	.	0.38	0.79			0.29	0.42		0.36	0.86			
	(79)	(80)	(54)	(90)	(88)			(0)	(0)	(0)	(84)	(76)			(51)	(51)	(0)	(54)	(54)			
g	0.22	0.04	0.06	0.26	0.40	0.44		.	.	.	0.28	0.49	0.46		0.10	0.18		0.25	0.43	0.27		
	(80)	(81)	(53)	(91)	(85)	(94)		(0)	(0)	(0)	(85)	(79)	(89)		(56)	(56)	(0)	(62)	(60)	(56)		
h	0.26	0.07	0.25	0.44	0.66	0.68	0.49	.	.	.	0.56	0.68	0.68	0.48	0.02	0.07		0.50	0.65	0.51	0.28	
	(82)	(83)	(54)	(93)	(91)	(98)	(95)	(0)	(0)	(0)	(87)	(82)	(89)	(90)	(57)	(57)	(0)	(64)	(64)	(61)	(66)	
	1% conf. interval							5% conf. interval							10% conf. interval							

Number of observations in parentheses.

a: R&D expenditure as a share of value added in the sector

b: R&D employees as a share of total employment in the sector

c: EPO patent applications per employed persons

d: Innovation expenditure as a share of total sales

e: Share of firms conducting R&D in-house continuously

f: Share of firms having introduced any type of innovation

g: Share of sales from total product innovations

h: Share of product/process innovative firms with innovation cooperation.

Source: Own calculations based on Eurostat R&D, IPR, innovation and structural business statistics.

All in all, the correlation analysis reveals that most innovation indicators - except for the sales share of product innovations - are highly correlated at the sector level. The varying levels of correlation as well as the fact that some indicators are not correlated for some sectors suggest the use of a multi-indicator approach to measuring innovation-related competitiveness. For example, innovation intensity in sectors C22, C25 and H seems to capture different aspects of the innovation process that are not captured by R&D-based indicators.

A special situation is with the sales share of product innovation. This indicator is not only rather loosely related to other innovation indicators. In some sectors, one even finds significant negative correlations with other indicators (C21, C29) which challenge the reliability of this indicator. In any way, this indicator seems to represent different features of innovativeness than the other indicators and should be used with some caution.

D. Country Rankings across Sectors

The ranking of a member state for a given innovation indicator is quite consistent across the 15 sectors. On average across the 28 EU member states and the eight innovation indicators considered, the standard deviation of a country's rank across the 15 sectors is 5.1 (Table 3-19). Member states with low values, i.e. similar rankings for each sector, include Austria, Poland, France and Italy (average standard deviation ranges from 3.4 to 3.9). Several small member states (Luxembourg, Malta, Estonia, Cyprus) show high average standard deviations of their sector rankings (ranging between 6.8 and 7.3).

Table 3-19: Standard deviation of a member state's ranking across 15 sectors (average 2008 to 2014), by innovation indicator

	RDI exp	RDI pers	Patent	InnExp	RD cont	InnShare	InnSales	InnCoop	Mean
AT	3.5	3.7	2.0	4.8	3.9	3.0	3.6	2.9	3.4
BE	4.8	3.8	3.9	5.1	2.9	3.5	6.3	2.1	4.1
BG	6.5	6.5	2.4	7.0	5.5	6.3	6.9	1.7	5.3
CY	4.6	7.0	9.0	5.7	7.3	5.6	8.1	7.3	6.8
CZ	4.6	5.5	3.5	5.4	3.5	4.1	5.8	4.4	4.6
DE	6.4	6.0	2.4	4.7	3.7	2.3	4.5	6.0	4.5
DK	6.2	6.9	4.5	8.1	n.a.	4.5	6.5	6.4	6.2
EE	7.8	4.1	6.8	8.9	7.5	7.8	7.3	6.2	7.1
EL	6.3	5.8	3.7	5.7	3.8	4.1	6.9	6.0	5.3
ES	2.9	3.3	2.8	6.7	4.0	6.0	3.6	5.3	4.3
FI	4.0	4.7	2.7	4.5	5.0	6.0	6.1	5.3	4.8
FR	5.6	5.5	2.3	4.3	1.7	3.0	5.0	3.1	3.8
HR	7.1	6.5	3.3	7.4	4.1	5.0	7.6	4.7	5.7
HU	6.8	6.6	2.0	6.3	3.0	3.3	7.5	3.7	4.9
IE	6.5	5.3	4.2	7.1	n.a.	3.6	7.7	4.3	5.5
IT	4.6	3.8	1.7	5.6	3.0	3.2	4.6	4.6	3.9
LT	6.4	4.3	4.1	8.2	4.8	5.6	7.8	5.4	5.8
LU	7.8	7.3	6.3	8.5	7.0	3.6	8.7	9.7	7.4
LV	8.3	4.8	6.7	5.2	5.0	6.0	8.5	5.7	6.3
MT	3.4	9.3	6.3	9.0	6.7	5.8	8.9	7.5	7.1
NL	6.0	5.8	3.3	6.7	2.6	4.2	6.8	4.4	5.0
PL	4.6	4.7	2.2	4.5	2.1	2.9	5.6	2.9	3.7
PT	4.9	4.7	2.6	6.6	3.4	3.0	4.5	4.8	4.3
RO	5.5	3.6	3.3	6.4	4.4	7.0	4.5	3.3	4.8
SE	3.7	4.6	3.8	7.0	3.9	3.2	4.3	4.1	4.3
SI	5.3	5.2	2.6	6.3	3.0	3.9	5.5	5.1	4.6
SK	5.2	3.5	3.8	6.4	5.6	5.4	9.2	5.1	5.5
UK	5.9	4.6	3.5	6.9	n.a.	6.2	3.7	3.6	4.9

n.a.: not available; RDI exp: R&D expenditure as a share of value added in the sector

RDI pers: R&D employees as a share of total employment in the sector

Patent: EPO patent applications per employed persons

InnExp: Innovation expenditure as a share of total sales

RD cont: Share of firms conducting R&D in-house continuously

InnShare: Share of firms having introduced any type of innovation

InnSales: Share of sales from total product innovations

InnCoop: Share of product/process innovative firms with innovation cooperation.

Mean: mean of the standard deviation of the average rank for the eight innovation indicators

Source: Own calculations based on Eurostat R&D, IPR, innovation and structural business statistics.

Luxembourg, for example, has a very high variation in its sector-specific rankings for the indicators on innovation cooperation (taking the first or second rank for four sectors while showing very high ranks for three other sectors) and the sales share of product innovation. Austria, in contrast, reports for most innovation indicators very similar ranks for most sectors. The lowest rank variation across sectors is found for France with respect to the share of firms with continuous in-house R&D (ranks between 1 and 7 which gives a standard deviation of 1.7) and for Italy with respect to patent intensity (ranks between 10 and 17, also giving a standard deviation of 1.7).

Table 3-20: Average rank of member states across 15 sectors (average 2008 to 2014), by innovation indicator

	RDI exp	RDI pers	Patent	InnExp	RD cont	InnShare	InnSales	InnCoop	Mean	Std.Dev.
AT	6	5	5	6	5	4	6	3	5	1.0
BE	6	6	6	10	4	6	14	3	7	3.5
BG	20	21	24	19	21	20	13	24	20	3.5
CY	22	21	16	21	15	18	18	19	19	2.6
CZ	13	14	21	12	14	16	10	14	14	3.2
DE	9	10	6	6	6	3	10	12	8	2.8
DK	9	10	6	13	n.a.	14	16	14	12	3.3
EE	16	21	16	18	15	21	18	14	17	2.5
EL	15	17	18	15	13	12	8	9	14	3.5
ES	12	10	13	15	10	15	7	16	12	3.2
FI	6	7	5	9	7	10	12	10	8	2.5
FR	6	8	6	7	5	7	9	8	7	1.3
HR	20	20	23	13	17	17	19	19	19	3.1
HU	16	16	21	17	18	23	18	20	19	2.4
IE	14	13	9	15	n.a.	7	12	12	12	2.7
IT	12	11	13	13	14	12	12	19	13	2.5
LT	16	17	20	11	17	15	12	12	15	3.2
LU	11	9	11	17	9	3	14	9	10	4.1
LV	16	20	13	19	17	20	16	23	18	3.2
MT	18	14	8	13	16	16	18	21	16	3.9
NL	9	6	5	11	3	8	12	9	8	3.0
PL	17	18	20	13	19	24	18	22	19	3.1
PT	12	13	18	13	9	8	17	14	13	3.4
RO	21	22	23	21	19	23	22	24	22	1.6
SE	5	6	8	7	10	9	17	9	9	3.6
SI	8	9	15	17	8	14	16	9	12	3.8
SK	19	21	23	17	18	20	14	17	19	2.8
UK	12	11	9	15	n.a.	12	4	5	10	3.9

n.a.: not available;

RDI exp: R&D expenditure as a share of value added in the sector

RDI pers: R&D employees as a share of total employment in the sector

Patent: EPO patent applications per employed persons

InnExp: Innovation expenditure as a share of total sales

RD cont: Share of firms conducting R&D in-house continuously

InnShare: Share of firms having introduced any type of innovation

InnSales: Share of sales from total product innovations

InnCoop: Share of product/process innovative firms with innovation cooperation.

Mean: mean of the average rank for the eight innovation indicators

Std.Dev.: standard deviation of the average rank for the eight innovation indicators

Source: Own calculations based on Eurostat R&D, IPR, innovation and structural business statistics.

When examining the average rank of a member state across the 15 sectors, one finds a group of member states with rather similar average ranks for most indicators (Table 3-20). Austria's and Belgium's average rank for the indicator on innovation cooperation is only 3, indicating that these two countries rank very high in almost every of the 15 sectors. Austria is the country with the most homogenous innovation performance across sectors and indicators. Its average rank is 5 or 6 for most indicators. As the standard deviation of the ranks across sectors is rather low for Austria, this implies that the country takes one of the top ranks in most sectors. Romania also shows a low variation of its average sector ranking for the eight indicators as the country is ranking very low for most sectors and indicators. There are a few exceptions, however, indicated by a high standard deviation of sector rankings for the indicators 'sales share of new products' (with medium ranks for C10

and C21) and innovation intensity (caused by a high value for C20). France reports similar average sector rankings for most indicators (ranging between 5 and 9). The standard deviation of the sector rankings are high for some indicators (R&D intensity, sales share of new products), implying less homogenous results across sectors.

E. Country Performance over Time

The pattern of change of a country's performance over time is another important dimension when evaluating the appropriateness of indicators. If countries show a consistent trend over time (like a catching up or a gradual decline in performance), short-term changes in recent years can be interpreted with higher confidence to indicate the continuation or a change in development. In contrast, if country performance does not show clear trends, a certain current change is more difficult to interpret as a reverse development may happen in coming years.

The analysis of changes in the performance of countries over time is confined to the indicator **R&D intensity** as for this indicator annual data for a longer period of time is available while CIS-based indicators without a break in series are available for four years only starting from 2008 in a biennial rhythm. We focus on R&D expenditure in the business enterprise sector as a percentage of total value added (GDP) and analyse the time period 2000 to 2015. Five indicators on the pattern of change in this indicator are used:

- compound annual rate of change (CARC) in the indicator value (percent)
- absolute change of the indicator value per year between the first (2000) and last year (2015) (percentage points)
- standard deviation of the annual absolute change of the indicator value
- number of years with a positive change in the indicator value
- number of years with a negative change in the indicator value

For member states that joined the EU during the time period 2000 to 2015, the second indicator is split into two, one covering the period prior to EU accession, and the other after the EU accession.

22 member states show an increase in the indicator value from 2000 to 2015 while 6 report a decline. The strongest increase in terms of compound annual rate of change is reported by Malta, followed by Bulgaria, Estonia and Portugal. In terms of the absolute change in the indicator value (i.e. the difference between the 2015 and the 2000 value) is reported by Austria and Slovenia (0.062 percentage points each), followed by Hungary and Bulgaria. The highest decline is in terms of CARC is shown by Luxembourg (-5.0 percent) and in terms of absolute change by Sweden (-0.054 percentage points).

Table 3-21: Pattern of change in business R&D expenditure as a percentage of GDP 2000 to 2015 by member state

	indicator value		CARC 00-15	absolute change per year			Std. dev. of annual absolute change	No. of years with negative change	No. of years with positive change
	2000	2015		00-15	prior to EU acces- sion	after EU acces- sion			
AT ^{b)}	1.38	2.18	3.6	0.062			0.08	2	9
BE	1.39	1.77	1.6	0.025			0.08	4	10
BG	0.11	0.70	13.1	0.039	0.003	0.071	0.06	2	11
CY	0.05	0.08	3.2	0.002	0.005	0.001	0.01	2	6
CZ	0.67	1.06	3.1	0.026	0.013	0.031	0.04	3	9
DE	1.68	1.95	1.0	0.018			0.04	6	7
DK	1.46	1.87	1.7	0.027			0.11	7	7
EE	0.14	0.69	11.2	0.037	0.048	0.033	0.23	4	10
EL	0.14	0.32	5.7	0.012			0.02	4	9
ES	0.47	0.64	2.1	0.011			0.03	6	7
FI	2.30	1.94	-1.1	-0.024			0.11	8	7
FR	1.30	1.45	0.7	0.010			0.03	3	9
HR ^{b)}	0.40	0.44	0.7	0.003	0.001	0.015	0.06	6	6
HU	0.35	1.01	7.3	0.044	0.003	0.059	0.05	2	11
IE ^{a)}	0.78	1.09	2.4	0.022			0.06	4	8
IT	0.50	0.74	2.6	0.016			0.02	2	10
LT	0.13	0.28	5.2	0.010	0.008	0.011	0.04	4	9
LU	1.45	0.67	-5.0	-0.052			0.11	9	2
LV	0.18	0.15	-1.2	-0.002	0.000	-0.003	0.07	7	8
MT ^{b)}	0.06	0.37	15.0	0.024	0.135	0.004	0.08	5	8
NL	1.00	1.12	0.8	0.008			0.08	7	6
PL	0.23	0.47	4.9	0.016	-0.018	0.028	0.05	3	9
PT	0.20	0.60	7.6	0.027			0.07	6	7
RO	0.25	0.21	-1.2	-0.003	-0.004	-0.001	0.03	8	6
SE ^{c)}	3.03	2.27	-2.0	-0.054			0.16	7	5
SI	0.76	1.69	5.5	0.062	0.040	0.070	0.15	5	10
SK	0.42	0.33	-1.6	-0.006	-0.043	0.007	0.05	8	5
UK	1.06	1.12	0.4	0.004			0.03	6	8

a) 2014 instead of 2015

b) 2002 instead of 2000

c) 2001 instead of 2000

Source: Own calculations based on Eurostat R&D, IPR, innovation and structural business statistics.

For member states that joined the EU between 2000 and 2015, no clear pattern of pre and post accession performance emerges. Bulgaria, the Czech Republic, Croatia, Hungary, Poland, Slovenia and Slovakia report a significantly stronger absolute increase per year in business R&D intensity following the EU accession while Estonia and Malta show a slower increase after the accession. In Cyprus, Lithuania, Latvia and Romania, the difference between pre and post accession performance is very small. In Cyprus, Latvia and Romania, business R&D intensity only marginally changed both before and after the EU accession.

When looking at the annual change in the indicator for those countries that showed a particularly strong increase in business R&D intensity, either for CARC (Malta, Bulgaria, Estonia, Portugal) or for the absolute change (Austria, Slovenia, Hungary, Bulgaria), no uniform upward trend emerges. In Malta, business R&D intensity increased in 8 years but fell in 5 years. Austria reports 9 years with increase and 2 years with decline (with no annual data for 2000 to 2004) and in Slovenia, business

R&D intensity increased in 10 years but fell in 5 years. A similar pattern is shown by Estonia. Bulgaria and Hungary are the two countries with the most consistent upward trend on an annual basis, showing 11 years of increase and only 2 of decline.

For the countries with a significant decline in business R&D intensity between 2000 and 2015, Sweden reports 5 years in which R&D intensity went up and 7 years of a negative development. In Luxembourg, the downward trend was more consistent (9 years with a decline, though no annual data for 2000 to 2003 is available).

All in all, annual changes in business R&D intensity are not necessarily a good indicator for a longer term trend. For that reason, analysis should always follow a longer-term perspective.

3.2.4 Conclusions

Measuring innovation-related competitiveness should aim at covering all stages of the innovative process, including inputs to generating new knowledge, the direct results of these efforts (i.e. measures of new knowledge generation), and the transfer of knowledge into innovations. This clearly requires a multi-indicator approach. However, there is only a limited number of reliable indicators on innovation-related competitiveness, and each indicator has its shortcomings:

- For measuring the input to knowledge generation, **R&D expenditure** is the most reliable and widely available indicator. While it is a well-established measure with high policy attention, it still has a number of drawbacks. New knowledge generation in services is less well captured by this indicator as much of service sector efforts in new knowledge generation are based on human capital investment and re-design of organisational processes, and are less formalised and structured than R&D processes in manufacturing. Macro level R&D indicators are strongly influenced by a country's sector structure as industries show very different levels of R&D activities. R&D data also turn out to be quite volatile both at country and sector level as often only a few large firms determine the level of expenditure. R&D personnel data tend to be more stable.
- For measuring the direct results of knowledge generating efforts, **patent data** have long been used as a key indicator. There are a number of substantial limitations, however. Only a fraction of new knowledge is patented, either because some new knowledge is not meeting the patenting requirements (i.e. it does not represent technical inventions with a potential for industrial application) or because firms rely on other methods to protect new knowledge (Arundel, 2001; Hall et al., 2014; Hussinger, 2006). For services, patents are an inappropriate indicator. Though it has been proposed to use trade mark application data instead, these are not necessarily an indicator of new knowledge output.
- Measuring **innovation output** is still a main challenge. Efforts in the context of innovation surveys have produced internationally comparable data, though all available indicators have major drawbacks that limit their appropriateness for competitiveness analysis. The share of innovating firms is strongly driven by small

firms while their contribution to a sector's or country's competitiveness is limited. The sales share of new products is rather volatile over time and produces somewhat instable country rankings. Both indicators suffer from the fact that they merge 'real' innovations and the adoption of others' prior innovations. In addition, innovation data are subject to some measurement issues owing to differences in national data collection activities.

For measuring innovation-related competitiveness in the context of the European Semester, we propose to use the following indicators while interpreting the results with caution, having the above mentioned limitations in mind:

- R&D expenditure per GDP (at economy level) and number of R&D personnel per total number of employed persons (at sector level)
- Number of patent applications per GDP (at economy level) and number of patent applications per total number of employed persons (at sector level for manufacturing sectors)
- Number of innovating firms per total number of firms

In addition, sales from product innovation per total sales is another indicator that can be helpful for assessing the output dimension of innovation-related competitiveness, though particular caution is required owing to the above-discussed specific limitations of this indicator.

3.3 Export Competitiveness

Michael Peneder and Stefan Weingärtner

3.3.1 Motivation

The focus in this section is on export competitiveness at the macro level. Consistent with the conceptual considerations in the chapter 2, we can define *external competitiveness* as the ability to earn income from international transactions and *export competitiveness* as the ability to earn income from selling goods and services abroad. For the following reasons, this is of general importance to the study of competitiveness:

- First, if economies operate below their potential output at full employment, export demand allows the generation of income, production and employment over and above that induced by domestic demand. It thus provides a stimulus to overall growth and the creation of jobs.
- Second, if economies operate close to full employment, higher export demand tends to increase domestic factor prices. While raising costs it also tends to foster structural change towards more productive activities – together with positive spillovers and learning effects from international competition.
- Finally, since competition tends to be more intense in the international market than in the smaller domestic market, an economy's export performance can provide a clearer signal of its comparative strengths and weaknesses.¹⁶

3.3.2 Data Sources

All international trade statistics ultimately rely on the same primary source of information, which is the data series collected and produced by the national statistical offices. Nevertheless, amongst these series there are profound differences in aim, concept and scope, which ought to be understood for their accurate use.¹⁷

In the following, we briefly review the major databases that are of (potential) relevance to the regular monitoring of export competitiveness in the EU Member States, distinguishing between three different kinds of collections: (i) foreign trade statistics (FTS), (ii) National Accounts/ Balance of Payment (NA/BOP) statistics as well as (iii) trade-linked input-output databases.

¹⁶ This signal can, however, be distorted by different trends in domestic and global demand, such as asynchronous business cycles or persistent gaps in purchasing power. For example, if the domestic market offers more profitable opportunities than exports, it may absorb a larger share of investment and production without necessarily being a sign of weak competitiveness.

¹⁷ For a recent survey and thorough analysis see Egger and Wolfmayr (2017).

Foreign Trade Statistics (FTS)

COMEXT

COMEXT is the EU's reference database for international trade in goods published by Eurostat, and therefore also the most up-to-date source for comparative analyses of its member countries. It provides harmonised time-series of monthly, quarterly, and annual bilateral trade flows as reported by the EU Member States. Partner countries are covered only indirectly – that is, to the extent that an EU country reports its exports to or imports from them.

Eurostat provides aggregated data for the EU12, EU15, EU25, EU27, EU10 (NMS) and EU12 (incl. Romania and Bulgaria). It classifies traded goods by the European Harmonised System (CN8 – 8 digits) but also reports them for the nomenclatures of NACE (up to 4 digits) and SITC Rev. 3 (up to 5 digits). The earliest time series start in 1988, though coverage varies between countries and is tied to their respective years of membership in the EU. The data contain trade values in 1,000 euros together with various quantities.

Customs declarations are the primary source of foreign trade statistics. But in the European Union these are only available for trade with partners outside the EU (EXTRASTAT) and not for trade among EU Member States (INTRASTAT). Instead, firms must report their trade transactions with other EU countries above a certain threshold. Egger and Wolfmayr (2017) discuss its implications for the so-called *Rotterdam Effect* in European trade statistics:

"The EU's two tier-system to allocate trade flows to partner countries – country of origin for extra-EU imports, country of consignment for intra-EU arrivals – is a major source of discrepancy to other statistical sources [...]. In general, Eurostat trade figures exclude goods in transit from one member country to another. However, there is one exception: goods imported to the EU area from an extra-EU trading partner and released into free circulation in the member country of entry, which are then transported to another member country, are recorded in the Eurostat-COMEXT database. They enter EXTRASTAT as an import from a non-EU member (e.g., the US) in the member country of entry where the customs procedures are carried out (e.g., the Netherlands) and they are recorded in INTRASTAT as a dispatch from the member country of entry (Netherlands) to another member country (e.g., Germany) and vice versa, as an arrival in one member country (Germany) from the member country of entry (Netherlands). The same is true on the export side. Goods that originate in one member country, but leave the EU area as an extra-EU export from another member where customs procedures are carried out, are included in Eurostat-COMEXT" (Egger and Wolfmayr, 2017, p. 5).

In short, the Rotterdam Effect tends to inflate trade flows of countries harbouring important entry points of extra-EU trade and to distort the ratio of extra- to intra-EU trade in the other countries.

UN COMTRADE

The United Nations *Commodity Trade Statistics Database* (COMTRADE) contains detailed annual import and export data reported by statistical authorities in close to 200 countries.¹⁸ It is the most comprehensive source of annual trade data with some series going back to 1962. COMTRADE reports trade values in US dollars together with various quantity units.

Data are compiled from the national statistical offices and then processed by the UN Statistics Division. Since 2005 the data of OECD members are first processed by the OECD and then shared with the UN. When reporting to the OECD, EU Member States can apply national practices that differ from the harmonised EU rules for COMEXT (Egger and Wolfmayr, 2017). Furthermore, up to 2006 the UN's practice of exclusively aggregating data from the detailed data at the product level has resulted in an under-reporting of aggregate trade flows because of confidentiality problems at the most disaggregate levels. Since 2006 COMTRADE includes separate items to adjust for unreported data, but a potential bias remains with regard to detailed bilateral trade flows.

CEPII-BACI

The *Centre d'Etudes Prospectives et d'Information Internationale* has developed the *Base pour l'Analyse du Commerce International* (CEPII-BACI).¹⁹ It builds on the UN COMTRADE database but aims to reconcile an inconsistency in the valuation of bilateral trade flows that is due to the different valuation of exports and mirror imports in the national foreign trade statistics (FTS).

In short, the FTS apply the principles of *cost, insurance and freight (c.i.f.)* in the valuation of imports, but *free on board (f.o.b.)* for the valuation of exports. Both include the

- Transaction value of the goods
- Value of the services performed to deliver goods to the border of the exporting economy

But only *c.i.f.* additionally includes the

- Value of services performed to deliver the goods from the border of the exporting country to the border of the importing country.²⁰

As a consequence, both in COMEXT and COMTRADE, bilateral trade flows reported by the exporting country do not mirror those of the importing country.

The major advantage of BACI is the consistency between bilateral imports and exports from the use of mirror flows to complete missing reportings and by adjusting imports to their *f.o.b.* valuation (i.e., they estimate and remove the third of the

¹⁸ <http://comtrade.un.org>

¹⁹ www.cepii.fr/en/bdd_model/presentation.asp?id=1

²⁰ See European Commission (2004, p. 7).

above elements of *c.i.f.*). Furthermore, CEPII uses the overall reliability of country reportings to determine their weights in the reconciliation of the bilateral trade flows.²¹ In return, the higher consistency of mirror trade flows comes at the cost of a later publication date.

Other FTS databases

Examples of further international collections of trade data are the OECD's *Quarterly International Trade Statistics* (which replaced the *Monthly Statistics of International Trade* in 2014) and the *Direction of Trade* (DOT) statistics produced by the International Monetary Fund (IMF). Both are compiled from the data reported by their respective members or associated countries. According to Egger and Wolfmayr (2017), the OECD data from the national sources are not further modified (except for the conversion to US dollars), whereas the IMF's Statistical Department extensively substitutes missing data by its own estimates for the DOT.

National Accounts (NAs) and Balance of Payments (BoP)

National Accounts (NA) and *Balance of Payments* (BoP) statistics are also compiled from the Foreign Trade Statistics (FTS). BOP is produced by the International Monetary Fund (IMF) and reports international payments and investment positions on a quarterly and annual basis for approximately 182 countries. It currently applies the guidelines of the Balance of Payments Manual (BPM6 – sixth edition). It contains time series on the various components of the balance of payments (flows) and the international investment position (stocks).

NA and BoP serve different purposes than the FTS. On the one hand, they report aggregate numbers and therefore lack the disaggregation of trade by products or bilateral exchanges, e.g. precluding their use in the analysis of export structures and comparative advantage. On the other hand, they include information on the international Trade in Services (ITS) and Foreign Direct Investment (FDI) statistics. Another advantage is the consistency of data when used in conjunction with other macroeconomic variables (GDP, employment, etc.).

Though supporting different purposes, "[a] user can nevertheless be puzzled when realising that for the same period, reporter and partner country, the figures for the item 100 (goods) in the current account of the Balance of Payments, and in External Trade are not the same" (European Commission, 2004, p. 3). The main reasons are conceptual differences and inconsistent practices among EU countries when adjusting data from the FTS to the particular needs of the BoP. For example, one source of ambiguity concerns the coverage and time of recording a transaction. In the FTS, transactions are generally recorded when a good enters or leaves the country, i.e. by the *change of territory*. In contrast, BoP defines an international transaction with the *change of ownership* principle in order to be consistent with the

²¹ See Gaulier and Zignago (2010).

NA. As a consequence, adjustments have to be made when constructing the data series for the BOP.²²

Another source of differences is the valuation of traded goods. As mentioned before, FTS apply the principles of *cost, insurance and freight (c.i.f.)* for imports, but *free on board (f.o.b.)* for exports. In contrast, BOP statistics consistently apply *f.o.b.* to both exports and imports. Since FTS are the primary source, data must be adjusted by subtracting the presumed cost of transportation and insurance during delivery towards the border of the importing country. Statistical offices typically apply a proximate ratio of *c.i.f.* to *f.o.b.* In the best (but not all) cases, a breakdown by mode of transport and geographical distance of the partner countries is available (European Commission, 2004).

Trade-linked Input-Output Data: WIOD and TiVA

The production of international datasets on trade-linked input-output data is a recent development, but has already spurred a wave of new research on global value chains. Unlike FTS, which record trade flows at their gross value, they aim to disentangle the international flow of intermediate inputs from the actual value added contained in cross-border transactions. Their foremost use is for analytic purposes, for instance, revealing the scope of distortions in our assessment of competitiveness that is due to the dependence on gross values in trade.

Trade in value added directly relates to the generation of income in an economy and is therefore very close to our concern for competitiveness at the macro level. But its construction depends on the availability of national input-output data, which causes a considerable publication lag and hampers its use in a regular monitoring of competitiveness at timely intervals.²³ For example, at the time of writing the *Trade in Value Added (TiVA)* database, which was jointly developed by the OECD and the WTO, provides indicators for 63 countries and 34 sectors only up to the year 2011. This is similar to an earlier edition of the *World Input Output Database (WIOD)*, which covered the period from 1995 to 2011. In contrast, the most recent edition of WIOD covers the years from 2000 to 2014.

The WIOD project was originally funded by the European Commission within its 7th Framework Programme. The aim was to compile a consistent time series of national Supply and Use tables (SUT), plus trade linkages for the EU27 and 13 major non-European economies (AUS, BRA, CAN, CHN, IDN, IND, JPN, KOR, MEX, RUS, TUR, TWN, USA). The national SUTs and the trade linkages together provided the basis for the inter-regional intSUTs. It distinguished between 35 Sectors producing 59 commodities

²² Though the term "change of ownership" may suggest otherwise, the international transaction of goods between affiliates of the same parent corporation are included as trade flows in both the FTS and BOP. Other examples where the guidelines have differed are the "repairs of goods" (excluded only in FTS) or "returned goods" (excluded only in the BoP). For more details, see European Commission (2004, p. 5f).

²³ One proximate solution is to update the database with more recent information, e.g. from the NA and FTS and adjust the input-output coefficients when the new official tables become available.

and using the NACE Rev. 1 classification. From the intSUTs the WIOTs (World Input-Output Tables) were derived – that is, symmetric IO-Tables of dimension (41 countries x 35 industries) x (41 countries x 35 industries).²⁴ In late 2016, a new WIOD data base was released, in which the number of countries was slightly expanded (adding Croatia, Switzerland and Norway). The classification changed from NACE Rev 1 to Rev 2, and the number of sectors and commodities increased to 56. For further details on the WIOD database see Dietzenbacher et al. (2013) and Timmer et al. (2015).

3.3.3 Indicators

In terms of the different layers of competitiveness discussed in Chapter 1, some popular indicators are best interpreted as *balancing constraints* to sustain an economy's competitiveness in the medium to long term. Most other indicators of export competitiveness belong to the layer of *structural factors*. As explained in section 2.3, many of these simultaneously measure a certain dimension of competitive performance as well as overall determinants of competitiveness. As measures of performance, they are shaped by institutional and other *deep level* factors (e.g., infrastructure, education & innovation systems; entrepreneurship, trust). As a determinant of competitiveness, export performance contributes to aggregate demand and structural change, thereby affecting the quantity and quality of how productive *resources* (e.g. labour, capital, knowledge) are used in the economy and hence the growth of per capita income.

In this section, we will organise the indicators along the following dimensions:²⁵

A. **Cost and price based constraints**²⁶

- Unit labour cost (ULC)
- Real-effective exchange rates (REER)

B. **External balances**

- Current account balance in % of GDP
- Trade balance in % of total trade
- Trade balance for extra/intra-EU trade (in % of total extra/intra-EU trade)

C. Change of **export market shares** sourced from different data sources

- COMEXT
- COMTRADE
- BACI

²⁴ Additionally, a data set of socio-economic variables (components of value added, prices and volume indices of output, as well as factors of production and employment and hours worked by three skill types) and environmental accounts were provided (energy use and emissions).

²⁵ In the next chapter we will additionally provide a detailed discussion of two further indicators: "openness" and terms of trade (ToT).

²⁶ In contrast to section 3.1, cost competitiveness indicators here refer to the macro level only.

- BOP

D. Export structure

- Inter- vs intra-industry trade (Grubel-Lloyd index)
- Diversity (Herfindahl and Theil indices)
- Sophistication of exports (technology intensity, quality segments, complexity)

We assess the robustness of relative performance among EU Member States with regard to these choices and illustrate the relative similarity of and distances between these measures in terms of the ranking of Member States. In a final step, we apply statistical cluster analysis to identify dominant groupings among the variables and provide a tentative taxonomy of countries according to their similarity of patterns in the selected dimensions of export performance.

There are innumerable possibilities for comparing different indicators in their alternative forms and characteristics. For the sake of clarity and facility of inspection, we try to be selective in the choice of variables. Furthermore, we restrict ourselves to the following set of quantitative representations that we consistently apply throughout this section. This choice of graphical representations is motivated by the particular nature and dimensionality of the country-wide indicators, which is therefore different from the two previous sections:

- To begin with, simple **bar charts** illustrate the respective values of selected indicators for the EU Member States in the latest available year. Countries are sorted such that being on top consistently implies better performance (typically a lower rank number). Since the report does not aim to analyse the performance of individual countries, these charts are used sparingly and only for the purposes of illustrative examples.
- **Quadratic heat maps** illustrate the similarity and dissimilarity between selected indicators in a compact form. Below its diagonal, the matrix depicts the Pearson coefficient of pairwise *correlation* applied to the country rankings (which in this case is equivalent to a Spearman coefficient of rank correlation). Higher coefficients indicate a stronger similarity between two measures. The range is between -1 and +1 with unity signalling redundancy in the sense that the two indicators produce an identical rank of countries.²⁷ Conversely, low values signal that the indicators depict independent dimensions of competitiveness. Above the diagonal, the chart reports the average *Manhattan (or City-Block) distance*²⁸, which is the sum of the *absolute* differences of two vectors.²⁹ The

²⁷ Or an exactly inverted rank, if the coefficient is -1.

²⁸ The name points at an intuitive explanation of the measure. Imagine a city in which the streets run vertically and horizontally. The common *Euclidean* measure corresponds with the shortest geometric distance 'a bird could fly' straight from point *a* to point *b* (i.e. the hypotenuse in the *xy*-plane), whereas the use of the *Manhattan* measure is consistent with the distance that 'people have to walk' around the city blocks. See, e.g., Peneder (2005) for further discussion and a geometric illustration of different measures of (dis)similarity.

²⁹ It therefore prescribes equal importance to any unit of dissimilarity. Operating with squared differences, the alternative Euclidean measure would, for example, rank two indicators with a

Manhattan distance is zero if two indicators produce exactly the same country ranking, and rises as the difference between them becomes larger.

For easier visual inspection, the cells of the matrix exhibit a different colour shading that corresponds to the degree of association. Dark colours signal a stronger association than light colours. For the correlation coefficient, the range of the shading is normalised between zero and one, so that the overall intensity of shading also reflects the overall degree of association between the variables. Conversely, for the Manhattan distance the range adjusts to the actual values, which implies that the shadings are always relative to the other tiles. Since the two measures produce very similar interpretations of the relatedness of the indicators, we will only discuss the correlation measure of similarity explicitly in the text and provide the Manhattan distances for additional visual inspections.

- Finally, **cluster heat maps** help us to organise much data within one chart that is both visually conceivable and rich in information. It starts from a rectangular tiling that is organised by countries in rows and indicators in columns.³⁰ Its main characteristics can be summarised as follows:
 - Providing for an easy visual inspection, the CHM represents the value of each tile by a different intensity or shading of the colours. In our case, lighter colours indicate a lower number or generally better performance than dark colours.
 - The algorithm further permutes the rows and columns in order to reveal their joint cluster structure. Using hierarchical clustering with the average linkage method and Euclidean distances, the dendrograms on the margins depict their relative degree of association.
 - The simultaneous clustering arranges the tiles such that similar variables and countries appear near each other. This avoids an otherwise confusing pattern of cells with contrasting colours and intensities, thereby facilitating the easy visual detection of joint patterns of similarities across both dimensions.
 - In a final step, we fill the matrix by the concrete numbers of the country ranks for each indicator. This produces a simple table within the chart that allows for the detailed comparison of how different indicators affect the country rankings.

As for all the country rankings produced in this study, the purpose is to illustrate, how the indicators work out with concrete data, and in particular, what difference the choice among alternative indicators can make. Therefore they are not meant to serve or be used as an assessment of the performance of EU Member States, which inevitably requires a more detailed examination of the specific historical, structural and institutional context of a particular country

difference of 1 unit in the first observations and 3 units in the second observations as farther apart than two indicators with a difference of 2 units in both observations.

³⁰ Wilkinson and Friendly (2008).

A. Cost and price based indicators

Concept and definitions

Indicators of cost and price based competitiveness are a natural point of departure. But two aspects require especial attention:

- First, many components are not under the control of the individual enterprises. Examples are exchange rates, general inflation and input prices determined on competitive factors markets (e.g. wage levels, interest rates or energy prices). This underscores our interest in the complementary macro perspective of competitiveness.
- Second, there is a general ambiguity of cost-based constraints to competitiveness. *Ceteris paribus* a rise in labour income implies an increase in purchasing power and hence of living standards. If, however, higher export prices come at the cost of a lower volume of foreign sales, it will cause employment and income to decline. In short, a rise in compensations paid per labour input contributes to the growth of aggregate demand and is desirable if backed by an according increase of productivity. But it must also be consistent with international developments.
- Finally, indicators of relative prices such as effective exchange rates (EER) or terms of trade (ToT) not only relate to an economy's average cost of production, but also to its average purchasing power relative to trade partners. As a consequence, they naturally tend to rise with increasing productivity, especially for tradable goods (*Balassa-Samuelson hypothesis*).

The upshot is that cost and price based factors do not constitute a proper measure of competitiveness *per se*. Instead, they indicate an economy's ability to maintain a sustainable balance between the change of factor prices, most importantly wages, on the one hand, and productivity on the other in international comparison. This explains why we generally consider indicators of cost competitiveness to be *balancing constraints* to economic development (see section 2.3). Consistently, they feature prominently in the European Commission's *Macroeconomic Imbalances Procedure* (MIP).

There are a variety of indicators which rely on different data and suit somewhat different purposes. To begin with, **unit labour costs** (ULC) measure the ratio of total labour cost to real output which is equivalent to the average cost of labour per unit of output. ULC thus relates wages to labour productivity. In the MIP these are calculated as the ratio of compensation per employee in current prices to a volume index of real GDP per person employed (indexed for the year 2010=100). The interest is thus in the changes over a given time interval t .³¹

³¹ The additional use of trade-weights to account for the relative importance of different partner countries produces the *relative unit labour cost* (RULC).

Section 3.1 already provided a detailed discussion of unit labour cost. In this section we will therefore focus on **effective exchange rates** (EER) – with “effective” meaning that nominal exchange rates are transformed by trade weights. These trade weights proportion the comparison with other countries to the extent that their firms actually compete on the same market. They rely on a trade matrix with own production for domestic use in the diagonal. The European Commission (DG ECFIN) applies *double export-weights* in order to also account for third-market effects. Thereby, the bilateral exchange rates are weighted by the

- foreign country's share in the total supply of goods in each market, and the
- relative share of each market in the total exports of the domestic country.³²

One problem is that structural changes in the composition of trade can cause considerable distortions. This renders the choice of appropriate adjustment periods of the trade-weights an important criterion. The European Commission uses a chain-linked moving weight matrix that is based on the trade data of the previous year.

Deflating *nominal effective exchange rates* (NEER) with an appropriate price index yields **real effective exchange rates** (REER). It is a comprehensive measure, which combines information on

- the nominal exchange rates and
- relative price developments between the domestic and foreign countries with
- the matrix of trade flows.

Again, the interest is in observing changes over time, with rising REERs implying that exports and a country's own production become more expensive relative to imports.

There exist several options, but no overall best solution for the critical choice of an appropriate deflator. In addition to practical concerns about the availability of reliable data, the choice depends on the precise purpose of the analysis and implicit or explicit theoretical notions. With regard to the latter, Chinn (2006) decomposes the REER into three distinct components:

- the price of tradables in the domestic relative to the foreign economy
- the price of nontradables relative to tradables in the domestic economy, and
- the corresponding relative price in the foreign economy.

In the unrealistic case that the law of one price applies to all products (and consumption baskets are identical), the REER is simply constant (i.e. all three elements above are zero). If the law of one price applies only to tradables (i.e. the first element is zero), REER corresponds to the difference between the relative price of tradables versus nontradables in the domestic and the foreign economy (i.e. the second versus the third element above). This is the world of the *Balassa – Samuelson*

³² See https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/price-and-cost-competitiveness_en. There are alternative options, such as bilateral export weights, bilateral import weights, or the use of a weighted average of double exports and bilateral imports. The latter is applied, for instance, at the ECB, OECD and BIS. In a comparative analysis conducted by DG ECFIN, the differences were shown to have a very minor impact on the calculations of the REER.

hypothesis.³³ In short, if productivity grows faster in tradables, their prices relative to nontradables will also decline. This is because the productivity increase either also leads to a rise in wages for nontradables that compete for labour on the domestic factor market (without enjoying a corresponding productivity gain) and/or would imply a decline of the output price of tradables relative to nontradables (even if productivity growth does not affect nominal wages). As a consequence, the REER tends to appreciate if a country experiences higher productivity growth in tradables than nontradables relative to its trading partners. This implies that a country's nontradable goods and hence the overall costs of living become more expensive.³⁴ Finally, if traded goods are imperfect substitutes, the law of one price no longer applies to the first component, and international differences in the price of tradables additionally affect the REER, making it sensitive, for instance, to differences in product quality or branding.

There are various options for the critical choice of an appropriate method of deflation. One of the most popular is based on a sensitive cost component:

- Deflation by *unit labour costs* is mainly of interest to the study of labour relations and whether the process of wage determination is capable of maintaining a balance with international developments of productivity and wages. An apparent limitation is that labour only accounts for an (often small) portion of total costs, whereas other factors such as the cost of capital and intermediate goods is ignored. This and the inability to account for factor substitution (such as increased capital intensity in response to rising wages) and structural change³⁵ (e.g. from labour to capital or technology-intensive tasks and industries) produces a biased characterisation of a country's overall cost position.³⁶ Typically, the measure is calculated either for the total economy or for the manufacturing sector.

The other measures are based on price series, which have the advantage of implicitly accounting for factor substitution.

- *Export prices* may seem an obvious choice but are rarely used in practice. One problem is their high volatility, as they are strongly affected by fluctuations in commodity prices or changes in the composition of trade. Another problem is that it only reflects the prices of goods that already sell successfully on the international market, which introduces a substantial selection bias to the analysis.³⁷

³³ Balassa (1964) and Samuelson (1964).

³⁴ This is also known as the Penn effect of high incomes leading to high average prices.

³⁵ As a solution to the latter problem, Mehrez et al. (2014) compute ULCs per sector and then aggregate them for the economy-wide measure.

³⁶ See also Köhler-Töglhofer et al. (2017) who report, for instance, that their ULC-based REER produces comparatively smaller estimation and forecast errors with respect to different measures of trade performance than those using the consumer price index (see the following paragraphs).

³⁷ Instead of deflating NEER by export prices, one may turn to the *terms of trade* (ToT) indicator. It measures the country-specific ratio of export to import prices and can be understood as a REER for a

- Producer price indices (PPI) remedy the latter problem by offering a comprehensive index of domestically produced goods. But establishing internationally harmonised and reliable series poses serious data problems, which generally limits their application to smaller groups of countries. Often they only apply to the manufacturing sector.
- The GDP deflator is an interesting alternative, which reports the implicit price of all domestically produced goods and services at their market value. It captures the relative price trends of the total value added produced in an economy, including that of exported goods. It is thereby consistent with a modern perspective on global value chains and also sensitive to changes in the structure of expenditures from both domestic and foreign demand.³⁸
- Finally, the (harmonised) index of consumer prices (HICP) is the most common method of deflating the REER. Its major advantage is the better availability of data produced by internationally harmonised standards for a large number of countries. Similarly to the GDP deflator, it captures relative price trends in both tradables and nontradables. Focusing on domestic consumption it cannot directly account for the relative price of investment goods.³⁹ Overall, one can argue that it better serves the purpose of detecting internal imbalances than the monitoring of export competitiveness.

Empirical illustration

Figure 3-13 presents a quadratic heat map for annual changes to be used when the focus is on the most recent developments. In contrast, Figure 3-14 uses 3-year changes, which dampens cyclical effects and provides a less volatile picture of developments in the medium term. Seven variables of cost and price based competitiveness have been selected for the pairwise comparisons. All of them originate from calculations and databases made publicly available by DG ECFIN, with two of them included in its Macroeconomic Imbalances Procedure (MIP). The first one is unit labour costs (ULC) and the second the real effective exchange rate (REER), with the (harmonised) consumer price index (HCPI) used for deflation. This index is available for a sample of 42 trading partners. To assess the sensitivity of the measure to the choice of countries, we include the same index for a smaller group

particular choice of deflators (European Commission, 2012, p. 10). The conventional reading, however, is that the ToT depicts the amount of imports that a country can purchase per unit of exports, which associates positively with the quality of exported versus imported products. We will discuss the terms of trade in more detail in Chapter 4.

³⁸ A deflator of *gross output* would additionally account for price changes in imported intermediate goods and services. Recently, the Deutsche Bundesbank (2016) has shown that REERs based on it perform similarly to the REER based on the GDP deflator and that both are highly correlated or even co-integrated.

³⁹ Investment goods sold to domestic producers may indirectly affect the HCPI, but probably with a time-lag. If investment goods are exported, i.e. directly or indirectly (when sold to domestic exporters), their price changes will not affect the REER based on the HCPI. See also Deutsche Bundesbank (2016).

of 37 industrialised countries (IC37)⁴⁰, which is the largest sample of trade partners available for the remaining indicators. Those include different REERs based on either the GDP deflator, unit labour costs for the total economy, unit labour costs for manufacturing, or export prices.

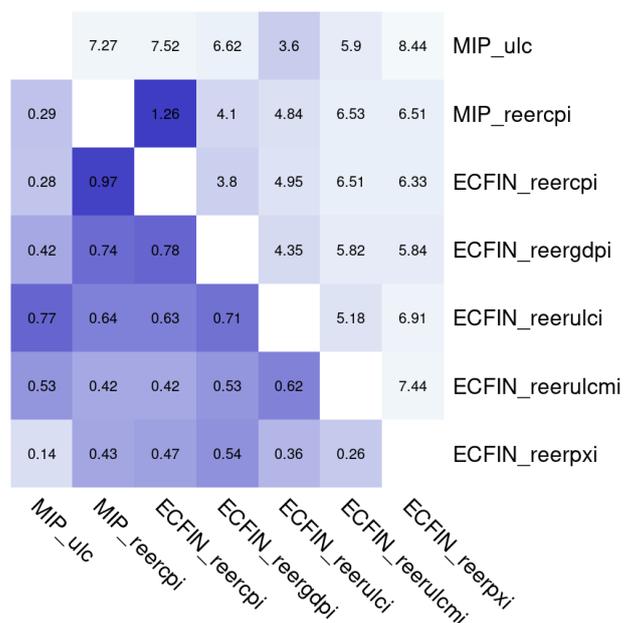
Not surprisingly the two REERs based on the HCPI produce almost identical rankings. This confirms that the slightly different set of trade partners does not pose a major distortion. For better comparability with the other indicators, we will therefore leave out the measure from the MIP and stick with the IC37 group of trade partners in the further analysis. The other measure from the MIP is unit labour cost (ULC). Though the lack of export weights has a pronounced impact on the country rankings, its coefficient of correlation with the REERs based on ULCs for the total economy still amounts to 0.77 and 0.73. The pairwise correlation drops considerably if one uses the REER based on ULCs for manufacturing only and it is generally low with respect to all other indicators. The REERs based on export prices associate little with other variables. The highest correlation is with the REER based on the GDP deflator. The latter displays the highest degree of association with the other REERs, and in that sense appears to be the most comprehensive single measure available, which simultaneously captures changes in the price of tradables and nontradables, exports, labour and other cost factors.

Figure 3-15 and Figure 3-16 present simple barcharts of selected indicators for the EU Member States in the year 2015. *Unit labour costs* (ULC) is the only measure that does not use export weights. Ireland shows the biggest 3-year decrease, followed by Greece and Cyprus. In turn, Latvia, Bulgaria and Estonia have experienced the biggest increase in their ULC. When the GDP deflator is used to calculate the 3-year change of the *real effective exchange rate* (REER), Greece, the Czech Republic and Cyprus have depreciated the most, whereas United Kingdom, Romania and Estonia had to cope with the highest appreciation among the EU Member States.

The heat map in Figure 3-17 reveals the joint cluster structure of the selected indicators in columns and the EU Member States in rows by ordering both dimensions so that similar entities are placed close to each other. Consistent with prior considerations about the nature of the different indicators, both measures for the change of unit labour costs (*MIP_ulc*) in $t=1$ and $t=3$ years as well as the real effective exchange rates based on export prices (*ECFIN_reerxpi*) appear on the margin. This reflects their larger dissimilarity with regard to the other indicators. The real effective exchange rates based on the ULC deflator (*ECFIN_reerulci*) are most similar to the ULC measure, with the main difference stemming from the fact that the latter does not use export weights. The real effective exchange rates with the consumer price index (*ECFIN_reercpi*) and the GDP deflator (*ECFIN_gdpci*) show the most pronounced similarity.

⁴⁰ The IC37 is comprised of the EU28 plus Australia, Canada, Japan, Mexico, New Zealand, Norway, Switzerland, Turkey, and the USA. The sample of 42 countries also includes Brazil, China, Hong Kong, Korea, and Russia.

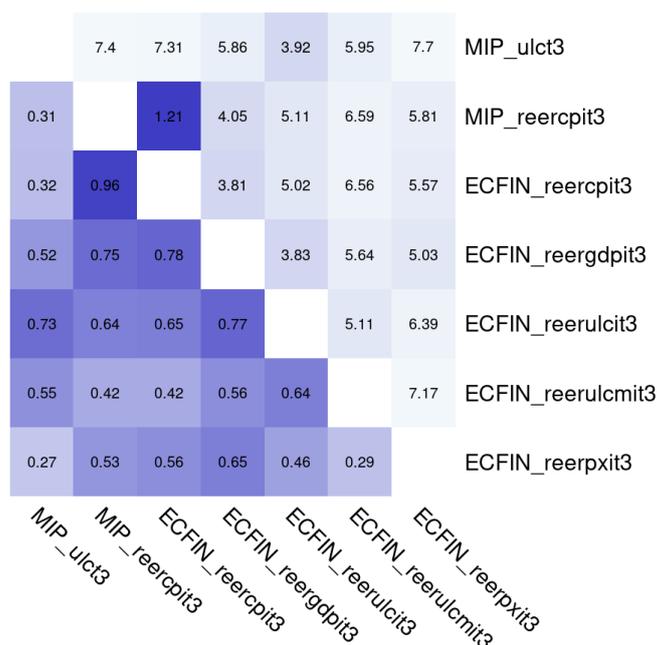
Figure 3-13: Quadratic heat map of cost and price factors: yearly changes, pairwise correlation of the country rankings, City-Block distance, 2006-2015



Note: The numbers below the diagonal present the correlation coefficient, those above the diagonal the Manhattan measure of distance (average absolute change in ranks). The individual indicators are explained in the main text.

Source: DG ECFIN, WIFO calculations.

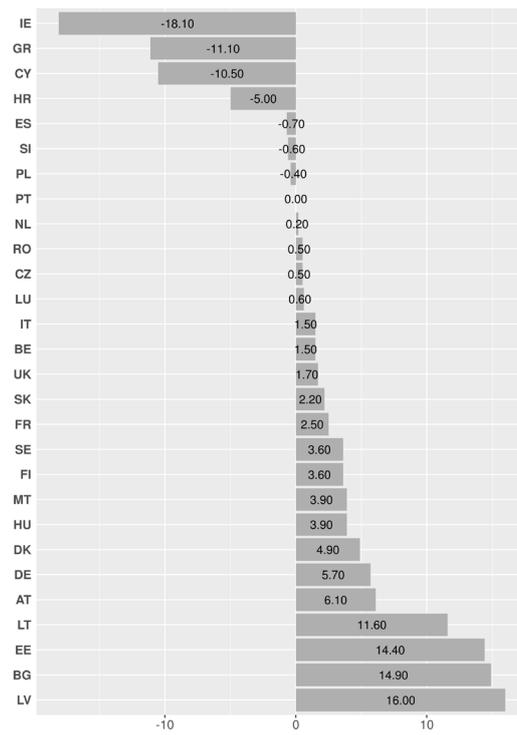
Figure 3-14: Quadratic heat map of cost and price factors, 3-year changes: pairwise correlation of the country rankings, City-Block distance, 2006-2015



Note: The numbers below the diagonal present the correlation coefficient, those above the diagonal the Manhattan measure of distance (average absolute change in ranks). The individual indicators are explained in the main text.

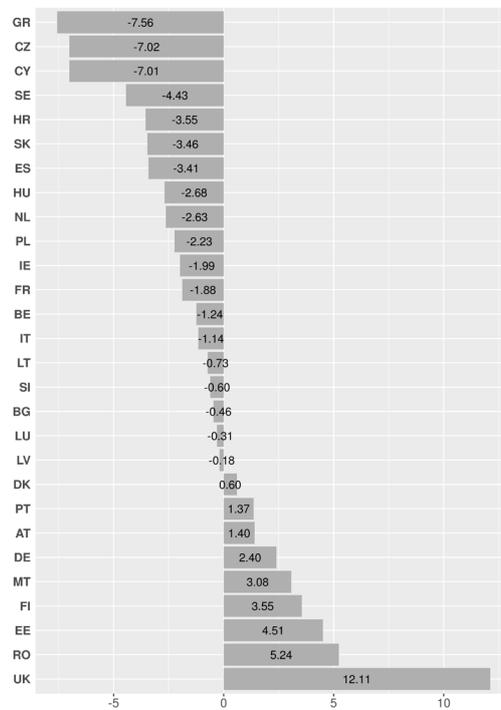
Source: DG ECFIN, WIFO calculations.

Figure 3-15: Unit Labour Cost (ULC) 2015, 3-year change in %



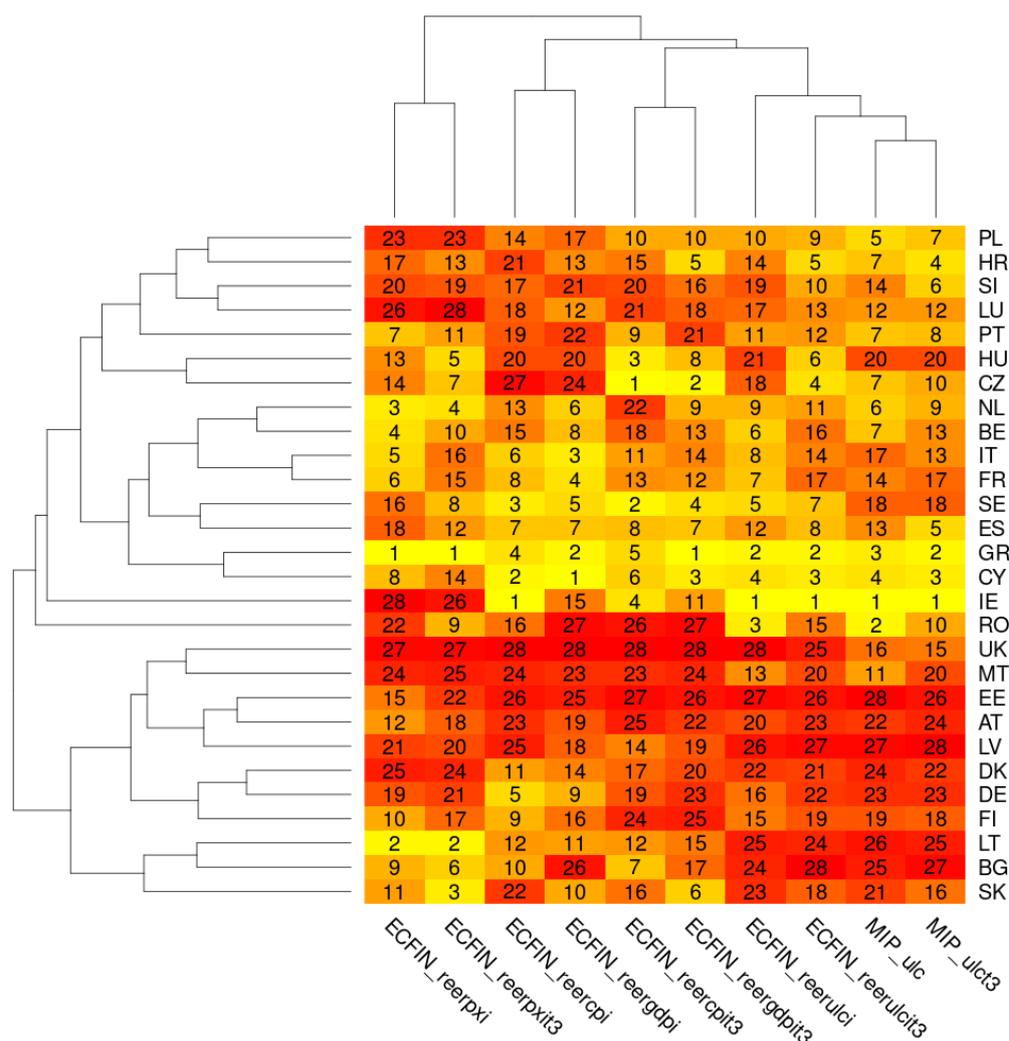
Source: MIPS, WIFO calculations.

Figure 3-16: Real Effective Exchange Rate (REER) 2015, 3-year change in %, GDP deflator



Source: DG ECFIN, WIFO calculations.

Figure 3-17: Cluster heat map of ranks in cost and price based competitiveness, 2015



Note: Numbers denote the country ranks, lighter colours better performance. Cluster dendrograms based on average linkage method and Euclidean distances.
 Source: DG ECFIN, BOP; WIFO calculations.

Greece and Cyprus are grouped together as the two countries which distinctly lead the ranking in terms of changes in their price and cost competitiveness. Apparently, the changes reflect the dramatic adjustment due to past imbalances. Countries such as Spain, Sweden, France, Italy, Belgium and the Netherlands also performed well in comparison to the other Member States. United Kingdom and Malta show the worst performance, followed by countries such as Estonia, Latvia or Austria. Ireland displays a particularly pronounced irregularity of its pattern and ranks at the top for all variables that relate to unit labour costs but very poorly for the REER based on export prices. Apart from such outlying cases, many countries show substantial differences in their relative position, which depends on the specific choice of indicator. If we take Germany as an example, the country performed well with regard to the one-year changes of the REER, deflated by the CPI or GDP prices (ranking 5th and 9th, respectively), but not for any of the other indicators.

B. External Balances

Concept and definitions

In this section, the indicators again combine aspects of differential performance with that of balancing constraints. The primary data source is the balance of payments (BoP) with the current account and the capital account as its main components. The **current account** is a comprehensive measure of the country's net income from transactions with the rest of the world, covering the *trade balance* for goods and services as well as *primary and secondary income*.⁴¹ It reports actual flows of goods and services that directly affect income, production and employment. Conversely, the **capital account** reports the according net change in ownership of assets, i.e. stocks. A surplus corresponds to an inflow of capital by means of either borrowing or selling assets. Conversely, a deficit corresponds to an outflow or increase in foreign assets.

By definition, a current account surplus implies a net capital outflow as the country increases its net foreign assets. Conversely, a current account deficit comes together with a net capital inflow, since foreigners, on net, increase their domestic assets (Mann, 1999; Breuss, 2006). Due to these identities, the economic interpretation can be ambiguous:

"A current account deficit can mean that a country is 'living beyond its means,' because overall consumption and investment exceed the national savings of the economy. Alternatively, it can mean that a country is an 'oasis of prosperity,' attracting investment from around the globe because the economy delivers higher investment returns at lower risk than other investment choices" (Mann, 2002, p. 131).

The **trade balances** of goods and services form the major part of the current account. It is defined by the difference between a country's exports and imports, and thus equivalent to the difference between its gross output and domestic expenditures. Positive net exports generally indicate higher competitiveness. However, similarly to the current account, one must interpret positive or negative balances within the context of a country's specific economic development:

- *Ceteris paribus*, a trade deficit/surplus is interpreted as an indication of competitive weakness/strength. The reason is that deficits must be financed either by an increase in debt or the sale of assets, which invokes the common interpretation that a country is spending beyond its means. Conversely, a trade surplus implies that the country is accumulating claims or reducing its debts. Moreover, if the economy operates below its potential output with full employment, export demand (net of domestic demand for foreign products) augments domestic production and hence aggregate income (GDP). This net contribution of the trade balance to aggregate demand directly relates it to our definition of competitiveness in terms of aggregate income and living standards.

⁴¹ That is, net income from abroad and net current transfers (except financial assets).

- Persistent deficits generally raise concerns about the long-term sustainability of an economy's growth path. The reason is that a "large stock of financial obligations implies flows of income payments and receipts – interest, dividends and the like – that must be paid out of the economy's current production and that could get large enough to reduce current consumption and investment" (ibid, p. 132).⁴²
- Prolonged deficits can be a consequence of healthy economic transformations. For instance, in emerging or catching-up economies that enjoy high rates of investments, many of which are imported machinery, the standard interpretation of the trade balance along the above arguments would wrongly indicate weaker competitiveness in the fast growing economy and vice versa.
- Temporary deficits can be triggered by transient shocks (e.g., natural disasters; cyclical downturns in important export markets, idiosyncratic events affecting large companies) and reflect the benefits of international capital flows that help to smooth domestic consumption. Analogously, temporary or prolonged surpluses are not necessarily a sign of competitive strength if forced upon an economy by increased interest payments for foreign debts that were accumulated in the past (involuntary saving).⁴³
- More generally, international differences in the business cycle affect trade balances such that strong economies with a robust growth of domestic demand tend to import more relative to countries with a weak domestic demand. As a consequence, the trade balance can move in favour of the weak economy and against the strong economy.
- Finally, persistent surpluses imply that a society prefers the accumulation of financial claims for future consumption over current consumption.⁴⁴ In aging populations this serves to smooth consumption over a generation's life time. But it also implies a strong belief in the long-run stability of the value of assets held against foreign citizens. If that expectation fails to materialise, the welfare implication can be considerable in terms of foregone consumption – a risk that grows with global imbalances such as those from correspondingly higher trade deficits in other economies.

To conclude, the impact of trade deficits can be likened to the borrowing of individuals (Lawrence, 2002). If invested in productive assets, the gains in future output will outweigh the cost and pay off the debt. If not, the increased debt will reduce the leeway for future investments. Large and persistent deficits can thereby put the long-run sustainability of the country's development at risk.

⁴² Note that the function of the US dollar as a global reserve currency creates an exceptional situation for the US. While the worldwide demand for dollars reduces its borrowing costs, it also tends to appreciate its exchange rate. Taken together, these effects can simultaneously raise the deficits in the trade balance and the ability to finance them via corresponding surpluses in the capital account.

⁴³ Blanchard and Fischer (1993).

⁴⁴ That is to say that the choice of an adequate discount rate is highly arbitrary and the time profile of future consumption uncertain.

Empirical illustration

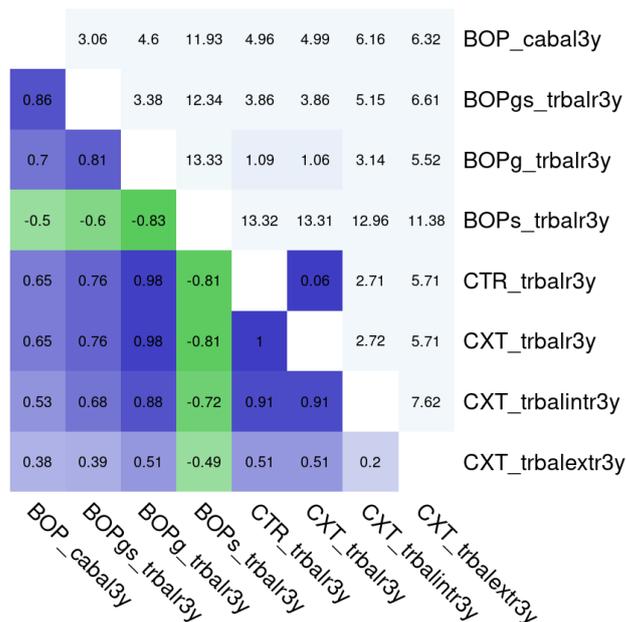
Year-to-year variations of the current account and trade balances would reflect business cycle effects more than shifts in competitiveness. For the quadratic heat maps in Figure 3-18 and Figure 3-19 we therefore computed 3-year and 5-year backward averages of seven indicators. The main data sources are the IMF's Balance of Payments (BOP), from which we take the comprehensive current account balance in % of GDP (*BOP_cabal3/5y*) and the trade balance, i.e. exports minus imports in percent of total trade (i.e. exports plus imports) for goods and services (*BOPgs_trbalr3/5y*) and only for goods (*BOPg_trbalr3/5y*). We further aim to compare the trade balance of goods from the BOP with two alternative sources of foreign trade statistics. One is the UN COMTRADE (*CTR_trbalr3/5y*) and the other is Eurostat's COMEXT database (*CXT_trbalr3/5y*). From COMEXT we additionally produce the analogous trade balances for intra-EU trade (*CXT_trbalintr3/5y*) with other Member States and extra-EU trade (*CXT_trbalextr3/5y*) with partners outside the European Union.

To begin with, the coefficient of pairwise correlation shows that the measure of the trade balance for goods from COMEXT and COMTRADE produces an (almost) identical ranking of the EU Member States and that the correlation is also extremely high if we use the trade balance of goods from the BOP. In the following determination of the joint cluster structure, we will consequently drop the redundant indicator from COMTRADE. Otherwise, we observe a high similarity of rankings if we compare the current account balance with the trade balance for goods and services, or the balances of the total trade with goods to that of the intra-EU trade with goods. These observations are consistent with the fact that the trade of goods and services is the major component of the current account, and that intra-EU trade is the major component of total trade of EU Member States. The balance of extra-EU trade is the most independent of the variables, generally showing the least statistical association with other indicators.

The cluster heat map in Figure 3-23 confirms this structure among indicators for the alternative measure of Euclidean distances. Simultaneously classifying the EU Member States according to their relative dissimilarity over six variables, Ireland, Germany, Denmark, Italy, Sweden, Netherlands, Hungary and Slovenia show the most favourable external balances.⁴⁵ Malta, Croatia and Luxembourg form a distinct group that is characterised by a distinctly pronounced patterns of a poor balance in the trade of goods, that is contrasted by far more favourable rankings if services are included. In contrast, Greece and Cyprus exhibit overall poor performance. Other countries take intermediate positions.

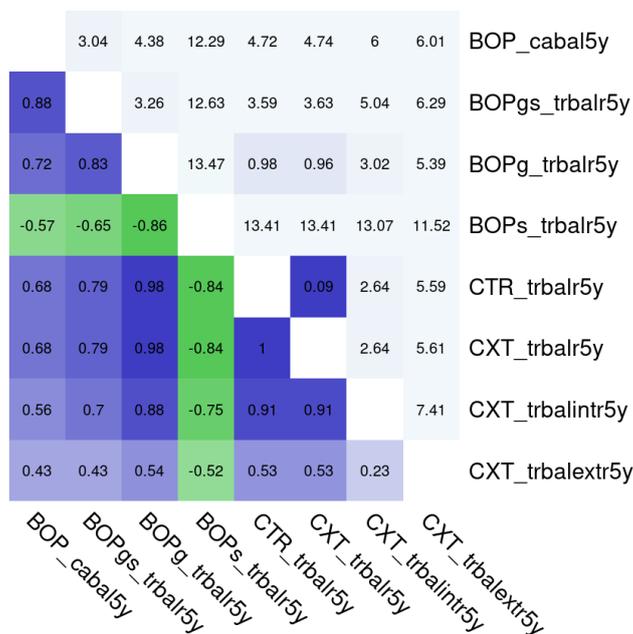
⁴⁵ That Netherlands is a pronounced outlier for the balance in extra-EU trade and points at the aforementioned statistical difficulties emanating from the so called "Rotterdam effect".

Figure 3-18: Quadratic heat map of external balances: 3-year averages, pairwise correlation of the country rankings and City-Block distance, 2006-2015



Note: The numbers below the diagonal present the correlation coefficient, those above the diagonal the Manhattan measure of distance (average absolute change in ranks).
 Source: BOP, COMEXT, COMTRADE; WIFO calculations.

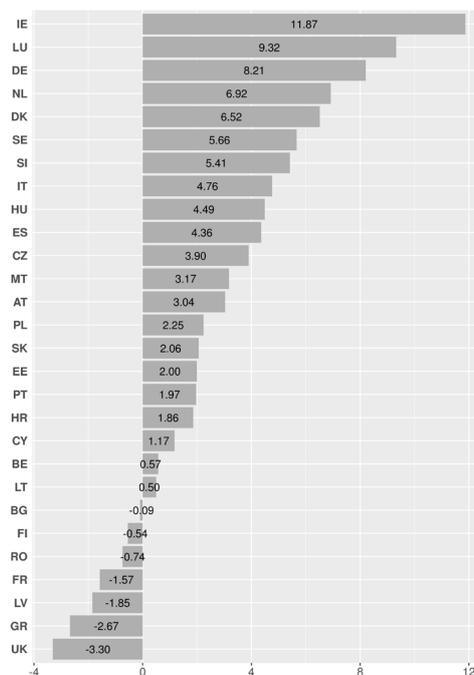
Figure 3-19: Quadratic heat map of external balances: 5-year averages, pairwise correlation of the country rankings and City-Block distance, 2006-2015



Note: The numbers below the diagonal present the correlation coefficient, those above the diagonal the Manhattan measure of distance (average absolute change in ranks).
 Source: BOP, COMEXT, COMTRADE; WIFO calculations.

Finally, Figure 3-20 to Figure 3-22 present selected bar charts for closer inspection of the actual values of the total trade balance of goods and services from the BOP, the trade balance only for goods from COMEXT and the same balance computed separately for intra- and extra-EU trade. These illustrate, for example, that for the average of the years 2013 to 2015 Germany's trade surplus was mainly due to its favourable net exports in extra-EU trade, whereas its surplus in intra-EU trade was relatively minor. One may also gain some idea of the importance of European value chains, when many Central and Eastern European countries show a pronounced surplus in intra-EU trade, whereas the biggest surpluses in extra-EU trade arise in countries such as Germany or the Scandinavian (and Baltic) countries. However, one must keep in mind that the comparison of intra- and extra-EU trade is compromised by the statistical problems of the EU's INTRASTAT system (see Section 3.3.2). This is best illustrated by the implausible values for the Netherlands, which rank first in the intra-EU and next to last in the extra-EU trade balance.

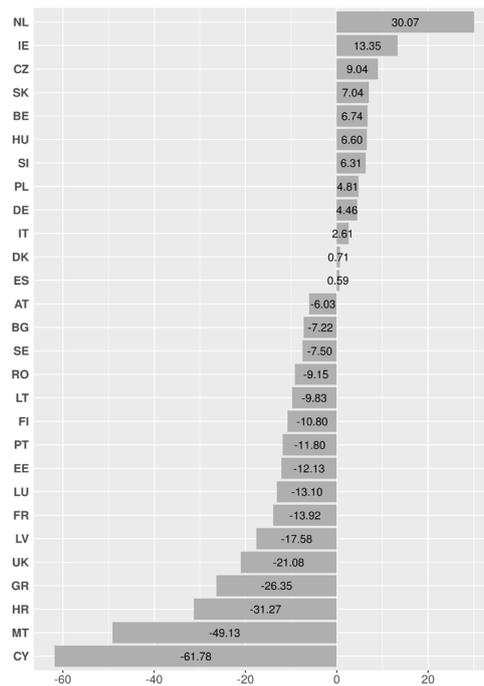
Figure 3-20: Trade balance of goods and services in %: 2015, 3-year backward average



Note: Trade balance = (exports-imports)/(exports+imports)

Source: BOP, WIFO calculations.

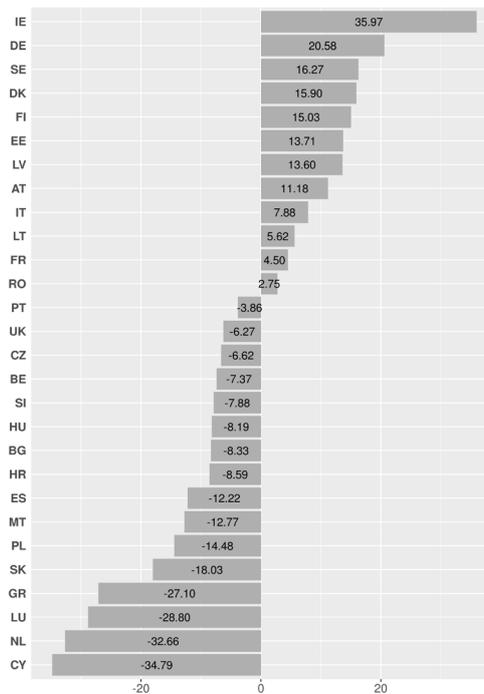
Figure 3-21: Trade balance of goods in %: intra-EU, 2015, 3-year backward average



Note: Trade balance = (exports-imports)/(exports+imports)

Source: COMEXT, WIFO calculations.

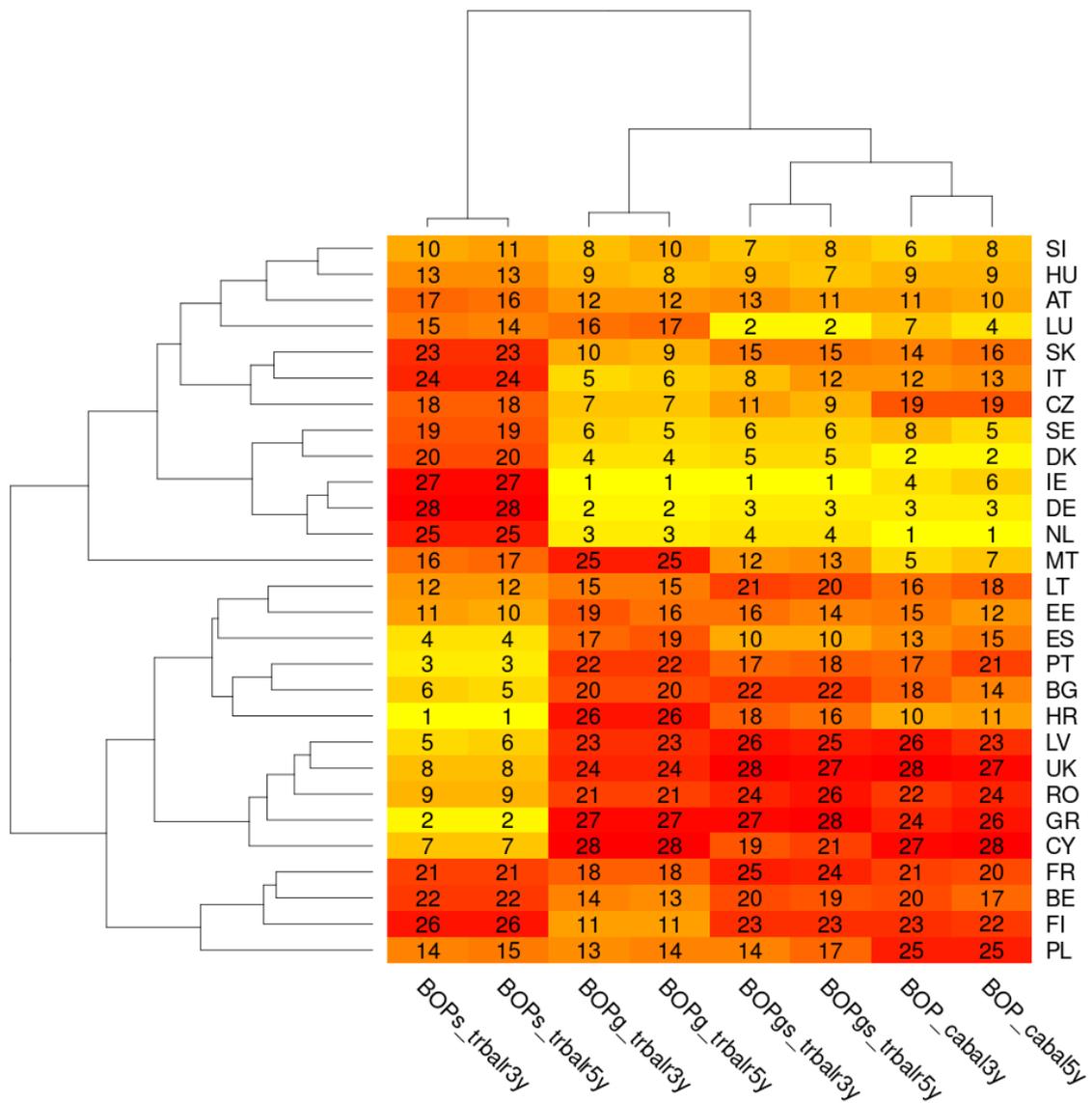
Figure 3-22: Trade balance of goods in % of GDP: extra-EU, 2015, 3-year backward average



Note: Trade balance = (exports-imports)/(exports+imports)

Source: COMEXT, WIFO calculations.

Figure 3-23: Cluster heat map of ranks in trade balances, 2015



Note: Numbers denote the country ranks, lighter colours better performance. Cluster dendrograms based on average linkage method and Euclidean distances.

Source: BOP; WIFO calculations.

C. Export market shares

Concept and definitions

The export market share for country i at time t and total imports M of the world w (or any other group of countries) can be expressed by the ratio

$$x_{i,t}^{M^w} = \frac{X_i^t}{M_w^t}$$

Or, if we replace world imports M_w by world exports X_w , alternatively by the ratio:

$$x_{i,t}^{X^w} = \frac{X_i^t}{X_w^t}$$

For ideal data with complete coverage of all countries and consistent mirror statistics, the two definitions must be equivalent. In practice, however, there are variations in the quality and reliability of trade statistics for different countries. As a consequence, one often defines the world market for a select group of economies with more reliable statistics, such as the OECD or the EU. In this case, it does make a difference whether one defines the world market in terms of imports or exports:

- Defining the world market as total exports of the OECD implies that we fully capture the competition with exports from other Member States of the OECD to the world, but not the competition with exports from countries outside the OECD.
- If we define the world market as total imports of the OECD, we capture the competition e.g. with exports from emerging economies outside the OECD to the OECD market. We then cannot account for the competition with exports from other OECD countries to emerging or developing countries that are not members of the OECD.

The current analysis is restricted to the comparison of export performance among the EU Member States. It therefore makes sense to define the world market in terms of their total exports to the world. Furthermore, it does not affect their relative performance and rankings, if the definition comprises all countries (the "world"), the OECD, or the EU as exporting nations, since either choice affects the denominator for all EU Member States in the same way.⁴⁶ For the regular application where export markets are defined uniformly for all countries (i.e. without differential weights for the country-specific distribution of exports to different destinations), the change of market shares actually boils down to the change of export shares and hence their differential export growth.

Notwithstanding these considerations, export market shares appear to be a straightforward measure of competitiveness, reflecting the differential success in selling goods and services on the international market. Since international competition tends to be high, differential performance directly relates to the relative

⁴⁶ Of course, the absolute shares must decline with the number of exporting countries included in the denominator (proportionately to their relative amount of exports).

strengths and weaknesses of the enterprises in an economy. Nevertheless, there are important caveats that bar simplistic interpretations:

- First of all, exports are highly correlated with *imports*, but only net exports directly affect an economy's aggregate demand.
- Relatedly, exports and imports are reported at *gross values* (sales), whereas the effect on income depends on the domestic value added content of trade. For example, if higher export growth is fully compensated by the increased imports of intermediate goods, income and jobs remain unaffected, except for indirect effects (e.g., spillovers or productivity gains from increased specialisation).
- New international databases that focus on *value added trade* come with a considerable publication lag and have so far only been updated at irregular intervals.
- Export market shares are typically computed at current prices, with fluctuations in certain commodities (e.g. oil and other raw materials) affecting the distribution of market shares among exporting and importing countries (Vondra, 2017). In turn, using real values renders export performance difficult to interpret, as the changing volume of exported commodities may, for instance, dominate the success or failure in upgrading the quality of differentiated products.
- There are *business cycle* effects, for example, when strong domestic demand absorbs capacities that otherwise may produce for exports; or vice versa, if a weak domestic economy pushes firms to seek opportunities abroad more aggressively. In both cases, strong or weak domestic demand can have an opposite impact on the export share.⁴⁷

If we further assume that for the majority of goods and services the development of trade relationships is costly and takes time (i.e. one cannot instantly reallocate exports between destinations), and that countries differ in the geographical distribution of their exports, then the differential growth of main export destinations affects the relative changes of Member States' export shares in at least two ways:

- Temporary crisis or differences in the business cycle of a country's main export destinations affect its export share without *ceteris paribus* implying a change in its underlying competitive strengths and weaknesses.
- To the extent that spatial proximity constitutes a trade advantage, the global shift of growth poles, e.g., towards emerging East Asian economies, has an enduring impact on export shares that is not due to traditional sources of competitive advantage.

A first group of alternative measures compares the export growth in country *i* with the import growth of its export destinations *l* weighted by the share of exports to country *l* in the total exports of *i*. The difference between growth rates can be

⁴⁷ Because of the additional import channel of trade, one may generally expect, however, that *business cycle* effects are stronger for trade balances.

interpreted as an approximation of the change in market shares, whereby the relevant export market is specific to each country. The *European Central Bank* (ECB) produces but does not publish such data in the process of its macroeconomic forecasts.⁴⁸ As *Vondra* (2017) demonstrates, they can provide a valuable complementary picture, but ought not substitute the conventional measure with a uniform definition of export markets. The reason is that one would then ignore two important aspects of export competitiveness in terms of an economy's ability

- to cope with temporary fluctuations in the business cycle of export destinations, e.g. through the successful diversification of products and geographical destinations, and
- to successfully export to emerging growth markets.

Another strand of methodological discussion aims at identifying non-price determinants of export market shares. A critical component is the elasticity of substitution between detailed product groups. While older approaches assumed a constant elasticity of substitution (CES) utility function, *Benkovskis and Wörz* (2014) estimate a system of supply and demand equations for detailed product groups and importing countries. Among others, they show that OECD countries specialise in manufactured goods with lower elasticities of substitution and hence less price competition, whereas Non-OECD countries tend to specialise in price-sensitive commodities with a high elasticity of substitution.

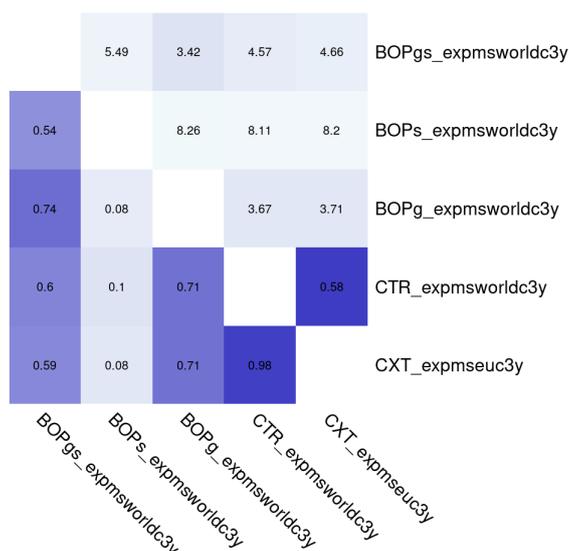
Empirical illustration

The quadratic heat maps in Figure 3-24 and Figure 3-25 present the correlation coefficient and Manhattan distances for 3-year and 5-year changes in five variables. Three of them measure the same share of a country's exports of goods in the total exports of goods of the 28 EU Member States (*expmseuc3y*, *expmseuc5y*) from different data sources: COMEXT (*CXT_*), Comtrade (*CTR_*) and the IMF's balance of payments (*BOPg_*). To this we add the export shares from the balance of payments for services (*BOPs_*) and for goods and services (*BOPgs_*). In short, the heat maps show that the choice between COMEXT and Comtrade hardly affects the ranking among EU Member States at all. In contrast, the export share of services from the BOP shows almost no correlation with either indicator on the export share of goods.

In Figure 3-26 and Figure 3-27, bar charts illustrate the actual distribution of the 3-year changes of goods and services from the IMF's BOP, as well as for goods according to COMEXT.

⁴⁸ The ECB relates the growth of the volume of exports in country *i* to the growth of imports of its trade partners, the latter weighted by the share of each destination in total exports of country *i*. The growth of export and import volumes is taken from the National Accounts, whereas the import shares are calculated from the Comtrade database. *Vondra* (2017) provides a detailed explanation and empirical validation of different approaches.

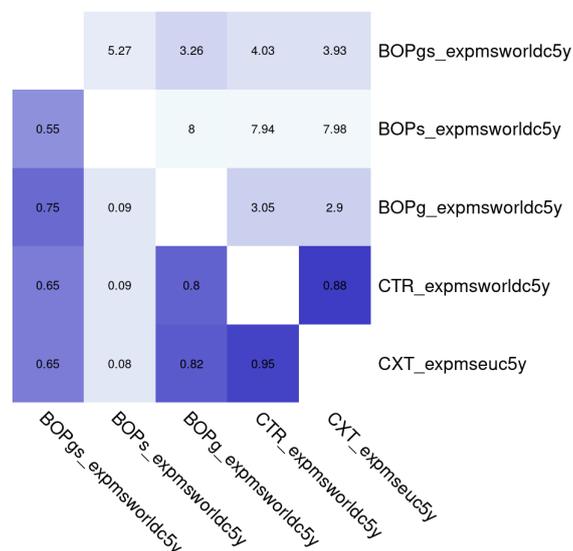
Figure 3-24: Quadratic heat map of export shares: 3-year changes, pairwise correlation of the country rankings, City-Block distance, 2006-2015



Note: The numbers below the diagonal present the correlation coefficient, those above the diagonal the Manhattan measure of distance (average absolute change in ranks). The individual indicators are explained in the main text.

Source: COMEXT, Comtrade, and BOP, WIFO calculations.

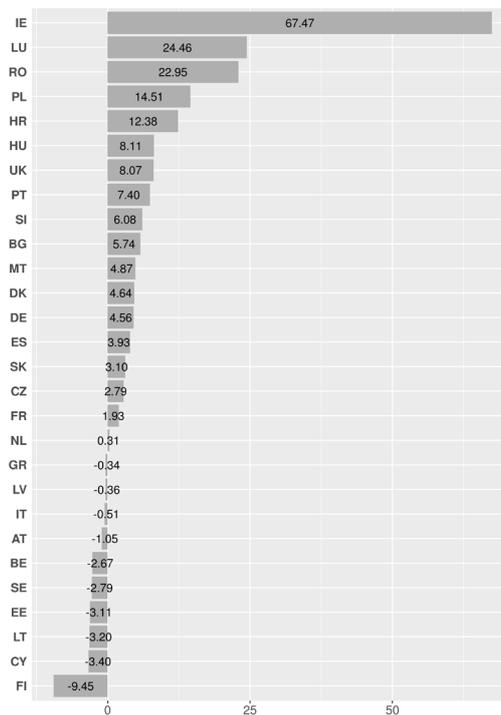
Figure 3-25: Quadratic heat map of export shares: 5-year changes, pairwise correlation of the country rankings, City-Block distance, 2006-2015



Note: The numbers below the diagonal present the correlation coefficient, those above the diagonal the Manhattan measure of distance (average absolute change in ranks). The individual indicators are explained in the main text.

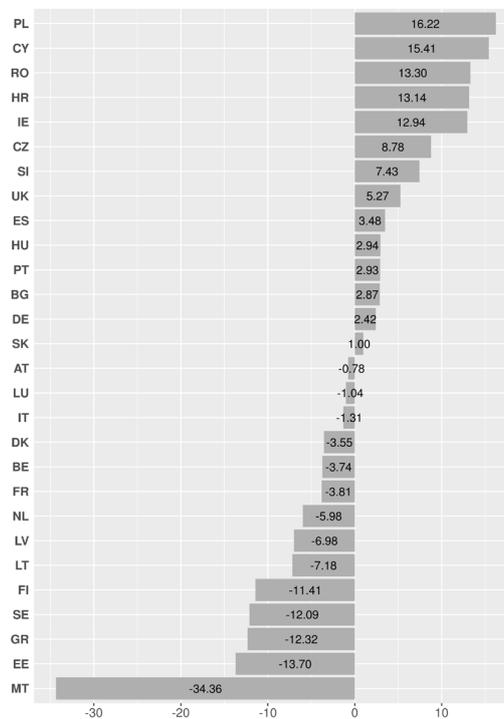
Source: COMEXT, Comtrade, and BOP, WIFO calculations.

Figure 3-26: Three-year change of share in total EU exports of goods and services in %, 2015



Source: IMF BOP; WIFO calculations.

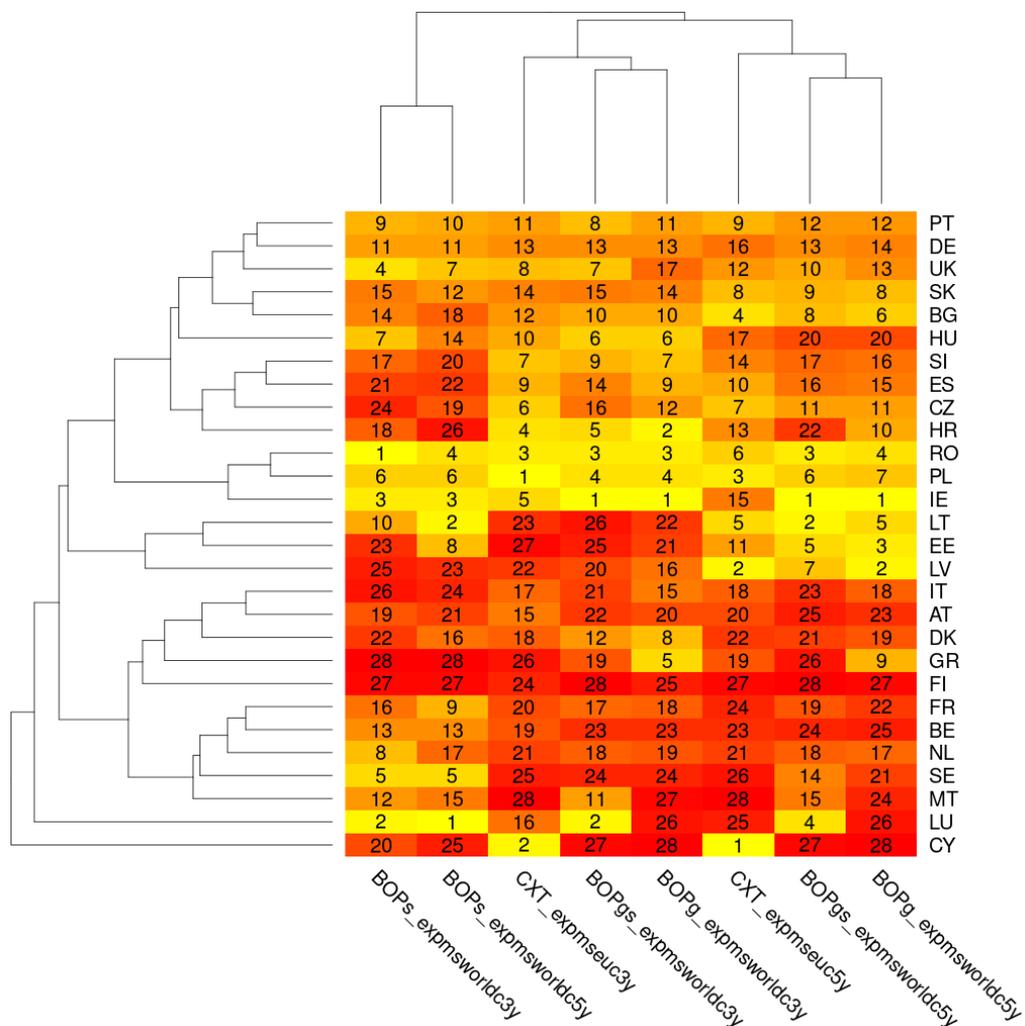
Figure 3-27: Three-year changes of the share in total EU exports of goods in %, 2015



Source: Eurostat COMEXT; WIFO calculations.

Finally, the cluster heat map in Figure 3-28 organises variables and Member States according to their relative (dis)similarity. The two measures for services are most distant to the rest of the indicators, which is mainly separated by the choice of either 3-year or 5-year changes. As for the EU Member States, Ireland, Poland and Romania show consistent improvements of their market shares, followed by countries such as United Kingdom, Bulgaria, Portugal, Germany and Slovakia. Other countries differ in their performance for different time periods. The three Baltic states have shown comparatively large increases of their shares in the export of goods over the past 5 years, but much less so if one considers only the past 3 years. Sweden, the Benelux, France and Malta performed well in the export of services, but not for goods. Finland, but also Austria and Italy, show a consistent decline in export shares relative to the other EU Member States. Furthermore, the cluster heat map easily reveals that for Cyprus the indicators based on COMEXT and the IMF's BOP produce an inconsistent picture. It thereby helps to detect particular cases that need to be checked and explained more carefully using the according data providers.

Figure 3-28: Cluster heat map of ranks in export shares, 2015



Note: Numbers denote the country ranks, lighter colours better performance. Cluster dendrograms based on average linkage method and Euclidean distances.
Source: COMEXT and BOP; WIFO calculations.

D. Export structure

Country-wide indicators of export structure combine the macro- and meso-perspective of competitiveness, with “meso” typically referring to product groups at different levels of aggregation. In this section, we will focus on the following aspects:

- The diversification of exports by
 - o product group and
 - o geographical destination
- The ratio of intra- to inter-industrial trade
- The degree of sophistication (quality segments) of exported goods

Structural analyses require accurate numbers for detailed disaggregated data. In this section, we therefore prefer to use the BACI database, because of its consistency between bilateral imports and exports. Conversely, since structural indicators tend to be very persistent over time, its longer publication lag is less of a problem than for other and more volatile indicators.

D1. Diversification of exports

Concept and definitions

The previous section on export market shares has pointed at the benefits of a diversified export structure in order to increase a country's resilience to adverse shocks and fluctuations. Potential sources are variations in the overall demand of particular export destinations or specific demand for certain products, as well as supply-side shocks, for example, from technological obsolescence or the emergence of more cost efficient competitors.

There are many possibilities for measuring the diversification of exports. We will focus on two dimensions, two measures, and three different levels of (dis)aggregation. The two dimensions are diversification in terms of

- product group and
- export destination,

and the two measures are the

- Inverted Herfindahl-Hirschman Index (HHI) of concentration, and the
- Shannon entropy (S).

Finally, the three levels of (dis)aggregation are for products at the 2-, 4- and 6-digit level of of the Harmonised System (HS).

Diversity relates to the number N of existing types j (e.g., species, or in our case products and geographical export destinations) as well as the distribution of observations across the various types. Among our two measures of diversity, the **Herfindahl-Hirschman Index** (HHI) is defined as the sum of squares of the export shares s_j for N types j (i.e., product groups or, alternatively, export destinations):

$$HHI = \sum_{j=1}^N s_j^2$$

The export shares are expressed as a fraction of total exports and hence range from 0 to 1. The HHI index can accordingly take values between $1/N$ and 1. The former results from a uniform distribution with equal shares for each type j , whereas the latter implies a maximum concentration with all exports being from one type only.⁴⁹ Since our interest is in export diversification, we invert the ranking such that the country with the lowest index performs best, whereas the country with the highest index is least diversified.

In information theory, the Shannon **entropy** (S) is a measure of the unpredictability of a state x_j defined by the negative of the logarithm of the probability distribution of possible events (Shannon, 1948):⁵⁰

$$S = -\sum_{j=1}^N p_j \log_2 p_j$$

For a given N , diversity reaches its maximum if for each type the probability p_j is evenly distributed, i.e. $p_j = 1/N$. In our case, the probability p_j of the system being in cell j corresponds to the share s_j of a particular product group or geographical destination in total exports. Consequently, we can compute the Shannon entropy as follows:

$$S = -\sum_{j=1}^N s_j \log_2 s_j = \sum_{j=1}^N s_j \log_2 \frac{1}{s_j}$$

Empirical illustration

All the data used in this section are from the BACI database. The quadratic heat map in Comparing export structures across countries, only Italy is shown to be highly diversified in products and export destinations. Germany, Sweden, Spain, France and Denmark also perform well in both dimensions. Greece, Malta, Cyprus, United Kingdom, Finland, Bulgaria or Lithuania are highly diversified in terms of the geographical destination of their exports, but specialised in comparatively fewer products. The opposite is true for Austria, Poland, the Czech Republic and Portugal, which all export a large variety of products but to comparatively fewer geographical destinations.

Figure 3-29 shows the (dis)similarity among alternative choices of indicators. First, it looks at diversification in terms of exported product groups distinguishing between the Herfindahl-Hirschman Index at different levels of disaggregation (*BACI_hhi2dig*, *BACI_hhi4dig*, *BACI_hhi6dig*) and the according measures of the Shannon entropy (*BACI_entpy2dig*, *BACI_entpy4dig*, *BACI_entpy6dig*). To this we add the diversification of export destinations (*BACI_hhigeo* and *BACI_entpygeo*).

With correlation coefficients consistently above 0.9 the choice between the Herfindahl-Hirschman Index and the Shannon entropy measures of diversification

⁴⁹ To avoid correlations with N , the index can be normalised to a range between 0 and 1. In our case, this is not necessary, since the number of product groups is the same for all countries.

⁵⁰ There are various options to the formula. Adding a constant K amounts to different choices of the unit of measure (Shannon, 1948, p. 11). Also, the basis of the logarithm can be freely chosen.

hardly makes any difference for the ranking of the EU Member States. What makes a difference, however, is the level of disaggregation for the measure of diversity across products. While the correlations are still high for the measures based on 6 and 4 digits, the similarity drops considerably if we compare either of them with the measure based on product groups at the 2-digit level. Here the conclusion is straightforward: while on theoretical grounds the higher disaggregation is generally preferable, computing our measures of export diversification at the level of 4-digit product groups is a valid option. The same cannot be said for calculations based on the 2-digit product level, which hardly constitute a meaningful indicator of export diversification.

Interestingly, the quadratic heat map further reveals that there is practically no statistical association between the diversification of exports in terms of products and that of geographical destination. Both appear to be independent and to characterise genuinely different dimensions of a country's export structure.

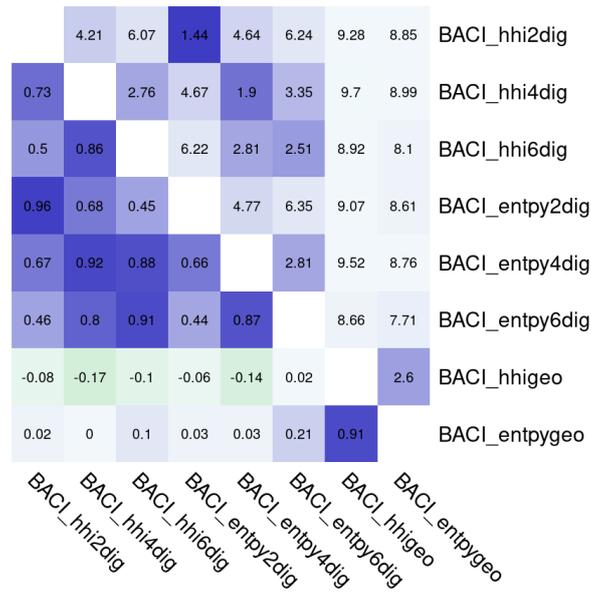
The barchart in Figure 3-30 illustrates the actual distribution of EU Member States for the measure of product diversification at the level HS 6-digits.

For the cluster heat map (Figure 3-31) we aim to simultaneously characterise the EU Member States in terms of both diversification by product and export destination. To avoid an implicit differential weighting of the two dimensions, we drop the indicators of diversification that were based on the 2-digit product classification. In turn, we compute two additional indicators of geographical diversification by export destination, where we drop all goods from primary industries (*BACI_hhigeo_npri*, *BACI_entropygeo_npri*). Consequently, the clustering can proceed with a symmetric number of four indicators on each general dimension.

The indicators are grouped as expected, clearly separating those on product diversification from those on geographical diversification. For product diversification, the difference between levels of disaggregation is stronger than that between the HHI and the entropy measure. Conversely, in the case of geographical diversification, the difference between the two measures dominates that between the choice of either including or excluding the primary goods sector.

Comparing export structures across countries, only Italy is shown to be highly diversified in products and export destinations. Germany, Sweden, Spain, France and Denmark also perform well in both dimensions. Greece, Malta, Cyprus, United Kingdom, Finland, Bulgaria or Lithuania are highly diversified in terms of the geographical destination of their exports, but specialised in comparatively fewer products. The opposite is true for Austria, Poland, the Czech Republic and Portugal, which all export a large variety of products but to comparatively fewer geographical destinations.

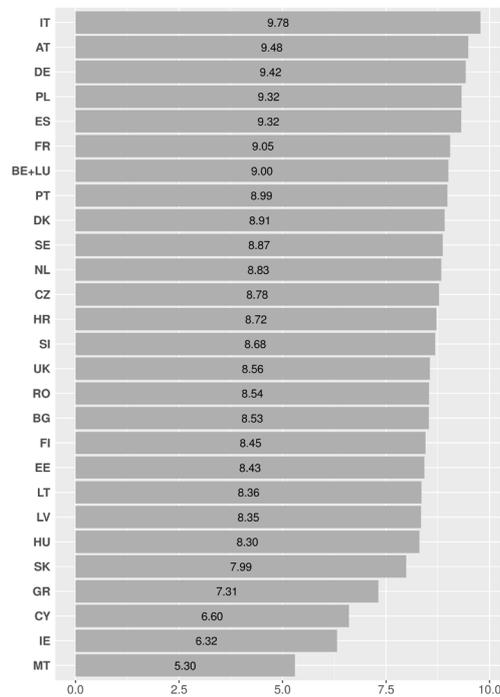
Figure 3-29: Quadratic heat map of diversification indices, pairwise correlation of the country rankings and City-Block distance, 2006-2015



Note: The numbers below the diagonal present the correlation coefficient, those above the diagonal the Manhattan measure of distance (average absolute change in ranks). The individual indicators are explained in the main text.

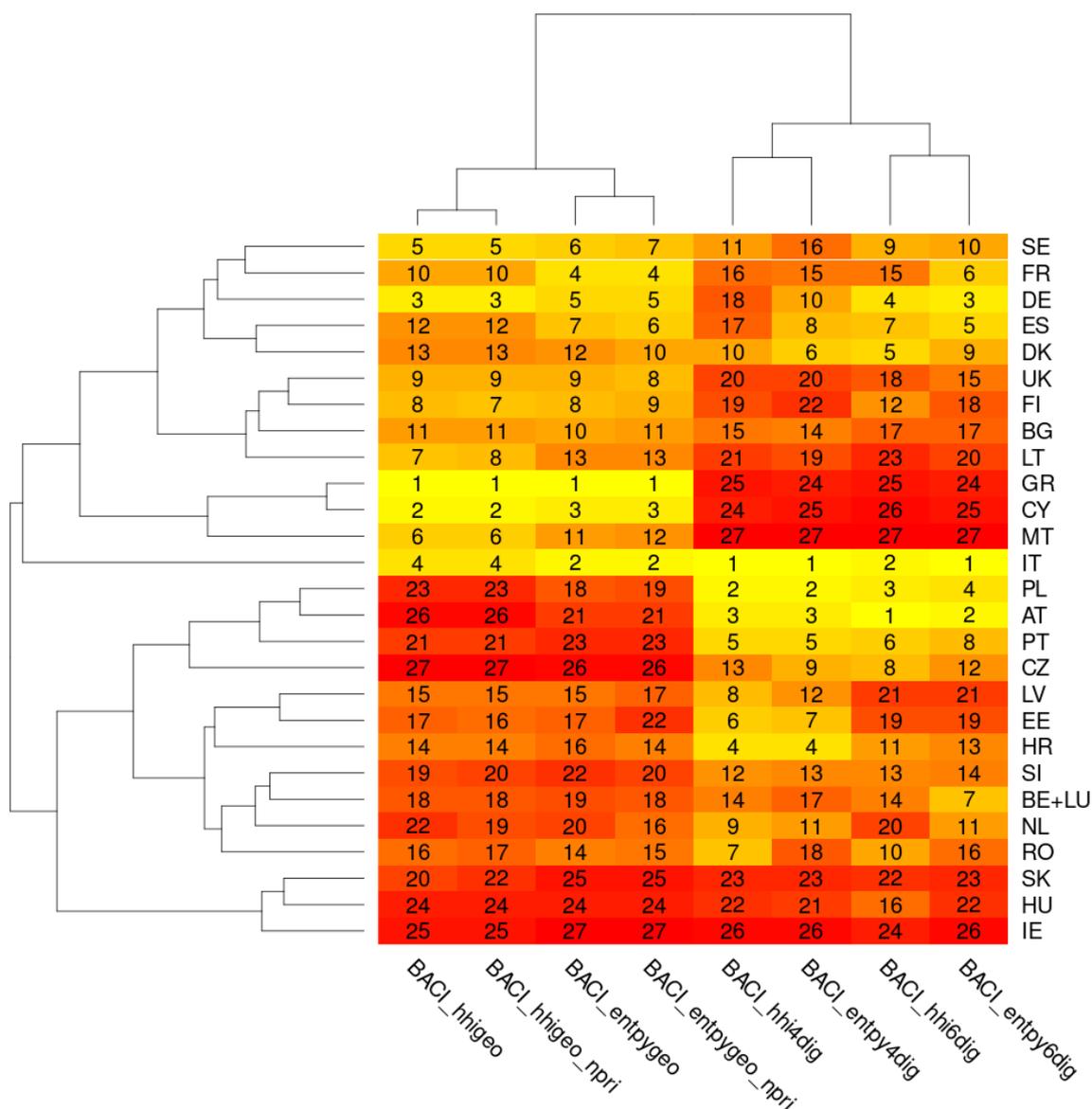
Source: BACI, WIFO calculations, 2014

Figure 3-30: Product diversification – entropy index for products at HS6-digits, 2015



Source: BACI, WIFO calculations.

Figure 3-31: Cluster heat map of ranks in diversification of export products and destinations, 2015



Note: Numbers denote the country ranks, lighter colours better performance. Cluster dendrograms based on average linkage method and Euclidean distances. Diversification is higher, the lower the Herfindahl index of concentration.
 Source: BACI, WIFO calculations.

For a final and more definite representation, we group countries by the ranking in terms of both their spatial and product diversification. In order to arrive at a consistent classification, we pick only one indicator for each dimension. We let the entropy measure excluding primary goods (*BACI_entpygeo_npri*) represent the country's spatial diversification and choose the entropy measure at the level of HS 6-digits (*BACI_entpy6dig*) for its product diversification.

Table 3-22 summarises the allocation of EU Member States into groups with high-, intermediate or low diversification, respectively. As only Spain, Germany, France and

Italy are in the group of countries with a high export diversification for both geographic reach and products, the size dependence of the measure is certainly an issue that deserves further attention. On the one hand, if we use it as a structural driver of competitiveness, it correctly represents the economic reality of a larger territory and should be consistent with other macroeconomic indicators that may e.g. display a better absorption of external fluctuations and shock. On the other hand, if we interpret it as a measure of performance, whether countries (and implicit its policies) are more or less successful towards achieving a better diversified export base, one must further think about measures which correct for its size dependence.

Table 3-22: EU Member States by their spatial and product diversification of exports, 2015 (entropy measure for 6-digit products)

		Products		
		High	Intermediate	Low
Spatial	High	Spain France Germany Italy	Finland United Kingdom Sweden	Cyprus Greece
	Intermediate	Belgium (+ Lux) Denmark Poland	Bulgaria Croatia Netherlands Romania Slovenia	Latvia Lithuania Malta
	Low	Austria Portugal	Czech Republic	Estonia Hungary Ireland Slovakia

Note: The following ranks identify countries into categories: "high" = 1 to 9; "intermediate" = 10 to 18; "low" = 19 to 28 for the entropy measures (6-digits, including primary goods). Countries are listed in alphabetic order of ISO codes.

D2. Intra- vs. inter-industry trade

Concept and definitions

In contrast to *inter-industry* trade, where countries specialise in different industries that reflect differences in comparative advantage from relative factor endowments (e.g. the abundance of natural resources, cheap labour, capital), *intra-industry trade* refers to the exchange of similar products with similar factor requirements that are both exported and imported within the same industry. Comparative advantage for particular products may then originate in economies of scale, learning effects or other first mover advantages, such as those from innovation or the early adoption of new technologies. Unlike, for example, natural resources or abundant labour, they tend to be actively created and shaped by entrepreneurial firms. In this sense, they reflect a higher level of development and competitiveness that relates to successful product differentiation.

The **Grubel-Lloyd index** is a popular measure of intra-industry trade. For each industry j it compares the trade balance of exports X minus imports M to the total value of exports plus imports (Grubel-Lloyd, 1971):

$$GL_j = 1 - \frac{|X_j - M_j|}{X_j + M_j}$$

The GL index ranges from 0 to 1 with high values indicating a greater importance of intra-industry trade.

Aggregation for country i over all industries N can be either unweighted, such that

$$GL_i = \frac{1}{N} \sum_{j=1}^N GL_j$$

or weighted by the total trade for each industry:

$$w_j = \frac{X_j + M_j}{\sum_{j=1}^N (X_j + M_j)}$$

which leads to the weighted Grubel-Lloyd index:

$$GL_i^w = \sum_{j=1}^N w_j GL_j$$

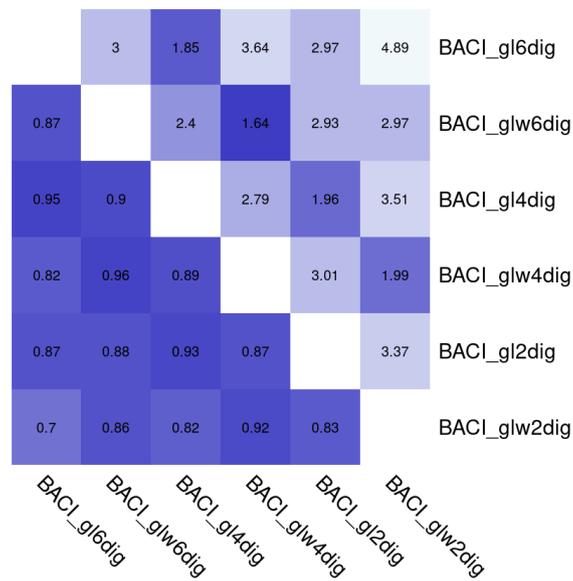
In addition to weighting, the level of disaggregation of product groups is a critical choice, since it precisely defines what one considers to be intra- or inter-industry trade. For example, if we compute the index at the level of HS 2-digits, all exports and imports within (or between) two-digit product groups are considered intra- (or inter-) industry trade.

Empirical illustration

Somewhat surprisingly, in the quadratic heat map of Figure 3-32 neither of the two options (weighting and level of disaggregation) appears to have a strong impact on the ranking of EU Member States, as the correlation measures of similarity are generally high and the according distance measures low. The bar chart of the Grubel-Lloyd index built from HS 6-digit product groups has the Benelux countries on top, followed by Germany and France (Figure 3-33).

Finally, the cluster heat map in Figure 3-34 also presents a rather consistent shading across all the six indicators. The major distinction by variables is between those that apply weighting or no weighting in the aggregation. Conversely, the level of disaggregation appears to make less of a difference for the ranking of Member States. Those countries with the most consistent lead in the share of intra-industry trade are Belgium/Luxembourg and the Netherlands. In contrast, Greece, Cyprus, Malta, Croatia, Romania and Bulgaria, but also Ireland and Finland, consistently rank at the bottom of the distribution.

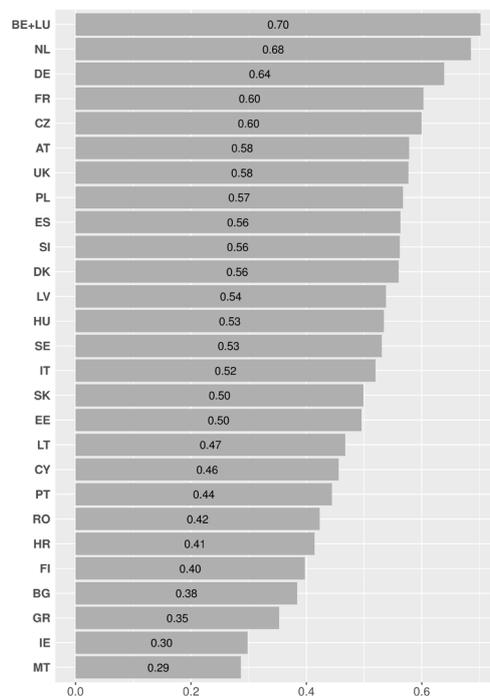
Figure 3-32: Quadratic heat map of the Grubel-Lloyd index of intra- vs interindustry trade: pairwise correlation of the country rankings and City-Block distance, 2006-2015



Note: The numbers below the diagonal present the correlation coefficient, those above the diagonal the Manhattan measure of distance (average absolute change in ranks). The individual indicators are explained in the main text.

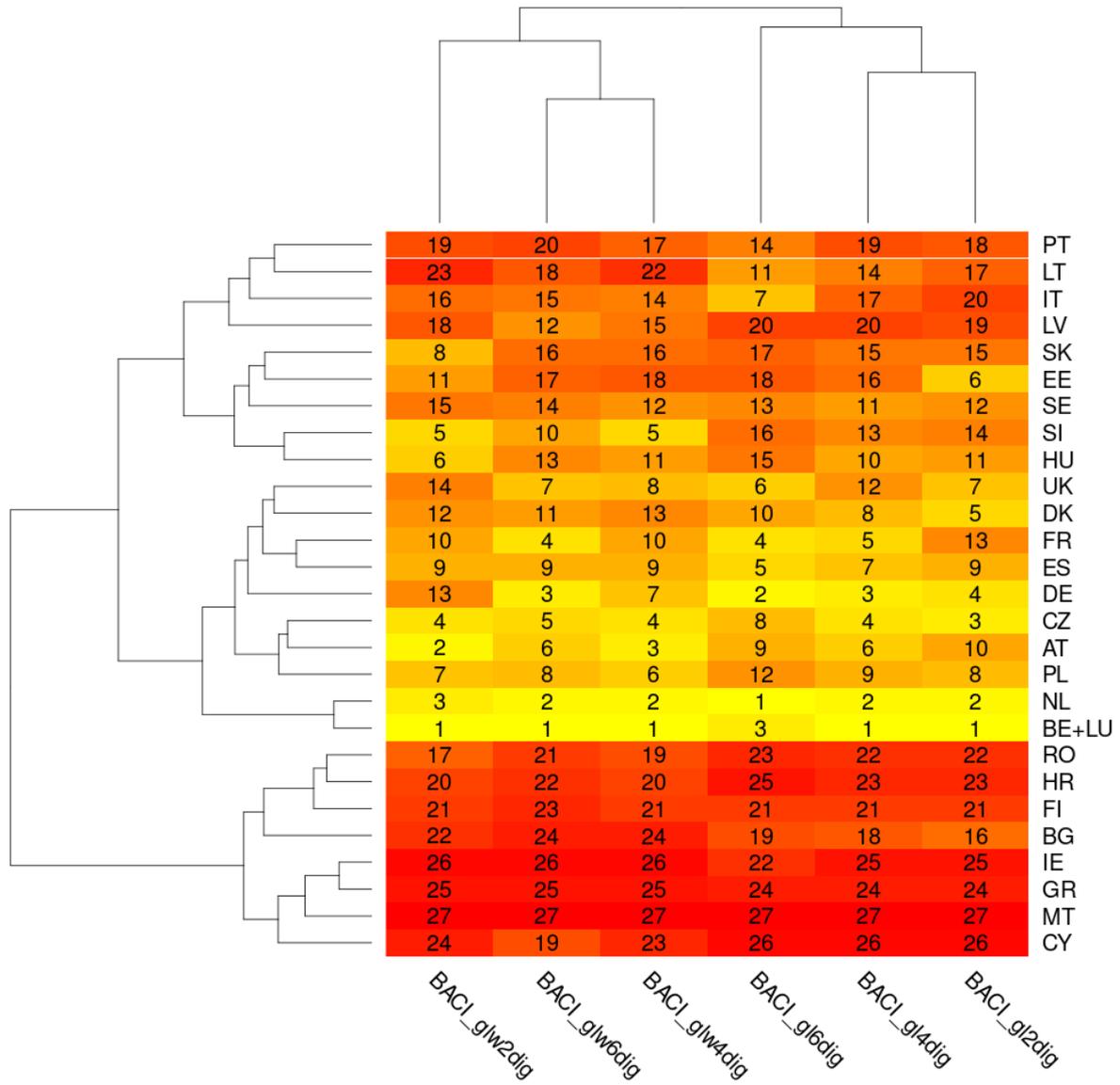
Source: BACI, WIFO calculations.

Figure 3-33: The Grubel-Lloyd index of intra- industry trade, products at HS6-digits – weighted, 2015



Source: BACI, WIFO calculations.

Figure 3-34: Cluster heat map of ranks in Grubel-Lloyd index of intra-industry trade, 2015



Note: Numbers denote the country ranks, lighter colours better performance. Cluster dendrograms based on average linkage method and Euclidean distances.
 Source: BACI, WIFO calculations.

D3. Sophistication: Technology, Quality and Complexity

Concept and definitions

Related and complementary to the study of intra-industry trade, measures of vertical specialisation aim to identify differences in the quality of exports or the implied degree of sophistication that is needed to produce them. The idea is that “advanced” products require more specific capabilities and other sources of competitive advantage that are difficult to emulate. Therefore, when aiming for a high degree of sophistication, the objective is to (i) increase an economy’s potential scope of innovation rents, thereby raising profits (and hence the financing capacity of firms) and/or wages; and at the same time to (ii) raise the barriers against low-wage competitors, thus protecting employment and current income.

There are many approaches to identifying the degree of sophistication in exports. A common feature with which to identify the share of certain **advanced products** $j = adv$ in total exports X :

$$x_{adv} = \frac{X_{j=adv}}{\sum_{j=1}^N X_j}$$

A first approach aims to identify X_{adv} with the knowledge or **technology intensity** of exports. The OECD classification of *high-tech* sectors is the most widely used and mainly reflects differences in the share of R&D expenditures at a broad sector level. By definition, products from high-tech sectors require sophisticated inputs such as R&D, which thus serve the above objectives (i) and (ii). In contrast, analytically oriented taxonomies in the tradition of Pavitt (1984) aim to link the characterisation of industries to a broader set of categories that are motivated by innovation theory. In the current analysis, we use the export share of *technology-intensive and research driven* industries (*tir*), a broader category of *technology-intensive* industries (*ti*) that includes those driven more by development activities than research, and a further category which additionally includes so-called marketing driven industries (*mti*) and hence focuses more on intangible factors of production:⁵¹

$$x_{tir} = \frac{X_{j=tir}}{\sum_{j=1}^N X_j}; \quad x_{ti} = \frac{X_{j=ti}}{\sum_{j=1}^N X_j}; \quad \text{and} \quad x_{mti} = \frac{X_{j=mti}}{\sum_{j=1}^N X_j}$$

The above taxonomy-based approach identifies characteristic differences in the industrial specialisation of countries typically at the level of 2- or 3-digit industries, which is usually the best disaggregation one can get for the study of performance in terms of production and value added. Also, for many firm-level data, the sectoral identification cannot be more detailed due to concerns about confidentiality. For these and other analyses, the above taxonomies have the advantage of characterising critical input factors (such as technology, marketing, capital or labour) and thus pointing at particular sources of a country’s competitive strengths

⁵¹ Both originate in a taxonomy of 3-digit manufacturing industries in Peneder (2002).

and weaknesses. A major disadvantage is the lack of information about the relative degree of sophistication and vertical specialisation within these industries.

Alternative indicators therefore aim to proxy the sophistication of products within industries by exploiting the higher degree of disaggregation in the trade statistics. Typically, they cannot point at the particular source of competitive advantage, but instead measure specific dimensions of export performance at a more fine-grained level, building their aggregate indicators, e.g. from data at the level of HS 6-digit product groups.

One such approach is to use export unit values in narrowly defined product groups to identify a country's relative position with regard to different **price** (or quality) **segments**. Export unit values correspond to the ratio of export values to a quantity measure (typically tons). Computation of the indicator requires the following steps (Stehrer et al., 2014):

- First, export unit values UV_{rc}^j are computed for each pair of trade flows from exporting country r to export destination c in each HS 6-digit product group j .
- Second, for each product group j and export destination c the unit values are ranked and exports categorised into one of three groups:
 - (i) the *upper* segment u if unit values are in the top quartile,
 - (ii) the *middle* segment m for unit values in the second or third quartile, and
 - (iii) the *lower* segment l if unit values are in the bottom quartile.
- Third, one can aggregate all exports in the upper segment u and compute their share in the total exports of country i :

$$x_u = \frac{X_{j=u}}{\sum_{j=1}^N X_j}$$

or alternatively aggregate exports in the middle and the upper segment:

$$x_{mu} = \frac{X_{j=m} + X_{j=u}}{\sum_{j=1}^N X_j}$$

For a different approach, Vandenbussche (2014) transposes the microeconomic model of di Comite (2012) with separate quality and taste effects on trade to the macroeconomic level. The theoretical underpinning is intriguing, but also very demanding in terms of data, such as the need of price-cost margins (PCM) for individual products at the firm level. In the empirical application, prices and variable costs are therefore averaged over products for each firm. In a rather bold step, the firm level Lerner indices are aggregated to compute an average PCM for products by country, which are then weighted by export unit values per product group and destination. In the end, these serve to construct product-level quality ranks and study their distribution for each European Member State's exports to a common destination market. Overall, the approach requires considerable confidence in the approximate validity of the underlying assumptions.

Finally, Hidalgo et al. (2007) and Hidalgo and Hausmann (2009) introduced another approach, in which they characterise a country's **complexity** of exports as higher, the more diversified and exclusive its basket of goods is. Countries are more diversified with a larger number of goods and a positive revealed comparative advantage (RCA). Conversely, a comparative advantage is more exclusive (i.e., less ubiquitous) if fewer countries enjoy a positive RCA value in that product.

Reinstaller et al. (2012) provide an empirical application and elaborate explanation of the algorithm. In short, the computation of the complexity score by country starts from a trade matrix, which is interpreted as a network of products j times countries i . The cells of the matrix (i.e., nodes of the network) are filled with binary entries of either 1, if the RCA is positive, or 0 otherwise. Summing the number of positive entries (i) by country gives the measure of diversification, and (ii) by products the measure of ubiquity. What follows is an iterative algorithm called the *method of reflections*, which capitalises on the network structure of the information by means of recursive substitution. For example, in the first iteration the information on diversity and ubiquity can be combined to determine how common the products are where country i has a comparative advantage, and how diversified the countries are that have a positive RCA in a particular product. By further iterations, the score measures how diversified countries are that export similar products, or how ubiquitous products are that are exported by product p 's exporters, and so on.⁵² While the economic interpretation becomes increasingly difficult for each additional iteration, the overall purpose is to characterise the product space as a network, where countries and products are embedded in a neighbourhood characterised by similar diversification and ubiquity.

Empirical illustration

Even though trade theory provides a strong link between industrial structure and the sources of comparative advantage, the empirical use of trade-based indicators suffers from several caveats:

- To begin with, distortions can arise from the data generating process, and in the European context particularly those caused by the INTRASTAT system (see Section 3.3.2).
- Second, the determination of quality segments faces difficulties in the accurate measurement of prices by means of the unit value of traded goods.
- Third, exports measured by the value of total sales can considerably diverge from the value added produced in a country. For example, this is the case when countries specialise in relatively labour-intensive processes in the final assembly of technology-intensive goods.⁵³

⁵² That is, iterations are repeated as long as the rank changes become smaller.

⁵³ While the high level of sector aggregation in trade-linked input-output data generally limits its applicability for the analysis of industrial structure.

Taking a brief look at the bar charts in Figure 3-35 to Figure 3-37 illustrates the difficulty. In two of them we find Ireland on top with countries such as Hungary, Cyprus or Malta also found among the countries with the most sophisticated exports in terms of technology intensity and price segments. In contrast, the ranking of Member States by the complexity score puts Germany on top, followed by Sweden, the Czech Republic, Finland and Austria. Compared to the two other indicators, it appears to be less affected by idiosyncratic outliers.

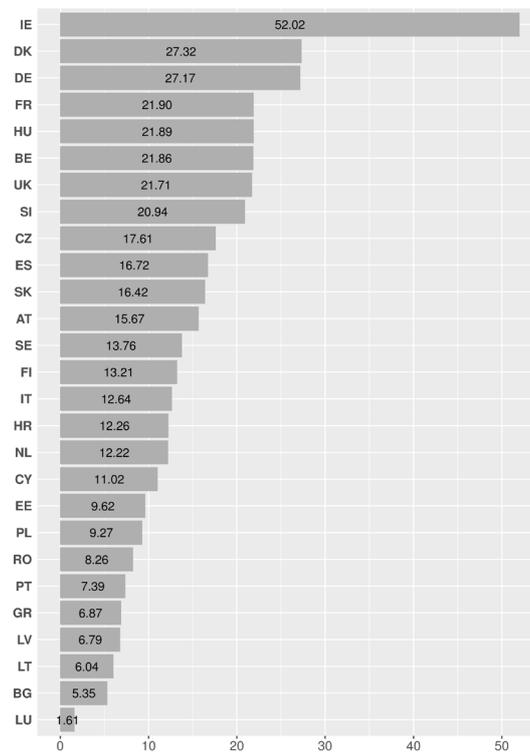
Whereas the measures of complexity and price segments require detailed trade data of highly disaggregate products, measures of technology intensity can alternatively rely e.g. on the share in total value added instead of exports. To assess their (dis)similarity with the trade-based measures, we also include the value added share of technology-intensive industries, either research driven (*SBS_vashtir*) or development driven (*SBS_vashtid*) in the quadratic heat map of Figure 3-38. The measures of relative (dis)similarity demonstrate the stronger association among variables derived from a similar concept, even if we broaden its scope. Consequently, it is highest for the three measures of technology intensity (*BACI_xshtir*, *BACI_xshti* and *BACI_xshmti*) as well as the two variables where we ranked the EU Member States in terms of high or medium price segments (*BACI_hprsh* and *BACI_hmprsh*). The rank correlations for the complexity measure (*BACI_complx*) are lower but surprisingly homogenous. The same applies to the value added share of technology-intensive and research-driven industries.

Finally, to determine the joint cluster structure across variables and countries in Figure 3-39 we select only one indicator to represent each of the dimensions of technology intensity, price segments and complexity, in order to avoid an implicit differential weighting. However, because of the aforementioned caveats of export data, we use the share of technology-intensive and research-driven industries in total value added instead of exports. In short, and being cautious about the precise ranking, we can finally group the Member States into three broad classes of product sophistication (in alphabetical order of the ISO codes):⁵⁴

- Member States with a high share of sophisticated products: Austria, Germany, Denmark, Finland, France, United Kingdom, Hungary, Ireland, and Sweden
- Member States with an intermediate share of sophisticated products: Belgium/Luxembourg, Czech Republic, Spain, Italy, Netherlands, Slovakia and Slovenia.
- Member States with a low share of sophisticated products: Bulgaria, Croatia, Cyprus, Estonia, Greece, Lithuania, Latvia, Poland, Portugal and Romania.

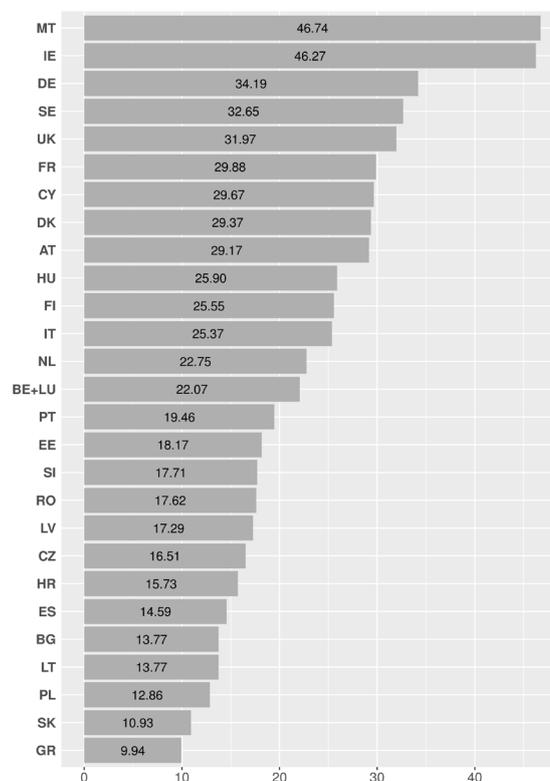
⁵⁴ Malta is not included because of limited availability of data.

Figure 3-35: Value added share of products in research or development driven industries ("high or medium tech"), 2014



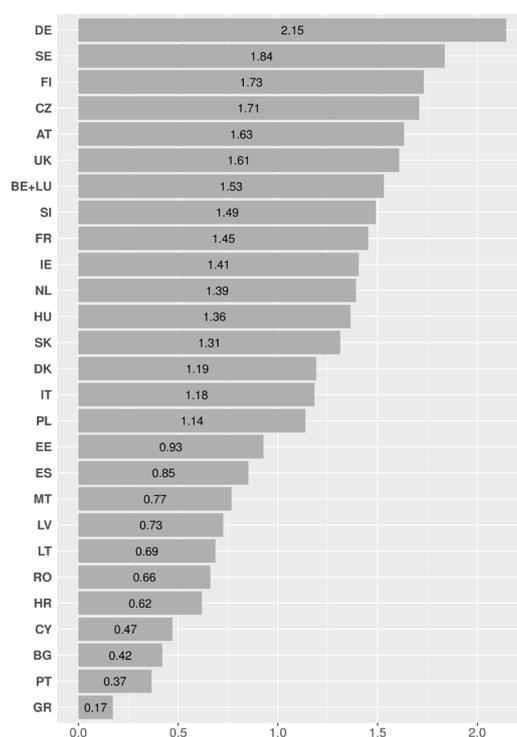
Source: SBS, WIFO calculations.

Figure 3-36: Export share of products in the high quality/price segment, 2015



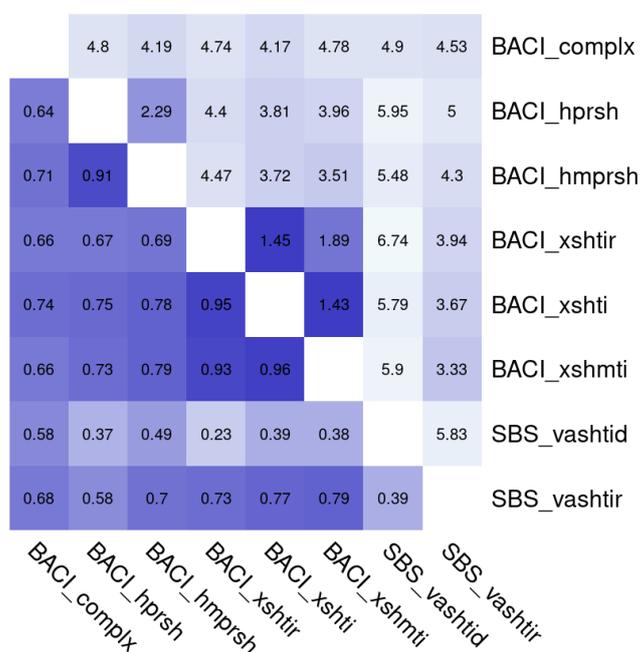
Source: BACI, WIFO calculations.

Figure 3-37: Complexity score of exports, 2015



Source: BACI, WIFO calculations.

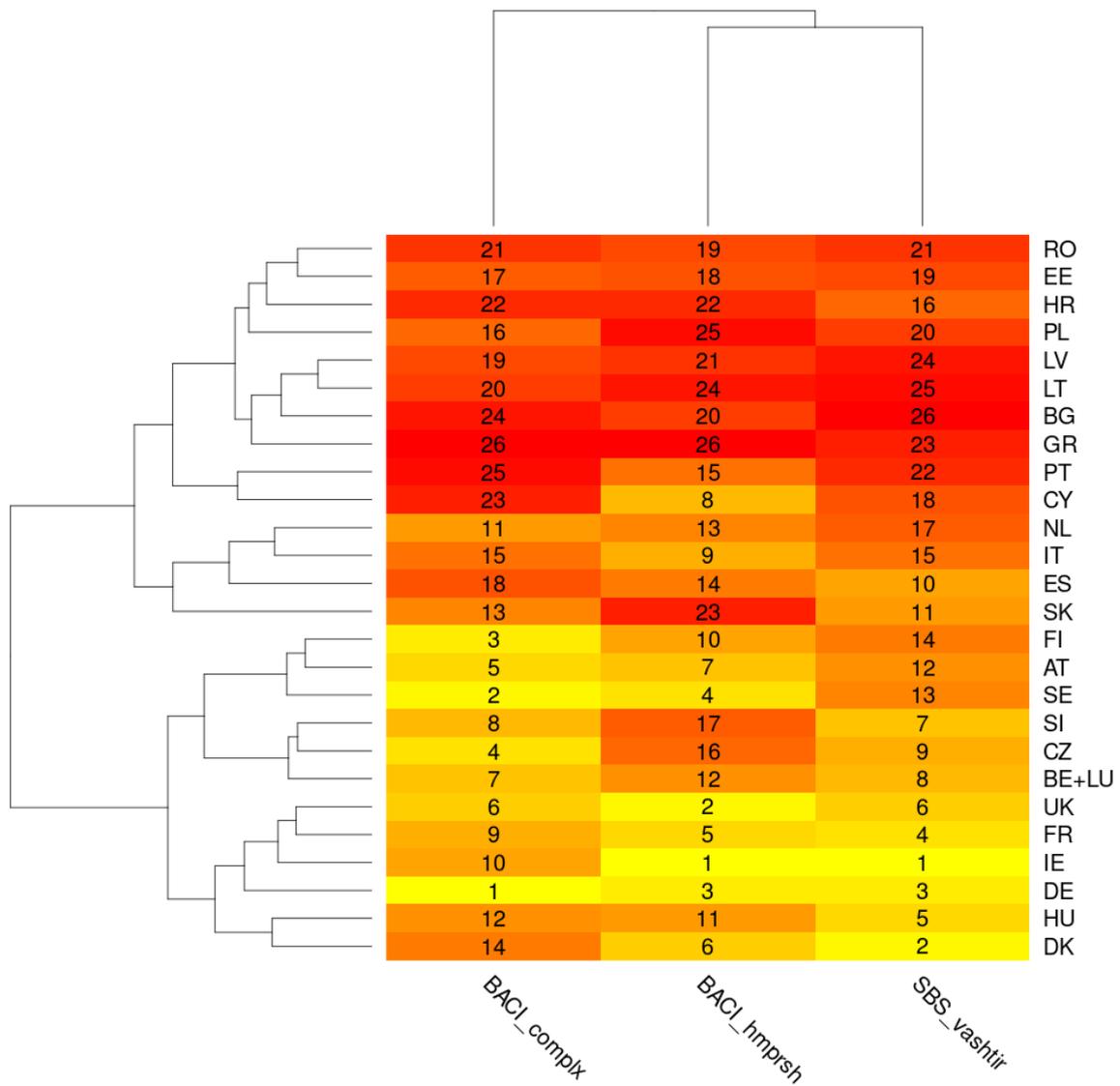
Figure 3-38: Quadratic heat map of export sophistication, pairwise correlation of the country rankings and City-Block distance, 2005-2014



Note: The numbers below the diagonal present the correlation coefficient, those above the diagonal the Manhattan measure of distance (average absolute change in ranks). The individual indicators are explained in the main text.

Source: BACI, SBS, WIFO calculations.

Figure 3-39: Cluster heat map of ranks in export sophistication 2015



Note: Data for the value added share of technology intensive, research driven industries (*SBS_vashtid*) is from 2014. Numbers denote the country ranks, lighter colours better performance. Cluster dendrograms based on average linkage method and Euclidean distances. Malta is not included because of limited availability of data.

Source: BACI, SBS, WIFO calculations.

Summary and Conclusions

We defined *export competitiveness* as the ability to earn income from selling goods and services abroad. Its particular importance originates in the additional stimulus exports provide to overall growth and the creation of jobs above that of domestic demand and as a driver of structural change. Since international competition is generally more intense than that for a smaller domestic market, export performance offers a timely and immediate indication of an economy's comparative strengths and weaknesses.

The concept of export competitiveness knows many facets and at least as many different indicators. In this section, we focused on four dimensions. For each of them we offered a detailed discussion of the most important ideas and definitions. These were further illustrated by empirical examples, tracking the relative (dis)similarity of alternative indicators, reporting concrete values for selected examples, and examining the joint cluster structure across variables and countries. By closer inspection one can assess in an exemplary manner, how alternative choices of indicators affect the ranking of EU Member States.

The general conclusion must be one of caution: While there are no single best indicators, the assessment of relative performance among member states is shown to be very sensitive to alternative choices among them. Consequently, one ought to strive for a comprehensive assessment by simultaneously employing various measures. Thereby a proper understanding of their individual meaning and limitations is a precondition for accurate interpretation.

Turning to the four dimensions of export competitiveness covered in this chapter, the main conclusions are as follows (and indicators in bold letters our choice of key measurements):

- *Cost- and price based* indicators refer to balancing constraints rather than being measures of competitiveness per se. Among them, **real effective exchange rates (REER)** are the most comprehensive indicator, particularly so for observations at the macro level. A critical choice is that of the appropriate price deflator. Unit labour costs suffer from addressing only part of total costs, while export prices are biased towards products successful sold abroad (thus missing potential exports, which may have failed due to high domestic costs) and producer prices lack international harmonisation. In contrast, the common consumer price index is among the best internationally harmonised series, but affected by movements in the price of imports and hence the development of costs abroad. Given these caveats, the real effective exchange rate based on the general **GDP deflator** appears to be an interesting option.
- Similarly, *trade balances* reflect long-term constraints to economic development. But they also relate directly to the above definition of export competitiveness, since positive net exports *ceteris paribus* contribute to domestic income and jobs. Even more than for other indicators, trade balances require an interpretation that is conditional on the general economic conditions of a

country. For instance, if deficits are used to smooth temporary exogenous shocks or finance a healthy economic transition with high investments, the consequences for a country's overall competitiveness are quite different from a situation, where people just consume more than they produce. Among country-wide indicators of competitiveness, we prefer the **balance of payments** (BoP) over the foreign trade statistics, because it also includes services and hence allows for the more comprehensive assessment.

- *Export market shares* appear to be a straightforward measure of relative performance, but also come with their particular caveats. As with trade balances, yearly fluctuations can result from other causes than changes in competitiveness. Most important are variations in the growth of a country's main export destinations. **Trade weighted** measures should therefore **complement** the regular indicator of export market shares. But they cannot substitute for them, since one would then miss to account for a country's ability to cope with fluctuations or differences in the trend growth of its main trade partners. More generally, yearly fluctuations must be taken with an extra grain of salt and assessment ought to focus on changes over several years instead.
- Finally, measures of *export structure* relate to particular sources of comparative advantage. The share of intra- as opposed to inter-industry trade is perhaps the most traditional among them. Measures of **export diversity** distinctly relate to a country's dependence on fluctuations in the demand of specific destinations and/or particular products. Finally, measures of specialisation in the export of **advanced products** aim to exploit detailed trade data in order to characterise the level of sophistication in a country's productive system. Looking at the distribution across EU Member States, however, many measures suffer from idiosyncratic outliers. It is therefore important to simultaneously explore different dimensions. This chapter provided an example by demonstrating the joint cluster structure across EU member states for the share of *technology intensive* industries (in total value added) together with that of exports in the high- and medium-price segment as well as a general measure of the *complexity* of exports.

4 Data Availability and Quality of Selected Competitiveness Indicators

The objective of this chapter is to analyse the availability and quality of the data for a selection of competitiveness indicators. Data quality includes the completeness and timeliness of data, likely measurement problems as well as validity issues, i.e. whether an indicator does measure the underlying theoretical concepts or whether data limitations and peculiarities result in biased measurement. Eight areas of competitiveness indicators are analysed:

- Total/Multi Factor Productivity
- Labour Productivity
- Unit Labour Costs
- Energy Costs
- R&D
- Innovating Firms
- Openness
- Terms of Trade

Each indicator is presented in a separate section based on a consistent structure which discusses underlying concepts and definitions, relevant data sources (particularly with a view on performing competitiveness analysis for the EU member states and considering different industries) and data quality issues. In addition, descriptive results for the 28 EU member states and - if applicable - at the industry level are presented. The presentation of the empirical analysis differs for each indicator in order to allow flexibility for discussing specific issues for each indicator.

4.1 Total/Multi Factor Productivity

Michael Peneder and Stefan Weingärtner

4.1.1 Concept and Definitions

If productivity is the quintessential measure of competitiveness, we may consider *total factor productivity* (TFP) as its kind of “gold standard”. This is for three reasons: First, in theory TFP measures the success in generating output by the transformation of various inputs more comprehensively than any other indicator. In its ideal form, the growth of TFP indicates the amount of disembodied technical change, or productive knowledge more generally (including improved management practices, organizational change or successful branding) as well as positive spillovers from the other factors of production.⁵⁵ Second, it is also the most challenging among measures of productivity, commanding the highest requirements on accepted theoretical assumptions and the according data generating process. But finally, it often may be too good to be true with regard to assumptions and data requirements not easily met in practice. The OECD and others consequently prefer to call it *multifactor productivity* or MFP, reflecting a more cautious interpretation that we will also apply in the remainder of this section. Another consequence is that most analyses focus on MFP growth instead of levels, thus eliminating distortions from time-invariant sources of measurement error or the violation of theoretical assumptions (constant returns to scale, perfect competition, etc.).

The concept of multifactor productivity applies to the level of individual enterprises, sectors and countries. In contrast to other measures of productivity, which relate output to a single input, such as labour, capital, energy or material use, multifactor productivity growth is measured as a *residual*, i.e. the unexplained part of the growth of output after the contributions of all other factors have been accounted for. Consequently, differences among alternative concepts to measure or relate output and known inputs directly affect the residual measure of MFP (Syverson, 2011).

Thereby concepts can differ in many dimensions. For instance, ten Raa and Shestalova (2011) distinguish between Solow’s aggregate production function and more general index number approaches. The former derives indices from strict economic principles, e.g. assuming that observed prices are competitive and therefore equal to the marginal product of factors, which then can be aggregated by their income shares. Further assuming that competition eliminates all slack in production, changes of the residual represent pure shifts of the production function. The same assumptions and interpretation typically apply to so-called *superlative* indices (Diewert, 1976) of TFP, which have to be exact for flexible aggregator

⁵⁵ Note that part of technological change is also embodied in the factors of production, e.g. when labour becomes better educated and trained or when the design and quality of capital assets or intermediate goods improves (OECD, 2017b, p. 54).

functions with discrete time series.⁵⁶ In contrast, *data envelopment analysis* (DEA) does not impose behavioural assumptions nor use observed price series, but instead applies linear programming techniques to infer the implicit shadow price from marginal values on the production possibility frontier. Changes of TFP in the according Malmquist index reflect shifts in both technology and efficiency.

Another important dimension is the choice of the appropriate output being measured either as gross output or value added. Using value added directly relates output with aggregate income and has the advantage that one can ignore difficulties in the measurement of flows of intermediate goods and services. Since one doesn't have to wait for the production of accurate input-output tables the publication lag tends to be shorter. Conceptually, however, one must assume an additive-separable production function, which does not allow for substitution between intermediate inputs and individual factors in the value added function (i.e. capital and labour).⁵⁷ Furthermore, one cannot account for spillovers from technological change in the production of intermediate inputs such as microprocessors, new materials, etc. While this would not matter in the case of a closed aggregate economy, it makes a difference for open economies and especially the study of MFP at sectoral levels.

4.1.2 Data sources

The data sources needed depend on the level of analysis. At the micro level, the analyses requires detailed information on outputs and inputs typically sourced from balance sheets and/or elaborate enterprise surveys. For aggregate analyses, information is sourced from the following data systems:

- *National Accounts* are the single most important source, providing data, e.g. on gross output, value added, labour inputs and investments.
- Labour force surveys (eventually complemented by earnings surveys) are used to proxy human capital inputs, e.g. in terms of the labour share by average attainment levels.
- Independent accounts determine capital services from capital stocks, which typically are computed by the perpetual inventory method (PIM) for distinct classes of capital goods⁵⁸ and weighted by the user cost of assets for the purpose of aggregation.

⁵⁶ Examples are the Törnqvist index (for the translog production function) and the Fisher index (for second order approximations to twice and continuously differentiable aggregator functions). See also Caves et al (1982).

⁵⁷ This implies, for instance, that changes in the price of intermediate goods cannot affect the relative use of labour and capital. Furthermore, one must assume equivalent price changes of output and of intermediate goods and services (Cobbold, 2003).

⁵⁸ For example, TED and PWT (see Table 4-1) compose capital assets from six subtypes: computer hardware, software, telecom equipment, buildings & structures, transport equipment, and non-ICT-machinery. EU-KLEMS adds four more assets for intellectual property products (R&D, other), cultivated assets, and dwellings.

- Input-output data are used to account for the flow of intermediate goods and services, which is of particular relevance to industry level MFPs.

Labour input is based on total hours worked or persons employed as a proxy for labour volume. The labour income share is sourced from the National Accounts, whereby income of self-employed is typically approximated by the average income of employees. Capital income shares are then calculated indirectly from the labour income share.

In this section, we draw estimates of eight MFP indicators from four data sources. Table 4-1 lists the eight indicators and specifies label, database, and carrier for each indicator. TED, ECFIN and OECD indicators are available as growth rates. All other indicators were transformed from indices. Differences between reported MFP indicators can arise e.g. because of broader or narrower concepts, the usage of different data sources, different degrees of disaggregation of input factors and different methods of computation.

Table 4-1: Summary of selected MFP indicators

<i>Indicator</i>	<i>Description</i>	<i>Database</i>	<i>Carrier/Operator</i>
<i>TED_tfpc</i>	Growth rate	Total Economy Database	The Conference Board
<i>PWT_tfpc</i>	Index at constant national prices (2011=1)	Penn World Table	UCD, GGDC
<i>PWT_wrtfpc</i>	Index (2011=1); welfare-relevant	Penn World Table	UCD, GGDC
<i>ECFIN_tfpc</i>	Growth rate	Available via CIRCABC	DG ECFIN
<i>ECFIN_tfpadjc</i>	Trend growth rate (adjusted for cyclical component)	Available via CIRCABC	DG ECFIN
<i>OECD_mfpc</i>	Growth rate	OECD Productivity	OECD
<i>OECD_eamfpc</i>	Growth rate; environmental adjusted	OECD Environment	OECD
<i>EUKLEMS_tfpc</i>	Index (2010 = 100); consistent sectoral data	EU KLEMS	The Conference Board, GGDC

Recently, there have been attempts to broaden the concept of MFP by general welfare aspects. For example, the OECD offers an environmental adjusted MFP indicator, which aims to account for the growth contribution of the changing use of natural resources and is adjusted for pollution abatement (Cárdenas et al., 2016). Another example are the Penn World Tables, which added a welfare relevant MFP measure targeting changes in domestic absorption (rather than GDP) that is based on prices and quantities observed by consumers rather than firms (Susanto et al., 2014). In contrast, DG ECFIN aims for a narrower determination by decomposing the cyclical component and trend of MFP.⁵⁹ Each of them is added to our selection of indicators in addition to the regular Solow-type residual measure of MFP by the same organisations.

⁵⁹ It uses a Kalman filter and Bayesian estimation of a bivariate model, which links TFP with capacity utilisation. See Havik et al. (2014) for further details.

Apart from the general scope and choice of factors, MFP measures can also vary with regard to the computational method and level of disaggregation applied to different inputs. Such differences include, for instance, variations in the computation of human capital and labour quality, rates of capital depreciation, the deflation of goods and services, etc.

For example, EU-KLEMS takes particular care to correct for changes in the quality of labour and capital inputs to capture embedded technological change. Thereby it distinguishes educational attainment, gender, age, and an approximation of work experience, which results in 18 labour categories. It further splits machinery data into ICT subcategories (as does TED) using US ICT price trends as an approximation for countries without data. The current release draws capital stock data from Eurostat/national accounts. For the TED measure of MFP, labour inputs include a factor for labour quality which segregates labour into three skill groups (low/medium/high-skilled). The amount of labour quality is obtained by average years of schooling, the education level of the population aged 15 and older, and EU-KLEMS data for shares of hours worked per skill group.

4.1.3 Data quality

Representativeness

Since a large portion of data is sourced from the National Accounts, representativeness of aggregate MFP measures is generally high.

Revision history

Periodic revisions of the source data, especially from the National Accounts, imply that MFP numbers must be regularly updated. Such nature is represented in the regular actualisation of most data sources. This includes the ECFIN, OECD, PWT and TED database. However, EU-KLEMS only receives irregular updates.

Classification changes must also be considered when working with MFP data. For several countries, MFP growth got extensively revised due to the implementation of NACE Rev. 2 by European countries. On aggregate, mainly labour input and output data changed.

Completeness and timeliness

The completeness and timeliness of the indicator reflects the availability and publication lags of the underlying data sources. Table 4-2 summarises the coverage in terms of countries, years and missing data for the EU28 during the past 10 years. Currently, only the MFP measures by DG ECFIN, TED and PWT offer a complete coverage of the EU member states with PWT offering the longest reach backwards. TED offers nowcasts to cover the latest years, whereas DG ECFIN also provides forecasts which currently go to the year 2021. In contrast, the indicators of the OECD

and EUKLEMS have a longer publication lag. Still several EU member states are missing in the latest release.

Reliability

Given the demanding theoretical assumptions and methodological options, reliability is a major issue for MFP. Theoretically, it should identify exactly the change in disembodied technological knowledge. But being measured as a residual any deviation from the theoretical assumptions can affect its value. Looking at differences over time, "constant" deviations (e.g., if economies of scale or market power do not change) won't affect its growth rates. But yearly variations, for example, in the degree of capacity utilization – and business cycles more generally – have a strong impact.

Figure 4-1 illustrates the variation between the selected indicators by plotting the normalised distance from the mean divided by the standard deviation (for example, a value of two means that the indicator deviates from the mean over all indicators by two standard deviations).

As expected, variations are generally high among indicators aiming for a non-standard scope of MFP, e.g. by including environmental use, domestic absorption or focusing on its trend growth (all drawn with dashed lines). For the regular Solow-type residual measures of MFP (all drawn with solid lines) the normalised distances are relatively high for the MFP series from PWT and low for those from DG ECFIN and the OECD, while the series from TED display an intermediate degree of deviation from the mean.

Table 4-2: Completeness and timeliness of the selected MFP indicators for the EU28

<i>Indicator</i>	<i>Maximum no. of data cells per year (countries/sectors)</i>	<i>Coverage</i>	<i>Missing data during last 10 years</i>	<i>Expected updates</i>
<i>TED_tfpc^{a)}</i>	28	1990-2016		Fall 2017
<i>PWT_tfpc^{b)}</i>	28	1950-2014		2018
<i>PWT_wrtfpc</i>	28	1950-2014		2018
<i>ECFIN_tfpc^{c)}</i>	28	1966-2021		Fall 2017
<i>ECFIN_tfpadjc</i>	28	1966-2021		Fall 2017
<i>OECD_mfpc^{d)}</i>	13	1989-2015	2015: ES, IE, PT	
<i>OECD_eamfpc</i>	28	1990-2013	2012: PT, 2013: PT, HR	
<i>EUKLEMS_tfpc^{e)}</i>	10 (countries) x 40 (sectors)	1995-2014	2014: IT	Summer 2017

a) <https://www.conference-board.org/data/economydatabase/index.cfm?id=27722>

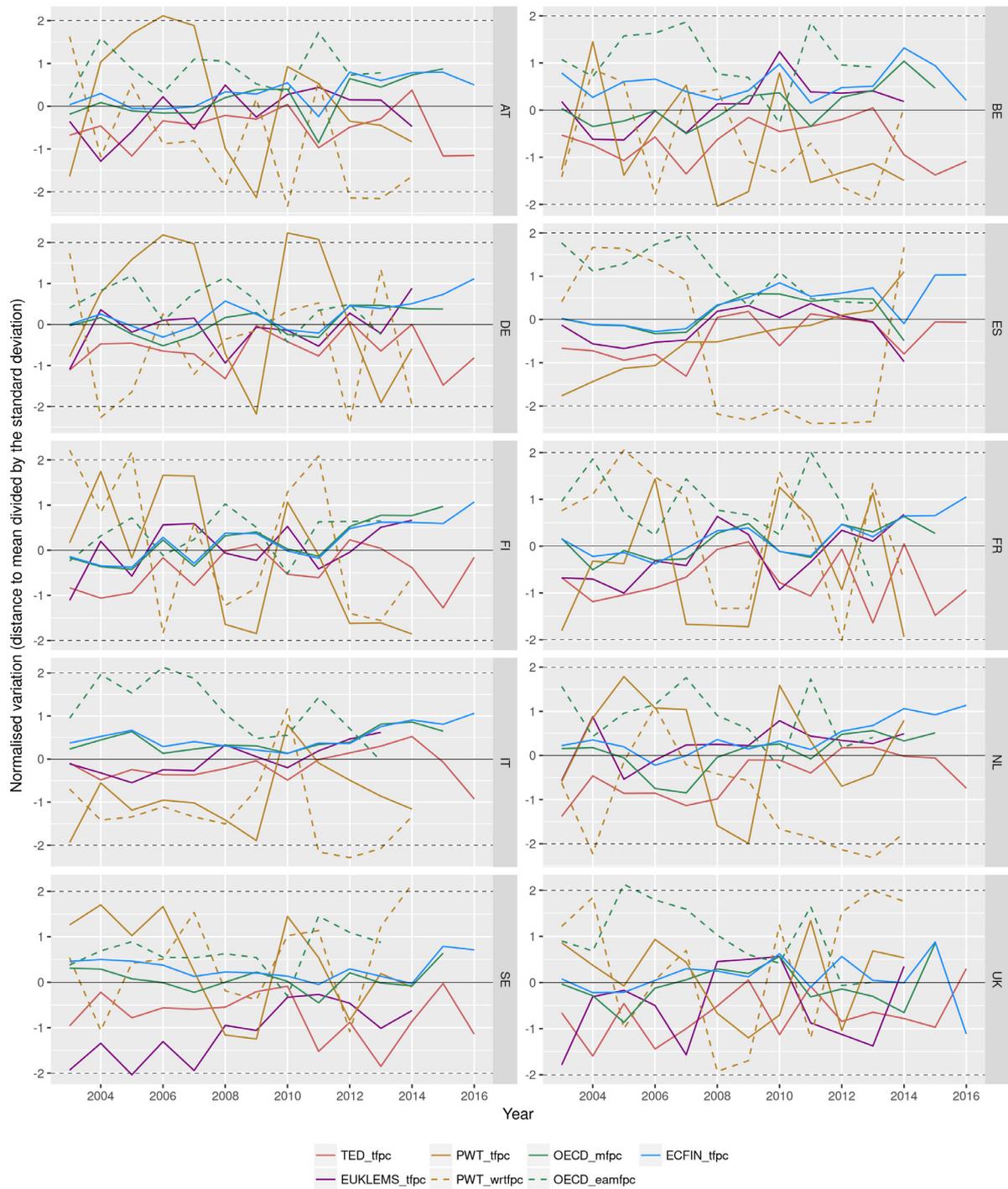
b) <http://www.rug.nl/ggdc/productivity/pwt/>

c) https://ec.europa.eu/info/business-economy-euro/economic-performance-and-forecasts_en

d) <https://data.oecd.org/>

e) <http://www.euklems.net/>

Figure 4-1: Normalised distance to mean of MFP growth indicators, expressed in σ (standard deviation)



Source: DG ECFIN, OECD, The Conference Board, PWT; WIFO calculations. DG ECFIN's trend MFP is not included because of its different concept and very time behaviour.

4.1.4 Data validity

The measurement of MFP is particularly commanding in terms of underlying assumptions and requirements on the data generating process. As a consequence, one must interpret empirical results with an extra degree of caution. Probably more than for most other indicators, a valid interpretation of the data poses the following additional requirements:

- Complementary information (if available) about the quality of the *source data*, in terms of the actual coverage, degree of disaggregation of inputs and outputs, and possible measurement errors.
- A proper understanding and careful study of the particular methodological approach. Examples are whether MFP is based on gross output or value added; the degree of disaggregation of various capital and labour inputs; or the particular strategy applied to control for endogeneity between unobserved productivity shocks and the choice of factor inputs in microeconomic studies.
- Additional knowledge about the general economic situation in order to understand the likely impact of deviations from theoretical assumptions. One example are differences in the business cycle, which affect the degree of capacity utilization. Another example are changes in the degree of competition and market power that may affect particular markets and firms.

If we adhere to Syverson's (2011) dictum "[w]hat happens at the micro-level feeds upwards into aggregates", the econometric literature on the estimation of multi factor productivity at the firm level illustrates well some fundamental difficulties in identifying a true residual MFP.⁶⁰ While an empirical assessment of firm-level measures of MFP is beyond the scope of this study, a brief general discussion shall highlight the main methodological issues at stake.

Following the notation of Akerberg et al. (2015), we can write the standard Cobb-Douglas production function for the log of output y of firm i at time t depending on the log of capital inputs k and labour inputs l as well as the observed error that is comprised of the unobservable productivity shocks ω and ε :

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \varepsilon_{it}$$

While ε_{it} is unobservable and unknown to the firm, problems of identification arise from the possibility that the firm knows or anticipates ω_{it} (e.g., relating to managerial ability or expected defect rates of new machinery), which nevertheless is unobservable to the econometrician. If ω_{it} influences the firm's choice of factor inputs (e.g. if higher productivity incites more investments or labour inputs), k_{it} and l_{it} will be correlated with the measured error $\omega_{it} + \varepsilon_{it}$ and lead to inconsistent estimates of the input coefficients β_k and β_l .

Since first observed by Marschak and Andrews (1944) many attempts have been pursued to remedy this problem of endogeneity. For example, early approaches

⁶⁰ See also the discussion in Berlingieri et al. (2017).

relied on panel estimations with fixed effects assuming that endogeneity arises only from time-invariant shocks ω_i . Dynamic panel models (e.g., Arellano and Bond, 1991; Blundell and Bond, 2000) generalised this approach to include an autoregressive component, where output linearly depends on its past values and a stochastic term.⁶¹ Another approach applied factor prices as instruments, assuming that they are exogenous to the firm and that observed differences in prices are unaffected by differences in quality across firms or their choice of location.

In recent years, the semi-parametric approach of Olley and Pakes (OP 1996) has inspired several successive refinements. It distinctively allows for input endogeneity from time-varying unobservables.⁶² The method proceeds in two stages,⁶³ first estimating a composite of the constant term and ω_{it} by means of a nonparametric inverted function of *investments*, which in the second stage is substituted in the production function. There one can further decompose ω_{it} into its conditional expectation at $t-1$ and an innovation term so that $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$. Like in the dynamic panel approach ξ_{it} is uncorrelated to the choice of inputs prior to t .

Levinsohn and Petrin (2003) criticised the use of investments in the first stage of the OP method, instead using an inverted demand function for *intermediate* inputs. The major advantage is that both labour and intermediate inputs are non-dynamic in the sense that they only affect current profits, whereas capital investment is lumpy and suspect to involve dynamic adjustment cost that must be ruled out by assumption. Furthermore, both approaches must assume that firms operate in identical output and labour markets, whereas LP replace the assumption of identical markets of investment goods in OP by the assumption of identical markets for intermediate goods and services.⁶⁴

In the latest episode, Akerberg et al. (2015) point at a *functional dependence problem* in the first stage of OP and LP. Functional dependence implies, for instance, that the contribution of labour to output cannot be separately identified, if labour inputs are fully determined by the values of capital inputs, intermediates and time.⁶⁵ As a further refinement, they propose to invert an input demand function that is conditional on labour l_{it} instead of the unconditional input demand functions used in the other approaches. Different from the other approaches, they use the first stage to "net-out" the unknown error ε_{it} from the production function and estimate all the coefficients in the second stage. As the authors claim, this approach is consistent

⁶¹ In the notation of Akerberg et al. (2015) the anticipated productivity shock can then be expressed as $\omega_{it} = \rho\omega_{it-1} + \xi_{it}$ with ξ_{it} being uncorrelated to all input choices prior to t .

⁶² With $\rho(\omega_{it+1} | \omega_{it})$ defining what the firm knows about the distribution of future productivity shocks. See Akerberg et al. (2015, p. 2417ff).

⁶³ Wooldridge (2009) pointed at the advantages (e.g. efficiency gains) of estimating the equations jointly in a simultaneous system.

⁶⁴ See e.g. Akerberg et al. (2015, p. 2421): "in summary, neither OP nor LP allow serially correlated, unobserved heterogeneity (across firms) in prices of labour or intermediate inputs, while only OP rules out unobserved heterogeneity (across firms) in the price of investment or capital adjustment costs."

⁶⁵ In practice, this dependence would go unnoticed, as e.g., firms generate variation in the data due to errors in their optimization, but produce inconsistent estimates of the input coefficients (Akerberg et al., 2015, p. 2427).

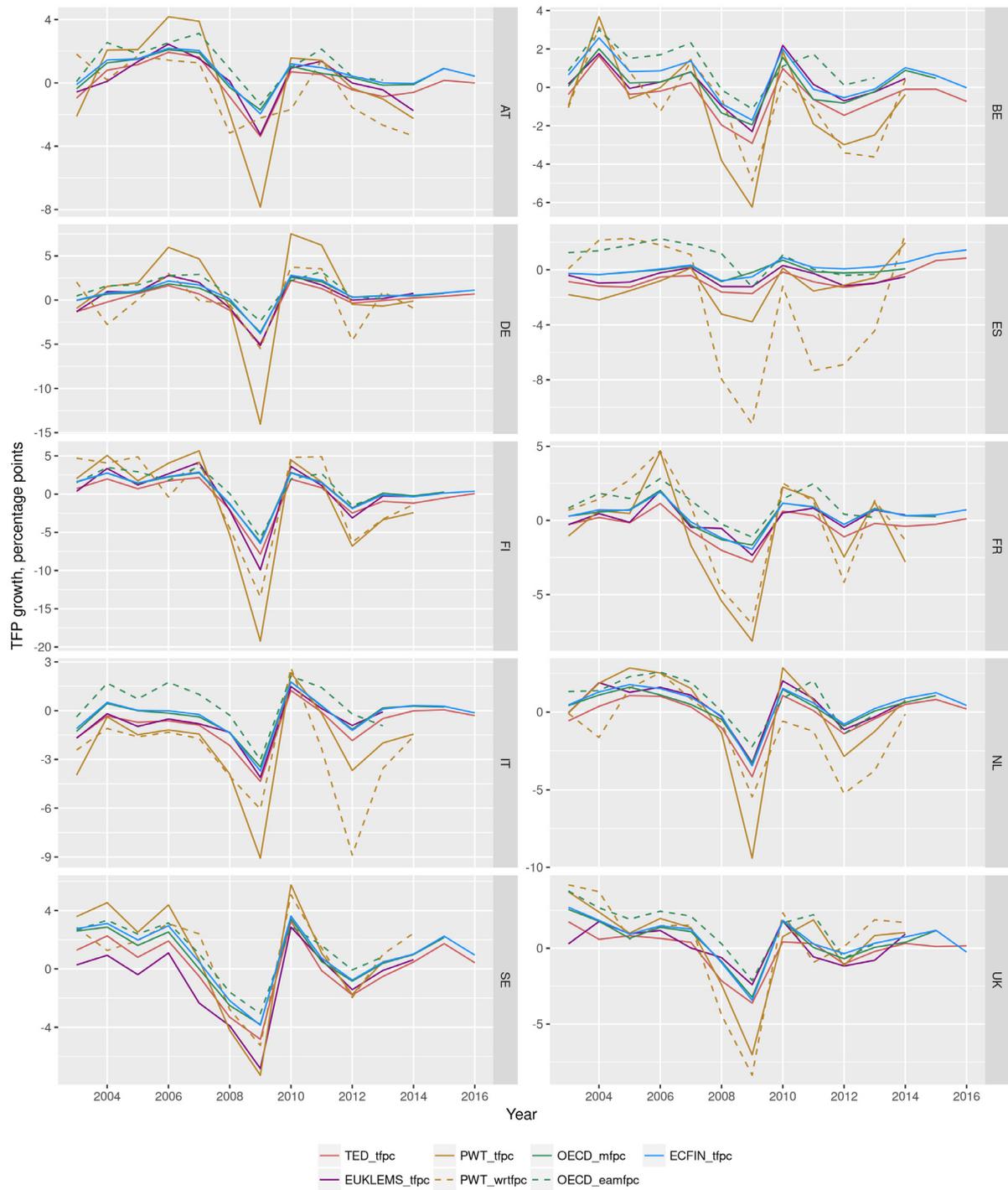
with less restrictive assumptions on the data generating process, for instance allowing for heterogenous wage conditions and adjustment cost of labour across firms.

4.1.5 Data analysis

As a brief illustration and without going into much detail, Figure 4-2 provides an example of the actual time behaviour of MFP by comparing the selected measures for individual countries since 2003. Even though the indicators tend to move in the same direction, the changes mainly follow the overall growth trends of a country. This illustrates a major weakness of MFP for the timely monitoring of yearly changes: Because of its residual nature, fluctuations in the utilisation of capital and labour are the dominant source of short term variations. As a consequence, one typically compares MFP numbers only as an average for several years (ideally, the full business cycle).

Alternatively, DG ECFIN's estimation of trend MFP directly deals with the problem of capacity utilisation. Since there is no good reason to expect much yearly variation in an economy's capacity for pure efficiency increases, the smooth shape of trend MFP is plausible. However, the same persistency also renders it of limited value to the yearly monitoring of competitiveness. Yet, it is of course highly relevant to long-term structural analyses and macroeconomic forecasts of potential output.

Figure 4-2: MFP growth indicators for selected countries, percentage points



Source: DG ECFIN, OECD, The Conference Board, PWT; WIFO calculations. DG ECFIN's trend MFP is not included because of its different concept and showing little variation by years.

4.2 Labour Productivity

Niklas Dürr and Stefan Frübing

Labour Productivity is a competitiveness indicator that measures the average output per person and per hour worked. Among the indicators that measure productivity, Labour productivity is a common measure that is typically used for country- as well as industry-level analysis. Holding other factors like labour costs constant, a higher Labour productivity implies that a desired amount of output can be produced in a shorter time or that in a given timeframe more output has been created which boosts the competitiveness of a firm, industry or country. Labour productivity depends on physical capital, human capital and technology and is commonly defined as a ratio of a volume measure of output and a measure of labour input use.

Volume measures of output, for instance GVA, are easily available. To compare Labour productivity across countries or firms, it is however also necessary to know the number of hours worked. The International Labour Organization (ILO) recommends the concept of actual annual hours worked. The advantage of using annual numbers is that different numbers of public holidays and diverging leave budgets are taken into account. It is important to note that actual hours worked often differ from scheduled working hours and that the difference between actual and scheduled hours may vary between firms and in particular between countries. Actual hours worked includes all working hours including overtime and any time spent at the workplace including short rest periods. It does not include the necessary time to commute, meal breaks and (paid or unpaid) absences. Alternative concepts such as normal hours, hours worked and usual hours of work are explained in Fleck (2009).

An alternative is to compute GVA per employee. The number of employees is easier to assess but it neglects how many hours an employee actually worked.

4.2.1 Data Sources

While output data is readily available, it is more difficult to acquire data on the working hours. National statistical offices often have data for their country (Bureau of Labor Statistics, 2012). According to Fleck (2009), the three most important datasets on working hours are:

- OECD Employment Outlook (Data on annual hours worked for 30 countries)
- Bureau of Labour Statistics (Data on annual hours worked can be derived from GVA per hour numbers that are available for 13 countries)
- Eurostat (Data on GVA, number of employees and a direct Labour productivity measure)

In general, the main sources for working hours are administrative data and survey-based data. Administrative data from social systems or government entities can provide normal hours for a large part of the population. Working hours are also

collected in order to enforce an hourly minimum wage which now exists in many countries.

Survey-based data is provided by either businesses (establishment surveys) or individuals (household surveys). Data from household surveys may reflect actual hours worked, whereas businesses are usually only able to provide paid hours.

4.2.2 Data Quality

Output data is readily available and of decent quality. Standard concerns about output measures, such as that certain types of work (informal labour, housework, subsistence work) are not taken into account and should apply less when the most-developed countries are considered.

However, for Labour productivity also working hours are needed and here there are some concerns about the quality, which are mentioned in the following subsections.

Finally, the number of employees as reported by Eurostat includes full-time as well as part-time workers, which might skew the measure of GVA per employee.

Completeness

Household surveys are probably the best way to get information about actual hours worked, but it is generally not feasible to survey all households. Administrative data and establishment surveys are likely to cover a more complete sample.

The potentially wide population coverage is certainly a big advantage of administrative data, but even here it has to be kept in mind that certain groups of workers might not be included, for instance self-employed persons or those not covered by collective-bargaining agreements. Administrative data is collected per job and not per person and thus holders of multiple jobs cause problems if hours worked per person are of interest.

Table 4-3 shows the percentage of missing data for GVA per hour worked and GVA per employee on the industry and economy level. The industry level is again separated into sections and divisions. In the early years 2006 and 2007 and the most recent one 2015 nearly all the data is missing, in fact 97 percent. In the years between the coverage especially for GVA per employee is very well. In the years from 2010 to 2014 it is equal or less than three percent. This very well data coverage suggests reliable data that can be used for comprehensive analyses.

Timeliness

Member states of the European Union agreed on continuous data collection. The necessary data is available with some delay. In June 2017 the last year available was 2015, but given the nearly completely missing coverage, effectively it is the year 2014.

Table 4-3: Percentage of missing data for labour productivity indicators at the industry and economy level: EU-28, 2006-2015

	Maximum no. of data cells per year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
a) Economy level											
GVA per hour worked	28	21	21	21	21	21	21	21	21	21	21
GVA per employee	28	0	0	0	0	0	0	0	0	0	0
b) Industry level (sections)											
GVA per hour worked	28x13	95	95	35	33	30	27	29	29	27	97
GVA per employee	28x13	95	95	18	16	12	9	11	10	9	97
c) Industry level (divisions)											
GVA per hour worked	28x68	96	96	34	33	30	30	29	29	29	97
GVA per employee	28x68	96	96	17	16	13	13	12	12	11	97

Source: Eurostat, Industry, trade and services and OECD Stat, Note: the sections and divisions represent the sections and divisions shown in the following figures.

Representativeness

Household surveys are potentially targeting all workers, including self-employed. The subset of answering workers may not be representative, but since certain demographic variables are also asked, it is possible to weighing answers such that the results are representative with respect to the desired demographic variables.

Reliability

Household surveys depend on the ability of employees to recall correctly how much time they worked. Faulty memory may thus bias the reported actual hours.

Administration data and establishment surveys are rather reliable in measuring scheduled or paid hours, but not with regards to actual hours.

For GVA per employee this measurement errors seem to be negligible as employees have to be registered which makes figures more reliable as they are not depending on memories. On the other hand, Eurostat makes no difference between full time and part time employees, which in turn could also affect the measure.

Revision history

Both GVA per employee as well as GVA per hour worked are well established measures for Labour Productivity that did not change over time. In the years preceding 2010, GVA is collected on the basis of the European System of Accounts (Council Regulation 2223/96) by member states and surveyed by Eurostat. The number of employees is calculated on the basis of the National Accounts Concept (ESA 95). Since, December 2014 the data is based on the ESA 2010 methodology for the years 2010 onwards. Eurostat again supervises the quality. As member states sometimes deviate from the ESA 95, statistics can sometimes differ.

4.2.3 Data Validity

Labour Productivity is strongly driven by the employment of capital. In industries with high capital intensity, Labour Productivity tends to be high, while for industries with a lower capital intensity, Labour Productivity is rather low. This mechanism can also work on the national level, if overall in a member state the employment of capital is very high, the Labour Productivity will be high, too. So, when interpreting Labour Productivity over countries or industries, capital intensity has to be kept in mind. In this sense however, Labour Productivity is a good measure for the stage of development in a country.

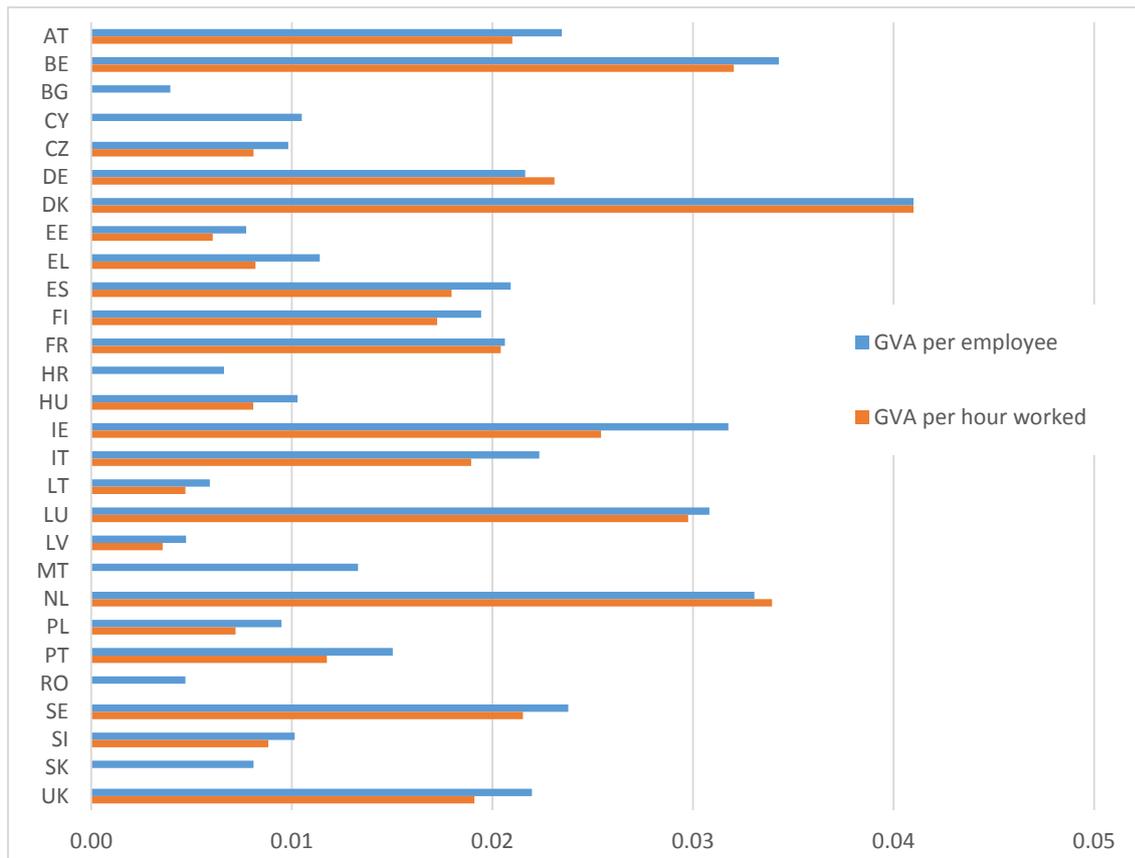
4.2.4 Data Analysis

The last available year 2014 shows that Denmark has the highest Labour productivity in GVA per hour worked as well in GVA per employee, followed by Belgium and the Netherlands. At the other end of the scale, i.e. with the lowest Labour productivity range, are the countries Bulgaria, Romania, Latvia and Lithuania, all located in Eastern Europe. The measure itself is an index, normalised to the maximum over all countries and divisions and then averaged over the divisions in a country. Generally, the two different measures GVA per employee and GVA per hour worked are very comparable in their parameter value. So, even potentially less detailed, GVA per employee could work as a substitute for GVA per hour if this data should be missing for some countries.

The highest productivity over sections is observed in D (Electricity, gas, steam and air conditioning supply), followed by B (Mining and quarrying) and L (Real estate activities) all very capital intensive industries. This can be explained by the high capital intensity in these sectors. Again, this is true for GVA per employee as well as for GVA per hour worked. The sections I (Accommodation and food service activities), N (Administrative and support service activities) and G (Wholesale and retail trade; repair of motor vehicles and motorcycles) are the ones with the lowest labour productivity. In these sections, the capital intensity is rather low. The economy-wide average is made up by the divisions shown in Figure 4.5.

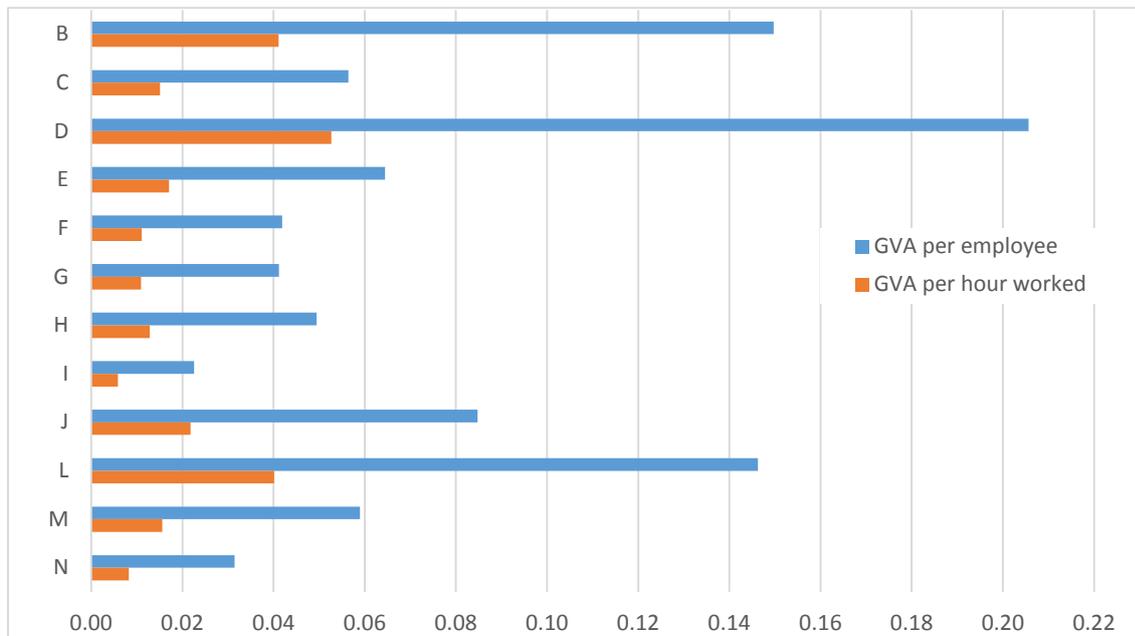
Within divisions, B06 (Extraction of crude petroleum and natural gas) is by far the one with the highest Labour productivity. With great distance follows D35 (Electricity, gas, steam and air conditioning supply) and N77 (Rental and leasing activities). The lowest labour productivity can be found in the divisions N81 (Services to buildings and landscape activities), I56 (Food and beverage service activities) and N78 (Employment activities). In fact the five most productive divisions over countries are B06 (Extraction of crude petroleum and natural gas) in Denmark and the Netherlands, N77 (Rental and leasing activities) in Luxemburg and Ireland and C21 (Manufacture of basic pharmaceutical products and pharmaceutical preparations) in Ireland.

Figure 4-3: Different measures of labour productivity, by EU member states (2014)



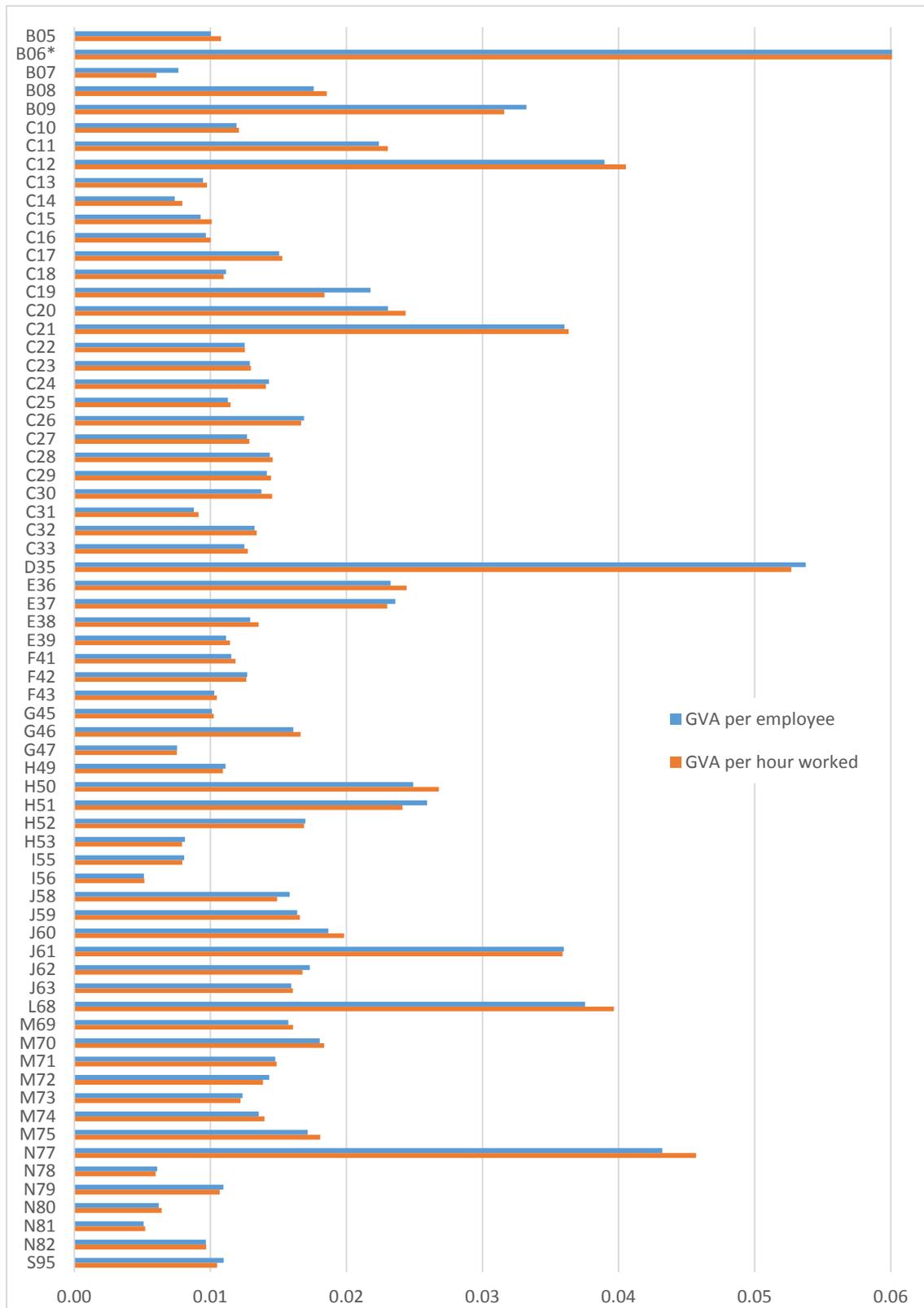
Source: Eurostat, Industry, trade and services and OECD Stat.

Figure 4-4: Different measures of labour productivity, by NACE sections (2014)



Source: Eurostat, Industry, trade and services and OECD Stat

Figure 4-5: Different measures of labour productivity, by NACE divisions (2014)



*Values for B06: GVA per employee: 0.228, GVA per hour worked 0.225.

Source: Eurostat, Industry, trade and services and OECD Stat

4.3 Unit Labour Costs

Niklas Dürr and Stefan Frübing

Unit Labour Costs (ULC) is the most commonly used indicator for cost competitiveness. ULC can be derived equivalently by calculating the ratio of total labour costs to real output or the ratio of mean labour costs per hour to Labour productivity if Labour productivity is output per hour.

ULC is thus taking both the productivity and the costs of labour into account, making it a decisive indicator of efficiency and competitiveness. Lower values of ULC directly translate into higher cost-competitiveness. Lower values may come from lower labour costs or an increase in the added value of labour, but since wages are often sticky in practice, the latter is more likely. An increase in labour costs translates into higher ULC and thus a lower competitiveness. ULC are fairly easy to compute and often used in country level analysis.

However, Altomonte et al. (2013) and Castellani and Koch (2015) also criticise the use of ULC at both micro and macro level. At the macro level, ULC cannot be a comprehensive measure of competitiveness as they only cover labour earnings and no other components that also lead to added value. In addition, an aggregation bias is likely to occur if firms have heterogeneous ULC. This aggregation bias affects the capability of standard aggregate cost measures to predict export success. At the micro level, differences in firm quality that are not reflected by added value may create a bias. As ULC is a compounded measure, problems of the compounds are often kept when using ULC (see for instance the section on Labour productivity).

As discussed in Section 3.1.1., a major drawback of ULC indices is that they ignore intra-sectoral quality heterogeneity, i.e. differences in quality of the products across countries. However, in reality for most products the concept of monopolistic competition between countries is more appropriate. A further problem when inferring competitiveness trends from ULC indices is that the choice of the benchmark year may affect the interpretation substantially as it assumes that in an arbitrary chosen base year all countries start from supposedly equal conditions. Thus, it is ignored that substantial disequilibria may exist at the moment when the index starts, so that the future evolution might reflect the adjustment of levels toward the equilibrium.

4.3.1 Data Sources

Both Eurostat and AMECO can be used to calculate ULC. Eurostat provides compensation per employee and gross value added for each two-digit NACE code. AMECO holds the same measures for the sectors C, F, G, H, I, and J. Di Comite (2016) uses data from AMECO for his structural model where he calculates selling capacity and quality index which have been discussed in Section 3.1.

4.3.2 Data Quality

ULC is an established indicator for price and cost competitiveness and thus high-quality data is available. The comparatively easy calculation comes at the cost of some drawbacks that were mentioned already in the introduction of this section on ULC.

Completeness

Both total labour costs and real output are generally available on country- and sector level for the years 2006 to 2015. Though being less detailed, the advantage of the AMECO Database is that it is more complete and offers a longer time series. As can be seen in Table 2 until the year 2009, the Eurostat Database misses ten percent of all data while AMECO is complete since the year 2006. Also, for the year 2015 data is already available.

Table 4-4: Percentage of missing data for ULC at the industry and economy level: EU-28, 2006-2015

	Maxi-mum no. of data cells per year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
a) Economy level											
Unit Labour Costs (AMECO)	28	0	0	0	0	0	0	0	0	0	0
Unit Labour Costs (Eurostat)	28	0	0	0	0	0	0	0	0	0	0
b) Industry level (sections)^{a)}											
Unit Labour Costs (AMECO)	28x4	0	0	0	0	0	0	0	0	0	0
Unit Labour Costs (Eurostat)	28x12	91	91	13	10	2	3	2	2	2	97
c) Industry level (divisions)^{b)}											
Unit Labour Costs (Eurostat)	28x68	93	93	20	16	12	12	11	11	11	97

Source: Eurostat, Industry, trade and services, Note: the sections and divisions represent the sections and divisions shown in the following figures.

Timeliness

Member states of the OECD agreed on continuous data collection. The necessary data is provided with some delay by Eurostat. In June 2017 the last year available was 2015, but given the significant missing on industry level in 2015, effectively it is the year 2014 for Eurostat data. AMECO and OECD data is provided rather timely.

Representativeness

As the ULC is a very basic measure, the representativeness is generally high. The missing values on the industry level of divisions are predominantly found in the section B – Mining and quarrying and in divisions C12 – Manufacture of tobacco

products and C19 - Manufacture of coke and refined petroleum products. Accordingly, apart from these industry codes the numbers are very reliable.

Reliability

As ULC are an established measure and the data is coming from statistical offices, reliability can be deemed reasonably high. Payments to workers are usually fixed in employment contracts and known to government agencies for the purpose of taxation and the calculation of social security contributions. Apart from unreported employment, this data reliably covers all employees. The OECD ensures comparability across its member states.

The interpretation should be done keeping other measures in mind, but generally lower ULC translate into higher cost-competitiveness. It is important to note that ULC control for GDP and thus productivity which is reflected by wages.

Revision history

ULC have been calculated for many years, but calculation methods used to vary across countries until 2007 when the OECD launched its system of unit labour costs indicators. The system provides ULC for a variety of sectors and ensures that member states are providing updates at the end of each quarter. Since 2007, the OECD has provided a specific methodology according to which member countries have to compile unit labour costs (OECD, 2007).

4.3.3 Data Validity

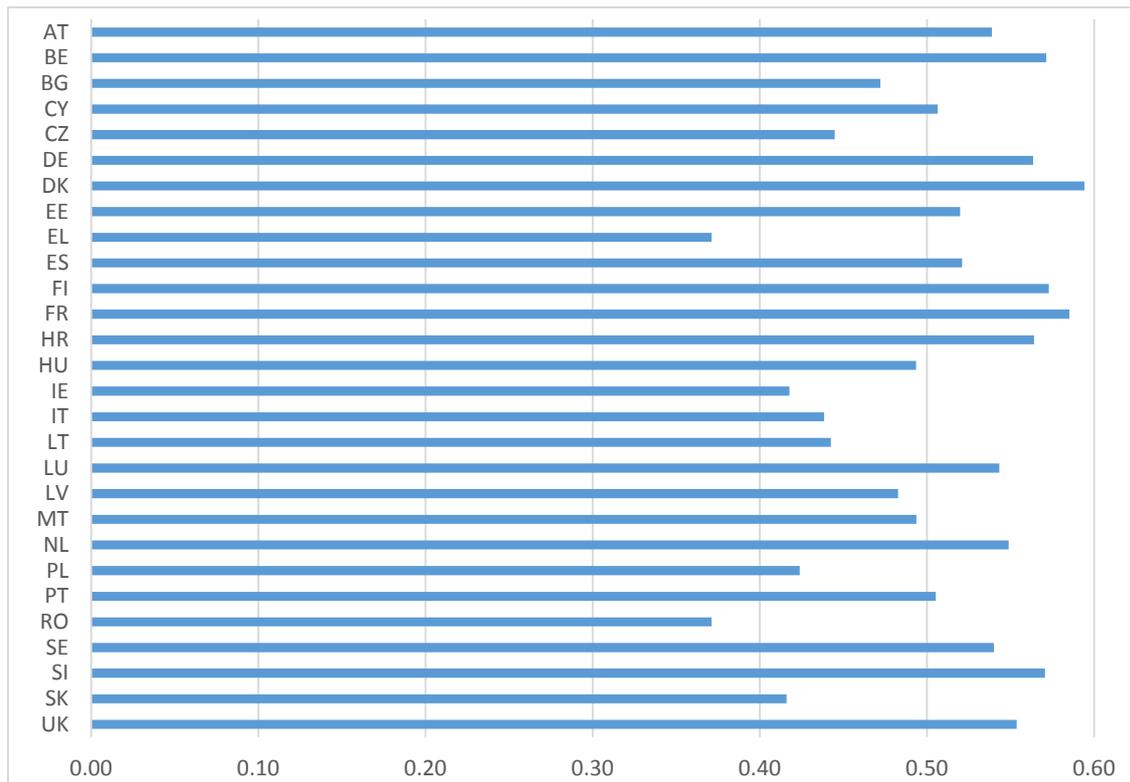
A drawback of the ULC is that in a few cases, GVA in a division can hold a negative value which makes the calculation of ULC technically possible, but in economic terms impossible to interpret. Between the years 2008 and 2014 Eurostat reports negative values for GVA for three to seven division per year.

4.3.4 Data Analysis

The lowest ULC in 2014 is found in Romania, followed by Greece and Slovakia. Denmark, France and Finland have the highest labour cost in 2014. Portugal and Malta are in the middle with their ULC closest to the mean of 0.5. The economy-wide average is made up by the sections shown in Figure 4.7.

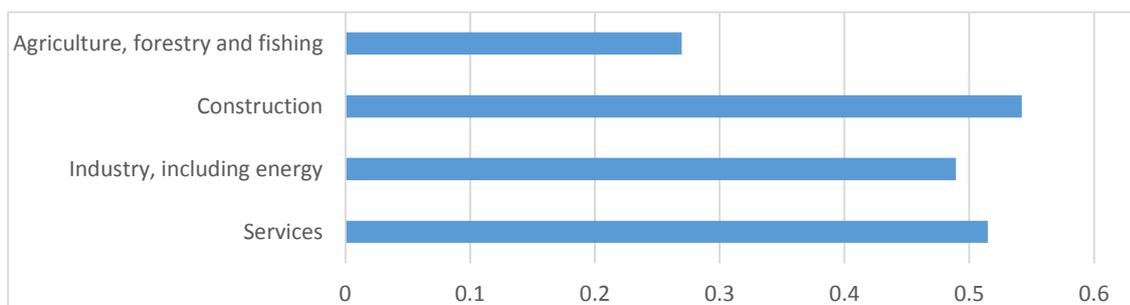
Across the rather coarse sections provided by AMECO, ULC are highest in Construction and Services. The section "Agriculture, forestry and fishing" corresponds to the NACE Code C1, "Construction" to NACE Code C2, "Industry, including energy" to NACE Code F4, G4 and H4, and "Services" to NACE Code H5, I5, and J5.

Figure 4-6: Unit labour cost based on AMECO data, by EU member states (2014)



Source: AMECO Database

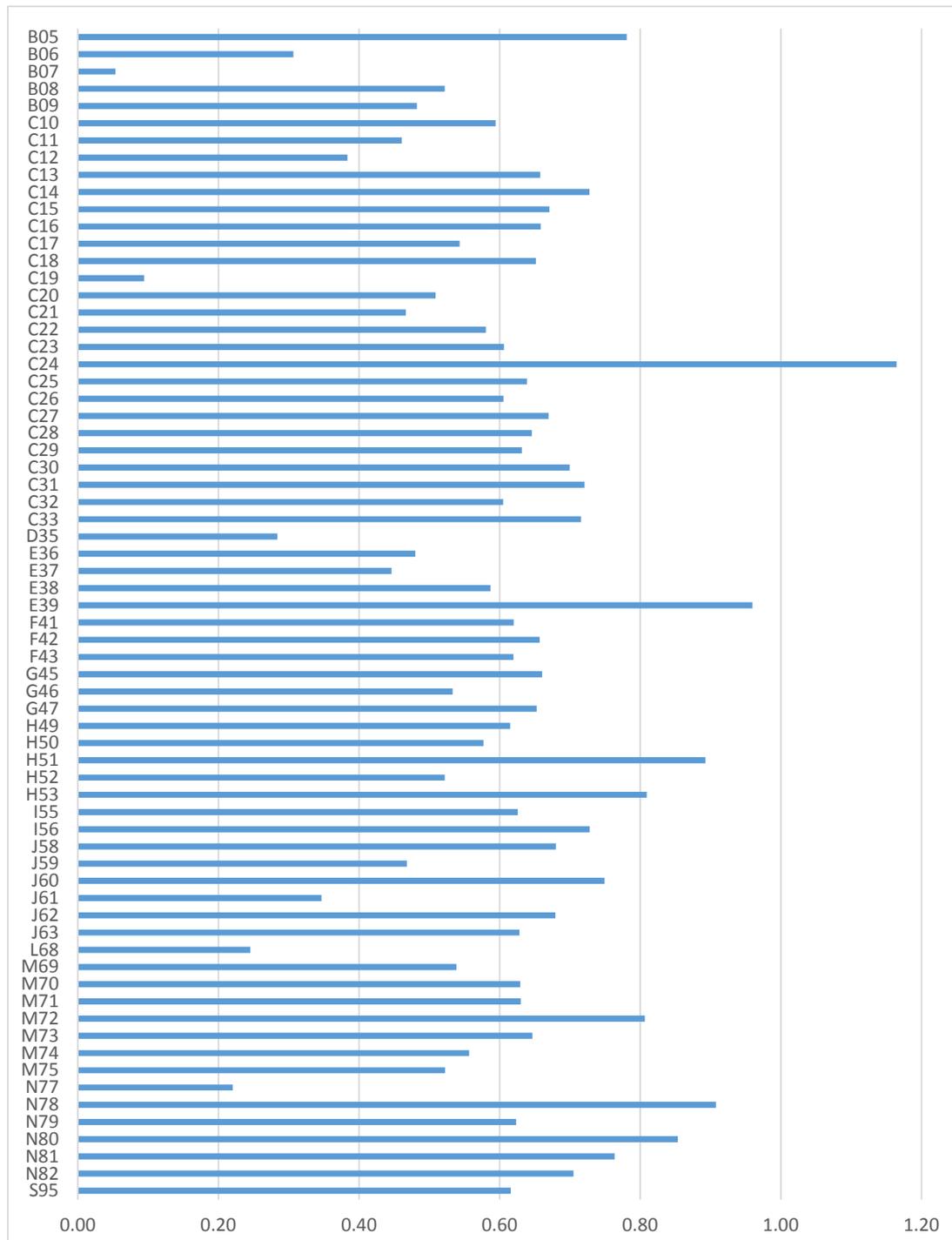
Figure 4-7: Unit labour cost based on AMECO data, by main sections (2014)



Source: AMECO Database

Across divisions, the highest ULC can be found in C24 (Manufacture of basic metals), E39 (Remediation activities and other waste management services), N78 (Employment activities), and H51 (Air transport). The sections B07 (Mining of metal ores), C19 (Manufacture of coke and refined petroleum products), N77 (Rental and leasing activities), L68 (Real estate activities) show the lowest ULC. C32 (Other manufacturing) and C10 (Manufacture of food products) are closest to 0.6 the average ULC over sections.

Figure 4-8: Unit labour cost based on Eurostat data, by NACE division (2014)



Source: Eurostat, Industry, trade and services

Across all countries and divisions, the Latvian C24 (Manufacture of basic metals) shows the highest ULC in 2014. This is followed by the Italian and Portuguese E39 (Remediation activities) and other waste management services. Number four in highest ULC across all countries is J62 (Computer programming, consultancy) and related activities in Slovenia.

4.4 Energy Costs

Niklas Dürr and Stefan Frübing

Depending on the sector, energy costs may be an important indicator for competitiveness. In many industries, firms need huge amounts of energy in their production process and thus the costs of procuring the necessary energy are important in terms of competitiveness. The so-called energy-intensive industries (e.g. construction, chemical, glass, nonferrous metals, steel, lime, cement, paper) make up a significant share of the industries in which export is feasible. Moreover, they are often at the very beginning of long value chains. This implies that energy costs are an important indicator both for sector-level comparison of energy-intensive industries and for country-level comparisons.

According to statistics of the International Energy Agency (2016), energy costs for firms differ substantially across countries. For instance, electricity prices for industry and per MWh ranged from 35 USD (Norway) to 162 USD (Japan). Notably, energy costs are also high in Germany (145 USD), the United Kingdom (143 USD), whereas firms in the United States (69 USD) and Sweden (59 USD) have lower procurement costs for electricity.

The price differences can be explained by several aspects. First, tax levels are very different. Second, the procurement sources for energy are different from country to country. For instance, France still heavily relies on nuclear energy, whereas Germany decided to phase out the usage of nuclear power. In most countries, households pay substantially more per MWh, but the amount that energy-intensive industries can save also differs substantially. Price levels are likely to vary also from industry to industry.

To compare energy costs while also taking into account the intensity of its use, the concept of unit energy costs (UEC) has been introduced (European Commission, 2014). Similarly in concept to unit labour costs (ULC), UEC describe the energy costs per unit of value added. UEC may be calculated for a sector or an aggregation of sectors.

4.4.1 Data Sources

The International Energy Agency provides data on energy costs in its member states, also specifically for industrial costs as opposed to household costs.

Also, Eurostat provides data on energy prices⁶⁶ and energy consumption⁶⁷. Energy prices are given in seven different bands depending on the amount of energy a consumer subscribes to. Also the price is differentiated into “Excluding taxes and levies”, “Excluding VAT and other recoverable taxes and levies” and “All taxes and levies included”. Prices are reported on a semi-annual basis.

⁶⁶ <http://appsso.eurostat.ec.europa.eu/nui/show.do>

⁶⁷ http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_100a&lang=en

The data on consumption is divided into three aggregation levels economy wide, an intermediate section level including 'Industry', Transport' and 'Other sectors', and a division level with 22 different sections. These divisions however do not map with NACE industry codes.

4.4.2 Data Quality

Whereas country-level information is available, data on energy costs of a sector across sectors is more difficult to acquire.

Large energy-intensive firms often use autoproduction to save on energy costs. In Germany for example, producing energy for own consumption is exempt from taxes. Autoproduction is not observable and not take it into account might bias the results in a way that too high energy costs are assumed.

Table 4-5: Percentage of missing data for Energy cost indices at the industry and economy level: EU-28, 2007-2015

	Maximum no. of data cells per year	2007	2008	2009	2010	2011	2012	2013	2014	2015
a) Economy level										
Energy Cost Index all incl.	28	4	0	0	0	0	0	0	0	0
Energy Cost Index VAT excl.	28	4	0	0	0	0	0	0	0	0
Energy Cost Index all excl.	28	4	4	4	0	0	0	0	0	0
b) Industry level (sections)										
Energy Cost Index all incl.	28x3	4	0	0	0	0	0	0	0	0
Energy Cost Index VAT excl.	28x3	4	0	0	0	0	0	0	0	0
Energy Cost Index all excl.	28x3	4	4	4	0	0	0	0	0	0
c) Industry level (divisions)										
Energy Cost Index all incl.	28x22	17	14	14	14	14	14	14	14	14
Energy Cost Index VAT excl.	28x22	17	14	14	14	14	14	14	14	14
Energy Cost Index all excl.	28x22	17	17	17	14	14	14	14	14	14

Source: Eurostat Energy, Note: the sections and divisions represent the sections and divisions shown in the following figures.

Completeness

The coverage on the economy level and on industry level section is very good, after the year 2010, all data is available. On the industry level divisions after the year 2009, 14 percent of all data points are missing

Timeliness

The IEA provides yearly reports with updates. The reports are published around May giving information on costs in the previous year.

The Data by Eurostat is also quickly available. In June 2017, the last available year was 2015, which was already complete.

Representativeness

In addition to most EEA member states, Australia, New Zealand, Canada, the United States, South Korea, Japan are members of the IEA. Results of IEA can therefore be deemed to represent the world's most important nations in terms of economic power.

Reliability

Data on Energy prices and consumption seem not to be very reliable for several reasons. The first one is that energy prices are given on an economy wide scale but not for different industries even though in reality they do change over industries. This is due to the fact that industries might have different plans depending on their consumption and that some companies or entire industries might be exempt from some taxes and levies. Additionally, as the industry divisions on which the consumption is reported does not match with NACE Codes makes it difficult to control for important industry characteristics such as size. However, this would be necessary to evaluate the actual energy intensity of a given industry.

Revision history

Data on consumption and prices have been published for nearly ten years. Generally, there are no specific guidelines on revisions on energy statistics.⁶⁸ Yet, Eurostat monitors the timing and the reason as well as the timing of revisions.

4.4.3 Data Validity

The presented energy cost indices can only represent a rough idea of the real cost burden that companies have to carry in a given industry. First, the division into the different industries does not map with the usual NACE Codes which makes it difficult to compare the Energy index with other competitive indicators and to put it in relation. Second, particular companies might be exempt from several taxes or levies and pay in reality not the price indicated in the statistics.

4.4.4 Data Analysis

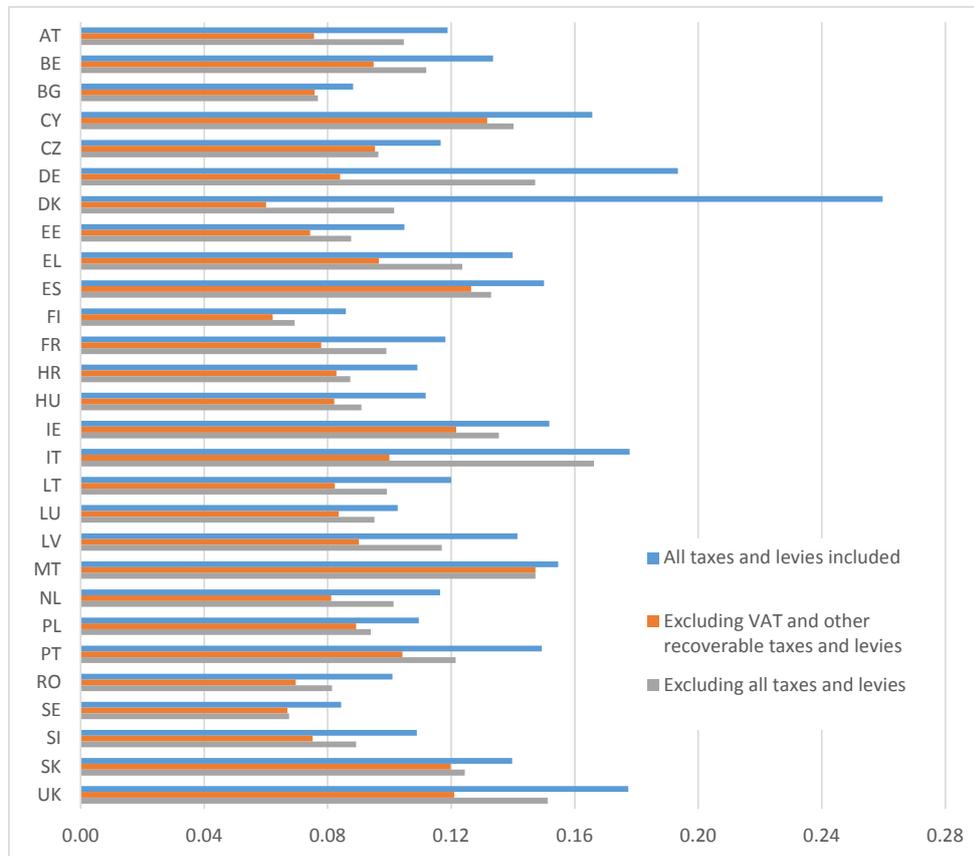
The energy prices indices have been constructed as follows. On the price side, first, the semi-annual values have been averaged to receive a single value for the year. Second, the seven different bands which cover different consumption volumes have been averaged as well.

On the demand side, the consumption in each section has been normalised to 1 within each section and year combination. This approach neglects the fact that a sector might just be bigger than another sector but is not necessarily more energy intensive per se. Nevertheless, it provides a rough indication how much energy is

⁶⁸ <http://ec.europa.eu/eurostat/documents/38154/4956233/Energy-statistics-Data-revision-policy.pdf/18d319a7-2df8-4e5a-bf26-9b035ce1a9b1>

needed. On the economy wide level, there is of course no such differentiation so that here the cost indices equal the average energy costs over the half years and bands.

Figure 4-9: Energy cost indices, by EU member states (2015)



Source: Eurostat Energy

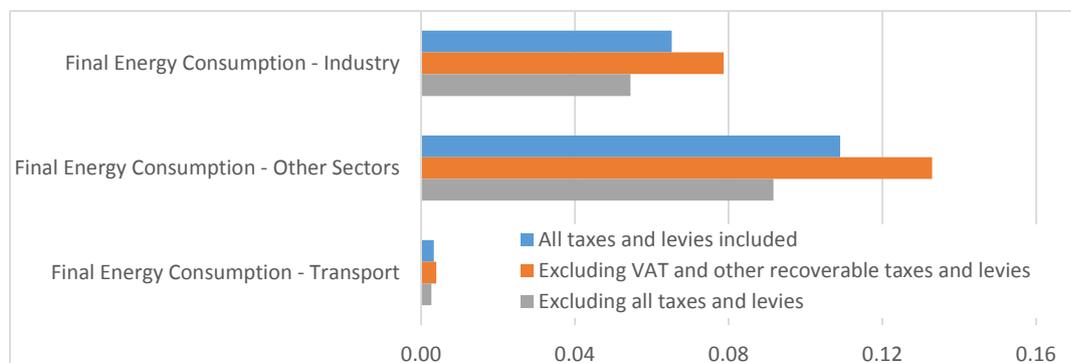
Furthermore, the energy costs are given in three different measures: With all taxes and levies included, excluded and with all recoverable taxes and levies excluded. Of course, these measures only vary over countries but not within countries. Accordingly, they do not vary across industries as well. Thus, the three different measures presented are proportionate within industries.

Finally, there are a lot of exemptions from taxes and levies for energy intensive companies so that possibly the measure with all taxes and levies excluded is the most reliable one.

In the year 2015, Denmark had the highest energy costs regarding all taxes and levies included, followed by Germany, Italy, and the United Kingdom. The countries with the lowest energy costs including all taxes and levies are Sweden, Finland, and Bulgaria. Regarding the index for energy costs with VAT and all other recoverable taxes and levies excluded, Italy is the country with the highest index, followed by the United Kingdom, Malta, and Germany with Denmark being very much in the middle on rank 15. In the third index where all the taxes and levies are excluded the most

expensive countries are Malta, Cyprus, and Spain. With all taxes and levies excluded Denmark is now the country with the cheapest energy prices, followed by Finland and Sweden.

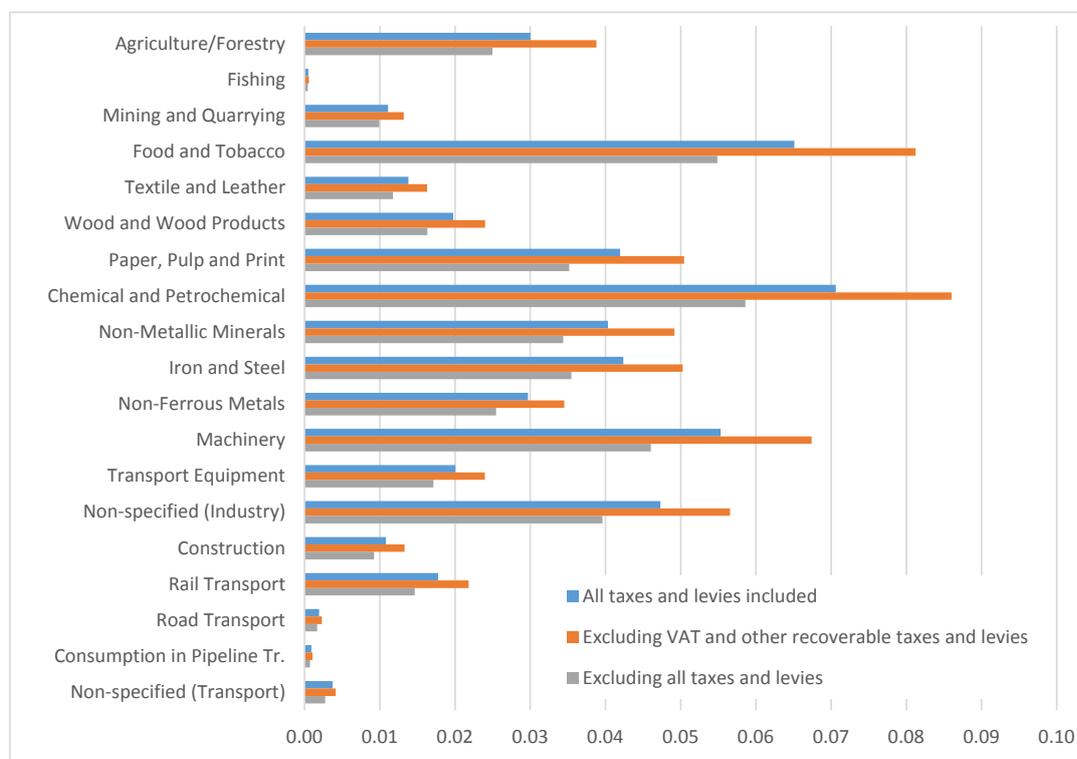
Figure 4-10: Energy cost indices, by main sections (2015)



Source: Eurostat Energy

Across industry level divisions in the year 2015, the highest energy cost indices can be found in the 'Chemical and Petrochemical' industry, followed by the industry for 'Food and Tobacco' and the 'Machinery' industry. The lowest energy cost indices can be found in the industries 'Consumption in Pipeline transport', 'Fishing' and 'Road'.

Figure 4-11: Energy cost indices, by NACE divisions (2015)



Source: Eurostat Energy

4.5 R&D

Christian Rammer

4.5.1 *Concepts and definitions*

R&D activities are a competitiveness indicator that relates to the competitive potential of firms, sectors and economies. R&D activities as such are not directly linked to competitiveness in the market. But by investing in R&D, new knowledge is generated that potentially can be transferred into new products, processes or ways of doing business, leading to competitive advantages in terms of products with higher utility, more efficient processes or offerings that address needs that have not been addressed before (or only in a less effective manner). R&D is regarded as the most important investment good that creates knowledge capital (see Griliches, 1998), though not the only one (see Corrado et al., 2005).

A specific feature of R&D which distinguishes it from many other types of investment is the public good character of the knowledge generated by R&D. It is difficult to exclude others from using R&D results (though legal instruments such as patent rights provide some protection) while using R&D results by one economic actor does not exclude others from using the same results. The spillover potential of R&D constitutes a barrier for investment on the one hand, but implies high potential for competitiveness increasing effects that go far beyond the R&D performer. Considering R&D spillovers is therefore important when employing R&D as a competitiveness indicator. Spillovers do not only take place within a sector, but also across sectors (Griliches, 1991) and internationally (Coe and Helpman, 1995). R&D spillovers also occur from the public sector (universities, government research centres). It is therefore important to analyse R&D beyond the business enterprise sector.

For statistical purposes, R&D is defined as creative work undertaken on a systematic basis to increase the stock of knowledge, and the use of this stock of knowledge for the purposes of discovering or developing new products, including improved versions or qualities of existing products, or discovering or developing new or more efficient processes of production (Eurostat 2013). This definition is derived from the Frascati Manual (OECD, 2015) and is applied in a very similar way in all countries across the world.

4.5.2 *Data Sources*

Data on R&D are collected in the EU based on the Commission Implementing Regulation (EU) 995/2012 concerning the production and development of Community statistics on science and technology. The regulation covers all sectors for the economy, including higher education and public sector research organisations (the latter is referred to as 'government sector' in R&D statistics), and the private non-profit sector. It also covers data on government budget appropriations and

outlays for R&D. The concepts and definitions related to R&D statistics are laid down in the Frascati Manual.

In most EU member states, R&D data is collected by National Statistical Offices. Data collection differs between the business enterprise sector and the higher education/government sector:

- R&D data in the business enterprise sector is collected through questionnaires based on a census approach, i.e. all enterprises that perform R&D (at a reasonable scale) are the target group of business R&D surveys. In some national surveys, sampling approaches are applied for the group of SMEs.
- R&D data for higher education institutions and public sector research organisations is usually collected by combining data from surveys and administrative data.
- R&D data on government budgets is collected from administrative data.

R&D data include the volume of expenditure and the number of total R&D personnel and the number of researchers which has to be reported on an annual base for all four sectors (business enterprise, higher education, government, private non-profit). Detailed breakdown has to be reported every second year only (for odd years). For expenditure data, breakdown has to be provided by source of funds, type of R&D, type of cost and region, as well as by economic activity, product field and size class for the business enterprise sector, and by field of science for the higher education and government sectors. For employment data, the breakdown includes sex, occupation, qualification, region, economic activity and size class (business enterprise sector), and field of science (higher education and government sectors).

R&D statistics for EU member states are published by Eurostat. Eurostat data also includes data for non-member states (Iceland, Norway, Switzerland, Montenegro, Serbia, Turkey, Bosnia and Herzegovina, Russia, United States, China, Japan, South Korea). On a global level, R&D data are published by the UNESCO for up to 158 countries, basically applying the same concepts, definition and variables as in the EU Regulation. However, the UNESCO data base provides less breakdowns. For example, no breakdown of business enterprise R&D data by economic activity or by size class is available. In addition, the OECD publishes R&D data for its member states as well as a group of other countries (Argentina, China, Romania, Russia, Singapore, South Africa, Taiwan). The OECD data include a sector and size class breakdown for the business enterprise sector.

R&D data can be used to establish a series of indicators for measuring competitiveness at different levels (firm, industry, economy). For most indicators, combination with other data sources, particularly from National Account Statistics, business enterprise statistics or labour statistics is required. Some commonly used indicators include:

- R&D expenditure as a percentage of GDP or value added (all levels);
- R&D personnel as a percentage of total employed persons (all levels);

- Change in R&D expenditure or the number of R&D personnel (all levels);
- R&D expenditure as a share in turnover (all levels);
- R&D specialisation: share of a sector's R&D expenditure/personnel in a country's total R&D expenditure/personnel (industry level);
- Industry-structure adjusted R&D intensity: sum of industry-level R&D intensity (R&D expenditure as a percentage of value added or R&D personnel as a percentage of total employed persons), multiplied with an industry weight that is uniform across all countries (e.g. the average value added share of an industry for the countries studied) (economy level)

Firm-level data on R&D is available from different sources. Access to micro data from enterprise R&D surveys varies by country. There is no uniform cross-country micro-level R&D data but access to R&D survey micro-data has to be obtained from the institution conducting the survey. However, the Community Innovation Survey (CIS) contains data on intramural and extramural R&D of firms and provides micro-level data through the safe centre of Eurostat (see section 4.6 for details on this data source). In addition, the EU Industrial R&D Investment Scoreboard provides micro-level data on R&D expenditure and some other financial data at the level of enterprise groups on an annual base. This data set is restricted to the largest R&D performers in Europe and globally, starting with a sample of 500 EU and 500 non-EU firms for the reference year 2003 and covering 1,000 EU and 1,910 non-EU firms for the reference year 2015.

4.5.3 Data Quality

R&D data have become a key data source in economic statistics over the past 20 years. As a consequence, efforts to provide high-quality R&D data have intensified in all member states, contributing to a high level of data quality today. One important momentum in this process was the decision of the European Council in 2002 at the Barcelona summit to use the share of R&D expenditure in GDP as a headline indicator for the Lisbon strategy, setting a 3% target for 2010. Another important development was the 2010 revision of European System of Accounts. After the revision, R&D is not treated as intermediate consumption anymore, but as investment in intangible assets. As a consequence, all R&D expenditure directly adds to GDP, making a reliable measurement of R&D essential.

Completeness

While efforts to provide complete data that comply with international standards have led to a very good R&D data base at the country level for the main sectors of performance (business enterprise, higher education, government, private non-profit), the situation is somewhat less good for the industry level in the business enterprise sector. Table 4-6 reports the share of missing data for the two main R&D variables. Data are complete at the country level for intramural R&D expenditure and R&D personnel in full-time equivalent. At the level of NACE sections (covering 18

different industries), 22 percent of all possible entries were missing for the year 2013. For even years, the share of missing data is higher since the EU Regulation requires member states to report a breakdown of R&D data by industry (and other variables) only for odd years. The share of missing data increases when looking at the division level of NACE (covering 48 different divisions for the purpose of R&D statistics). In 2013, 30% of all possible entries were missing. For 2014, the missing share increases to 45%. Incompleteness of data is very similar for R&D expenditure and R&D personnel data.

There are only a few countries providing non-missing R&D data for the full industry breakdown. At the section level for the year 2013, six countries provided complete data (CY, CZ, HR, MT, SI, UK). The country with the highest share of missing section-level data was LU (83% missings). At the division level, five countries provided complete R&D data in 2013 (the same as for the section level except UK). The country with the highest share of missing data in 2013 was SE (73% missings).

Table 4-6: Percentage of missing data for R&D indicators (business enterprise sector) at the industry and economy level: EU-28, 2009-2015

	Maximum no. of data cells per year	2009	2010	2011	2012	2013	2014	2015
a) Economy level								
R&D expenditure (in €)	28	0	0	0	0	0	0	4
R&D personnel (FTE)	28	4	4	0	0	0	0	4
b) Industry level (sections)^{a)}								
R&D expenditure (in €)	28x18	32	34	25	32	22	40	100
R&D personnel (FTE)	28x18	32	33	23	32	22	40	100
c) Industry level (divisions)^{b)}								
R&D expenditure (in €)	28x48	37	40	34	39	30	45	100
R&D personnel (FTE)	28x48	35	39	32	40	31	45	100

a) Sections D and E and sections S, T and U are reported jointly.

b) The following divisions are reported jointly: 10 and 11; 35 and 36; 37, 38 and 39; 87 and 88. No division-levels are available for the following sections: A, B, F, G, I, K, S, T, U. For section M, only division 72 is reported.

Source: Eurostat, R&D statistics

Timeliness

The EU Regulation defines that R&D data have to be submitted by member states 18 month after the end of the reference year latest, e.g. by end of June 2017 for data referring to the reference year 2015. In addition, preliminary results for total intramural R&D expenditure and total R&D personnel (as well as the total number of researchers) have to be provided within 10 months of the end of the reference year. The actual publication of the data by Eurostat usually takes place several months later owing to data quality checks and data processing. For example, data for 2015 have been released in November 2017. Timeliness is lower for industry-level data. By June 2017, 2014 was the most recent reference year available.

Representativeness

Since R&D data are based on a census of all R&D performing units, representativeness of R&D data is very high. However, the coverage of R&D activities in small enterprises and in sectors where only a small share of firms are conducting R&D may be incomplete. The effects of total R&D data both at the economy-wide and at the sector level of a potentially restricted coverage is very limited.

Reliability

Reliability of R&D data is generally viewed as being high. Nevertheless, caution is needed when interpreting R&D data, particularly at the sector level and for small countries. In some industries and countries, R&D is highly concentrated on a few firms. If these firms change their R&D behaviour for any reason, R&D indicators will change accordingly. Also shifts in the location of R&D resources within a dominant firm may cause significant changes in R&D data without actually indicating a substantial change in competitiveness.

Revision history

R&D data are based on a well-established data collection methodology based on internationally agreed concepts and definitions (Frascati Manual) that are applied by almost all countries when producing R&D statistics. Though the Frascati Manual has been revised several times in the past decades (in 2015, the 6th edition has been published), the basic concepts and definitions did not change substantially, allowing comparability of data over time.

4.5.4 Data Validity

A main challenge to the validity of R&D as a competitiveness indicator relates to the varying significance of R&D as source for new knowledge production, both in terms of the significance of intramural R&D for innovation, technological advance and productivity increases within a firm, and with respect to the role of R&D-based knowledge spillovers from others, including R&D performed in the higher education and government sectors. One dimension of variation in the significance of R&D is industry. In some industries, own R&D and the absorption of external R&D from public research is the single most important source for innovation. These industries are often called science-based industries (Pavitt 1984) or high-tech industries. For these industries, R&D is an excellent indicator for the efforts put into an innovation-based or technology-based improvement of competitiveness. In other industries, R&D is only one of many key factors. There are also industries where R&D does not play any significant role but innovation and productivity advance is based on organisational change, employee skills and learning, or the adoption of existing technology.

Another dimension of variation is countries. Depending on the state of technological development and scientific advance, firms may follow different paths to innovation.

If the R&D base in a country is less developed, non-R&D-based ways to innovation are more effective, e.g. the adoption of existing technology from abroad. For these countries, R&D will be a less relevant indicator of competitive potential.

In addition, the nature of R&D varies substantially across industries, resulting in different levels of R&D expenditure and employment of R&D personnel for achieving the same impact on innovative output (e.g. for developing a new prototype with a certain sales potential). This variation also applies to different industries within the group of science-based or high-tech industries. In pharmaceuticals, for example, R&D costs per unit of innovative output tends to be very high owing to high costs for clinical testing and a high probability of failure even at later stages of the development process. In other high-tech industries such as mechanical engineering or instruments, R&D costs per unit of innovative output tend to be significantly lower. These differences have two implications for competitiveness studies. First, comparing R&D indicators between different industries is of limited relevance. Secondly, differences in specific R&D costs call for differences in the appropriation conditions for R&D results. Industries with high specific costs will require a longer period for selling innovative goods, which for example has impacts on the length of patent protection. They will also need higher mark-ups on innovative products in order to refinance high R&D costs.

Another limitation of business enterprises sector R&D data for competitiveness studies concerns the fact that data are allocated to countries based on the location of the R&D activity. While this procedure is essential for producing R&D statistics that are consistent with other business enterprises statistics and National Account Statistics, it ignores the situation that the results of the R&D performed at different locations of a multinational enterprise is often under the control of the headquarters and can be used to enhance competitiveness not only at the firm's location where R&D results have been generated, but also at other locations. It may even be the case that all R&D results generated at one location are transferred to firm locations outside the country where the R&D took place. In that case, data on R&D activities by location can be misleading for competitiveness analysis or have to be used with caution at least. If one wants to analyse the amount of R&D activity that enterprise headquarters control by country, data from the EU Industrial R&D Investment Scoreboard can be used. The definition of R&D in this database may deviate from the R&D definition used in R&D statistics, however.

R&D data in R&D statistics refer to intramural R&D activities. At the country level, this procedure avoids double-counting of both in-house and external R&D expenditure of R&D performing units if external R&D is purchased from other units in the same countries.⁶⁹ At the country level, this procedure may underestimate the total amount of money invested into R&D if a significant fraction of external R&D is performed outside the country. At the industry level, this procedure can result in an even larger

⁶⁹ And if these units do report contracted R&D as in-house R&D. This is not necessarily the case if contracted out R&D services (e.g. conducting clinical tests in the process of developing new drugs) constitute a standard service for the performing unit and is hence not reported as R&D.

underestimate of the amount of R&D spent if extramural R&D expenditure is conducted mainly in other industries and the considered industry does not perform much contract R&D for other industries.

4.5.5 Data Analysis

The perhaps most commonly used R&D indicator in competitiveness analysis is the share of R&D expenditure in GDP. It measures the share of an economy's resources that is devoted to generating new knowledge. The indicator has been used by the EU and the European Council as a key indicator for monitoring the progress the EU and its member states made towards becoming a more innovative and competitive economy. A breakdown by main sector of performance shows which sections of the economy (businesses, universities, government research organisations, private non-profit organisations) contribute to a country's R&D intensity.

The most recent data for 2015 show that Sweden, Austria, Denmark, Finland and Germany have the highest R&D intensity, coming close or beyond the 3% goal of the EU Commission (Figure 4-12). In all five countries, the business enterprise sector makes the highest contribution to total R&D intensity. The higher education sector is the second most important R&D performing sector in all five countries while the government sector has a somewhat higher share only in Germany.

For competitiveness analysis, a breakdown by performing sector is relevant because it shows to what extent businesses invest into R&D and to what extent a country's R&D intensity is mainly driven by universities and government research organisations. The latter is the case for a number of member states, including Latvia, Lithuania, Slovakia, Greece, Cyprus, Romania, Poland, Portugal, Estonia and Malta.

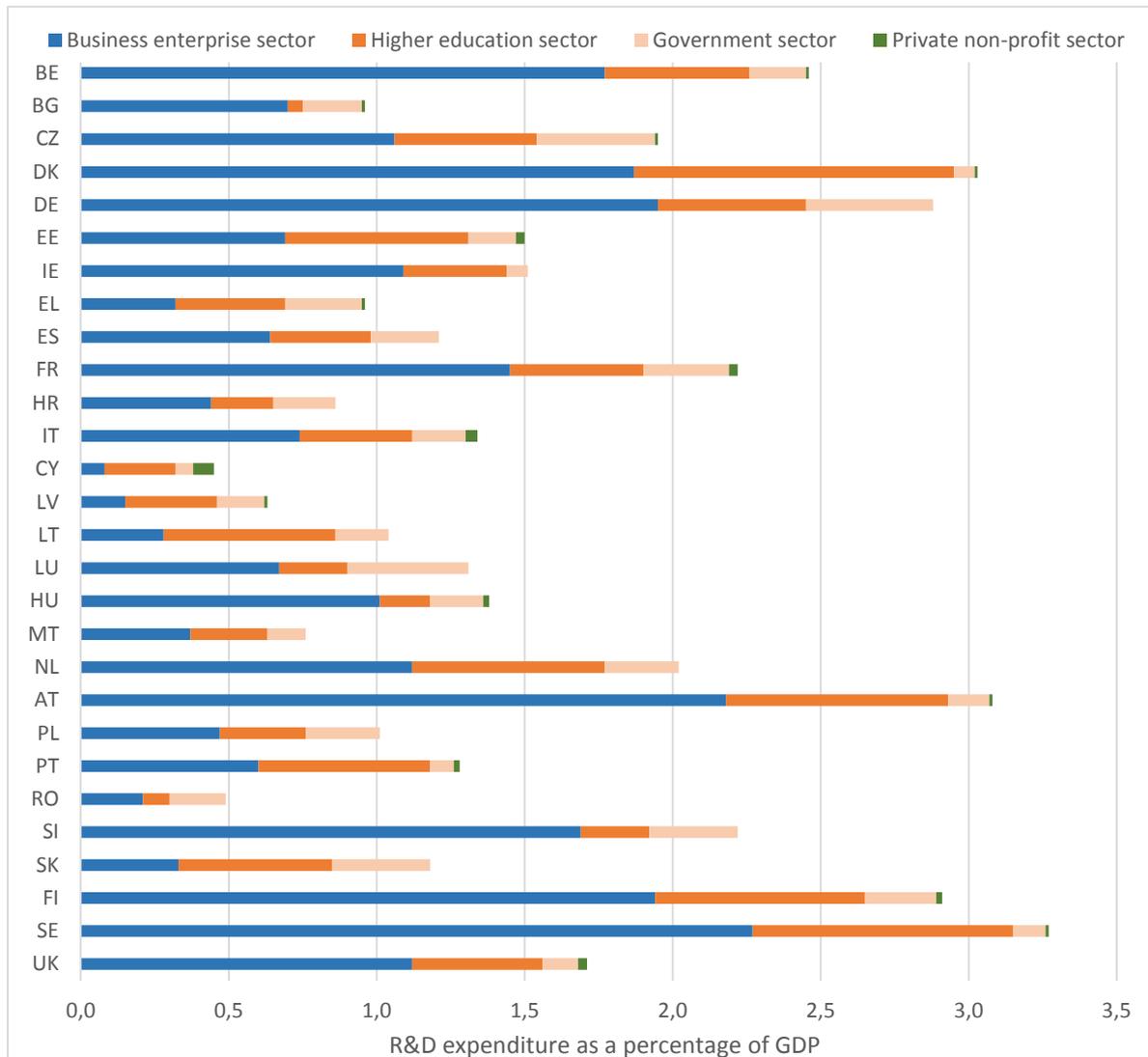
For more detailed competitiveness analysis at the industry level, R&D intensity can be measured by different indicators which can produce different findings. As an equivalent to an economy's total R&D intensity, R&D expenditure of sectors can be related to a sector's value added. Alternatively, R&D expenditure can be related to turnover or total production value. This indicator shows the share of direct own R&D input in the total value of products produced by a sector, though it does neither consider the R&D that is contained in intermediary products and in purchased capital goods used in production nor the externally acquired R&D (extramural R&D expenditure). A third indicator relates the number of R&D personnel to total employment.

When calculating all three indicators for the business enterprise sector in the EU 28 member states, one finds very similar results for R&D intensity based on expenditure per value added⁷⁰ and for expenditure per total production value (Figure 4-13). Naturally, value added based R&D intensities are always higher. The rank of

⁷⁰ Value added is measured by gross value added based on national account statistics in order to be consistent with the value added measure employed for industry level analysis below. As gross value added is smaller than GDP, the values for business enterprise sector R&D intensity deviate from those shown in Figure 1.6-1 based on GDP.

countries stays the same for 8 member states and changes by only one to two ranks for 16 member states.

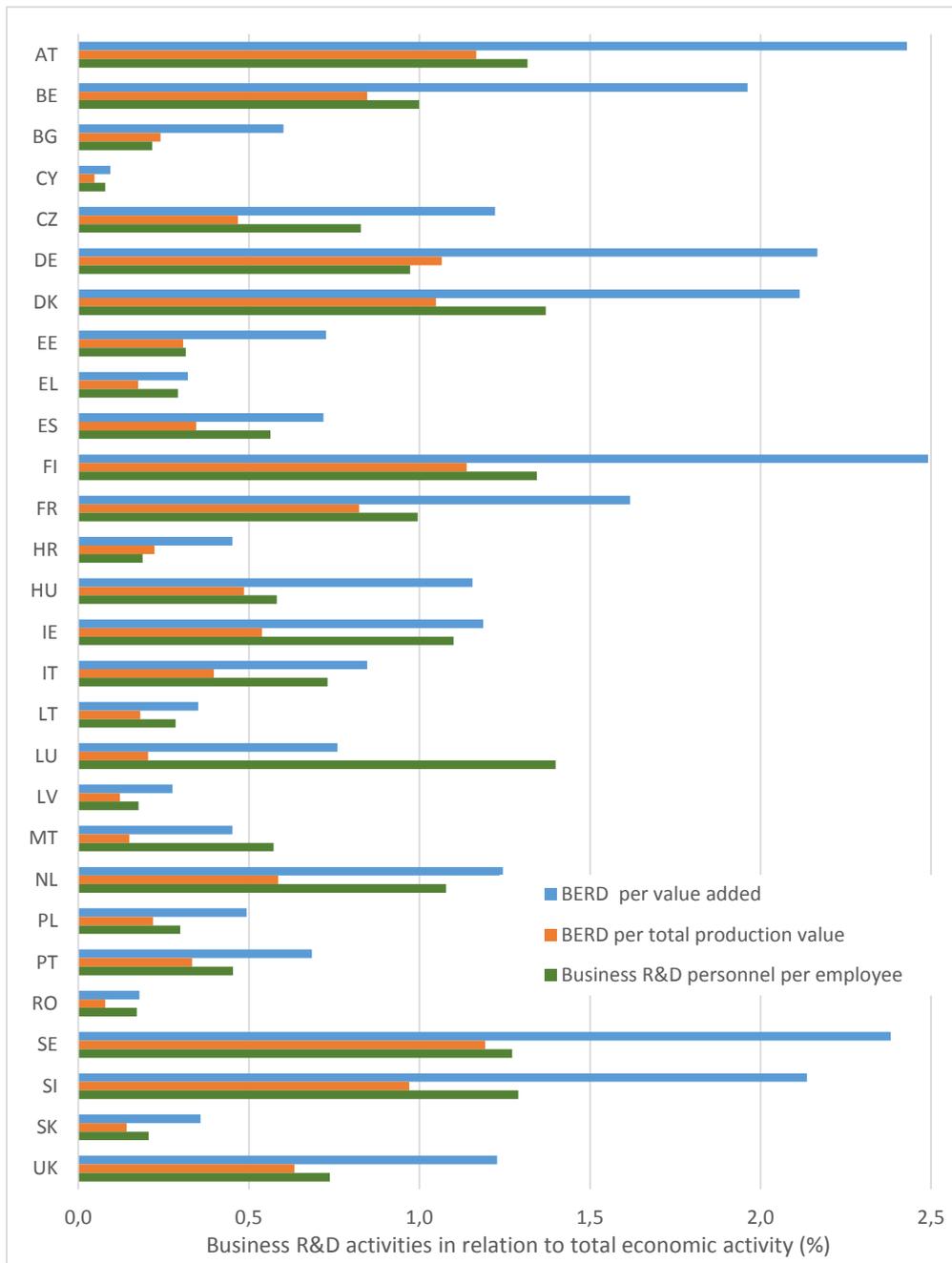
Figure 4-12: Total R&D intensity in EU member state (2015) by main sector of performance



IE: 2014.

Source: Eurostat, R&D Statistics (last data update: November 2016).

Figure 4-13: Different measures of business R&D intensity in EU member state (2014)



BERD: Business enterprise sector Expenditure on R&D
 Source: Eurostat, R&D Statistics

The only country for which significantly different findings are obtained is Luxembourg. Based on business R&D expenditure per value added, Luxembourg shows the 15th highest value among EU 28, while for R&D expenditure total production value the country only ranks 21. The reason for this difference is that Luxembourg hosts a number of industries with a high share of intermediate inputs (trade, financial services).

More deviating results are found when R&D intensity based on personnel is used. For this indicator, Luxembourg ranks second behind Denmark. In both countries, the business enterprise sector appears to be more R&D intensive based on personnel, indicating that the average productivity of R&D personnel is lower than for total employment. A similar situation is found in Malta. Countries that rank worse when looking at employment-based R&D intensity include Germany, Belgium, Croatia and Bulgaria. The choice of indicator is hence important.

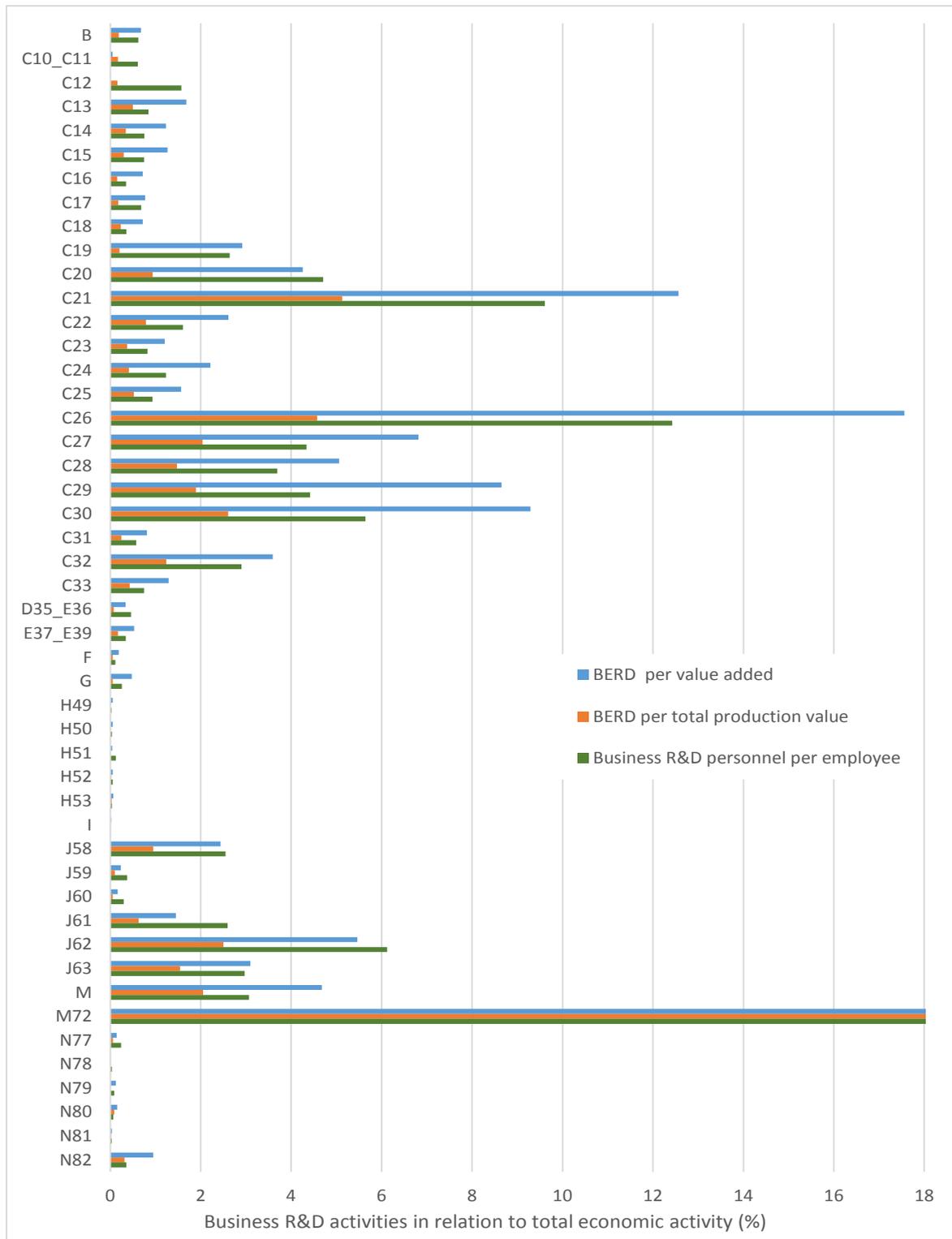
This is even more so at the industry level. Relating R&D expenditure to total production instead of value added gives relatively higher R&D intensities for some services (e.g. IT services) and some manufacturing industries (e.g. pharmaceuticals, food, beverages and tobacco) while it relatively worsens the results e.g. for manufacturing of chemicals, machinery and motor vehicles (Figure 4-14).

When using employment-based R&D intensities, the chemical industry shows a higher R&D intensity than other medium to high-tech manufacturing industries (machinery, automotive, electrical equipment) whereas it ranks clearly behind these industries based on R&D per total production value.

In the previous section, the role of extramural R&D as a potential source for limited data validity has been stressed. Data from the Community Innovation Survey (CIS) allows to calculate R&D intensities (based on an industry's total turnover) including and excluding extramural R&D expenditure (see 4.6 for more details on the CIS). The results show that there is indeed a large variation in the relation between extramural and in-house R&D (Figure 4-15). In some service sectors, extramural R&D exceeds intramural (E39, H52) or is equal to intramural (G45, N81).⁷¹ There are also a number of knowledge-intensive services with extramural R&D expenditure being 50% or more than intramural R&D (e.g. J60, J61, K66).

⁷¹ All data refer to unweighted averages of member state values for each industry.

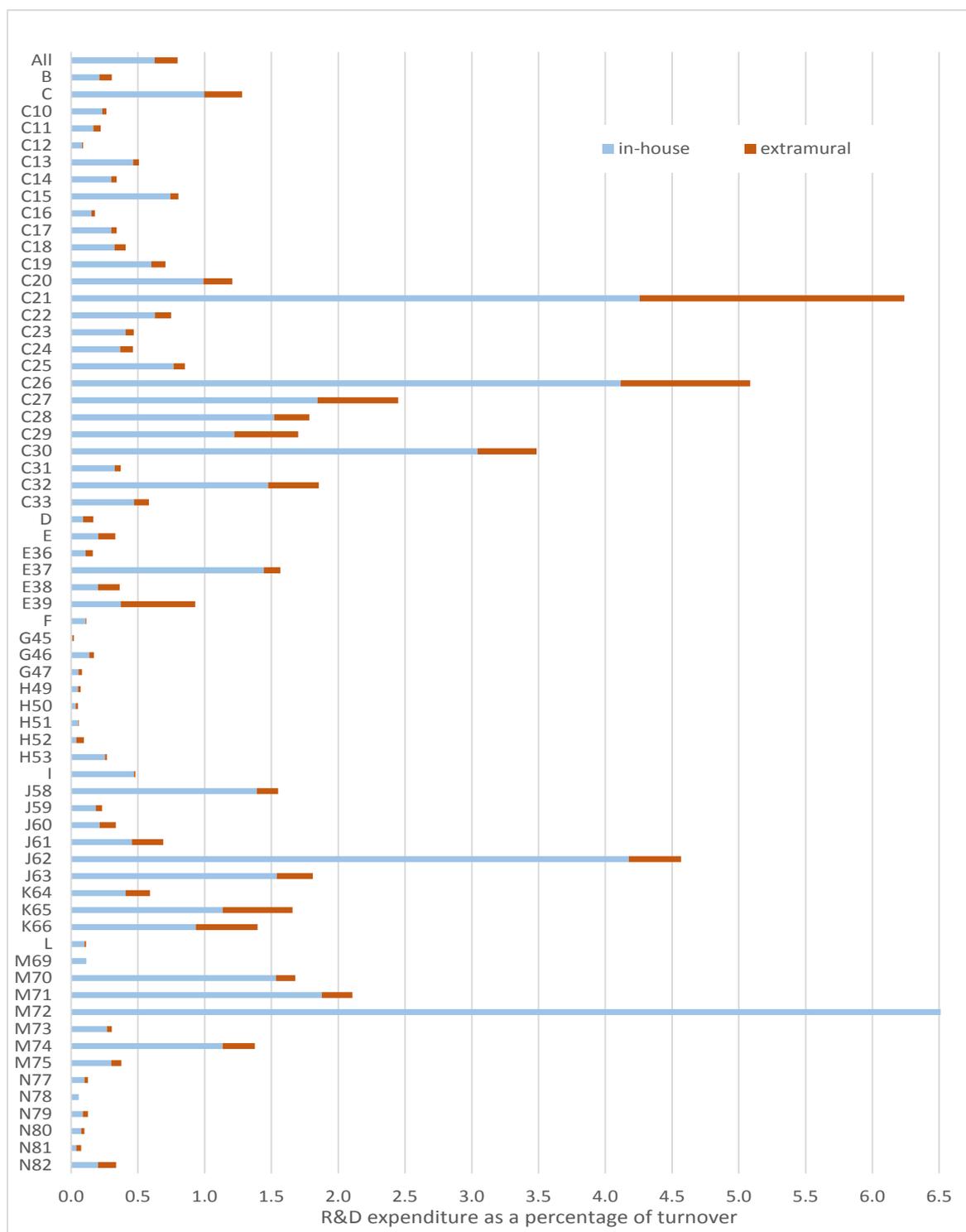
Figure 4-14: Different measures of business R&D intensity in EU member state by industry (2014 or latest year available)



Note: values for M72 are 78.4% (BERD per value added), 38.8% (BERD per total production value) and 42.5 (Business R&D personnel per employee).

Source: Eurostat, R&D Statistics

Figure 4-15: R&D intensity of industries excluding and including extramural R&D expenditure (EU 28, 2014 or latest year available)



Note: data are unweighted averages of the values for EU member states. Number of missing countries varies by industry.

Values for M72 are: 36.9% for in-house R&D expenditure and 5.7% for extramural R&D expenditure.

All data refer to enterprises with 10 or more employees.

Source: Eurostat, R&D Statistics

In manufacturing, pharmaceuticals (C21) show the highest importance of extramural R&D (47% of intermural R&D expenditure), followed by automotive (39%). Low shares of extramural R&D expenditure are found, among others, for IT services and engineering services.

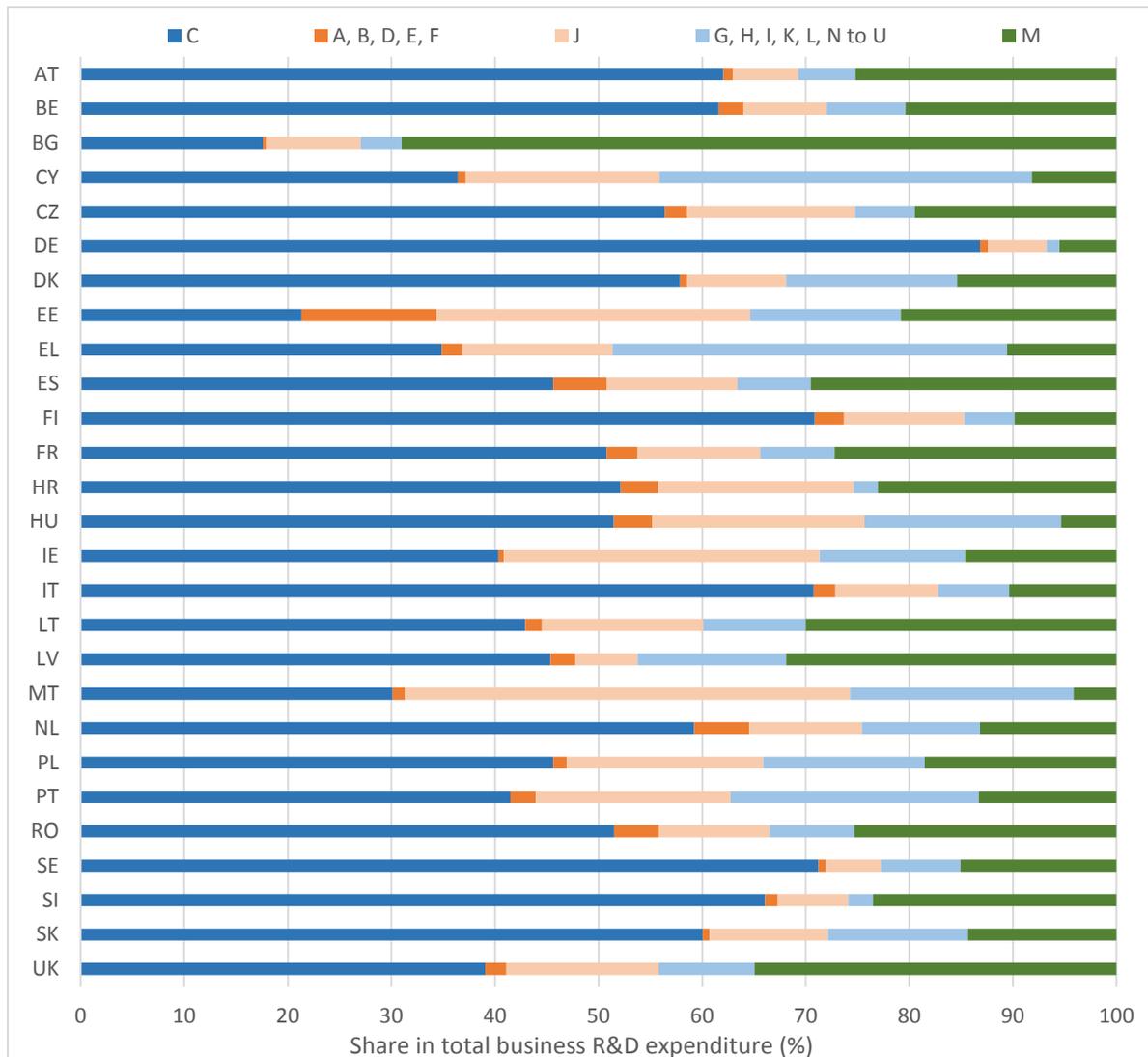
Including extramural R&D expenditure would not change the ranking of industries in terms of their R&D intensity substantially, however. Pharmaceuticals would show a significantly higher R&D intensity compared to electronics (C26) whereas based on intramural R&D expenditure the two sectors report similar intensities.

When using R&D indicators in competitiveness analysis one should take into account the large variation in the distribution of business R&D expenditure across industries. In some countries, the vast majority of business R&D activities take place in manufacturing and are hence much more directly related to international competitiveness as compared to R&D in service industries with little international trade. Member states with a very high manufacturing share in total business R&D expenditure include Germany (87%), Sweden, Finland and Italy (71% each) and Slovenia (66%) (see Figure 4-16). IT services account for a higher share in total business R&D in Malta (43%), Ireland and Estonia (30% each). Other services, including R&D services, have a high share in total business R&D activities in Bulgaria (73%), Greece (49%), Latvia (46%), and the UK and Cyprus (44% each).

Within manufacturing, the share of R&D expenditure in high-tech and medium to high-tech industries (which are roughly represented by NACE C20, C21 and C26 to C30; i.e. manufacture of chemicals, pharmaceuticals, electronics, electrical equipment, machinery, motor vehicles and other vehicles, incl. aircrafts) is particularly relevant for competitiveness analysis since in these industries, R&D is a major determinant of international competitiveness as competition in these industries is largely based on quality features of products and their innovativeness. Countries with a high share of high-tech and medium to high-tech industries in total manufacturing R&D expenditure include Germany and Croatia (90% each), Finland and Denmark (88% each), Austria and Romania (84% each), and Malta, Hungary, the UK, Slovenia, Cyprus and France (80 to 82%) (see Figure 4-17).⁷² Only a few member states report a majority of manufacturing R&D expenditure outside these industries, including Estonia, Portugal and Ireland.

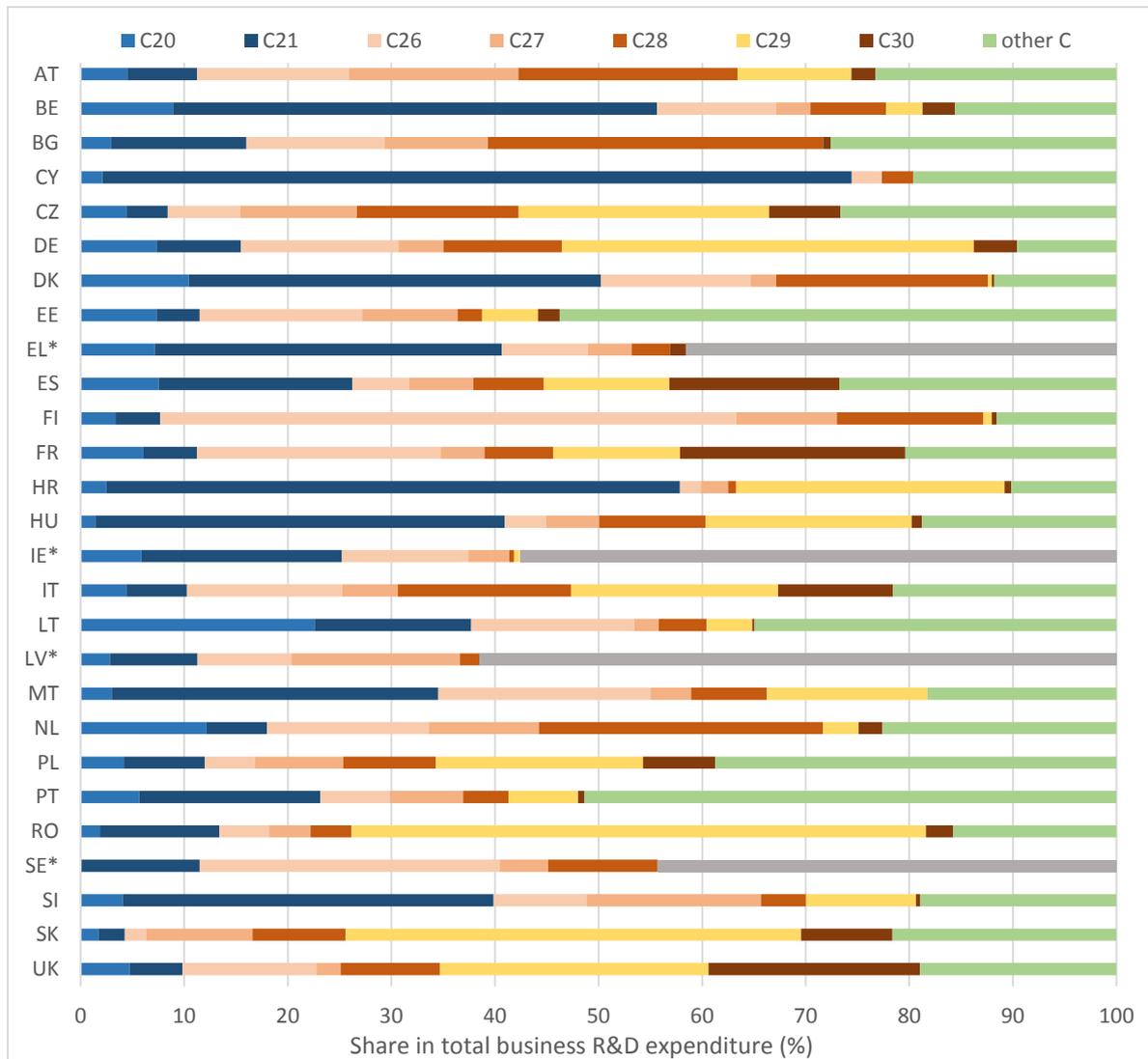
⁷² No data for Sweden.

Figure 4-16: Distribution of business R&D expenditure in EU member state by main industry groupings (2014 or latest year available)



Source: Eurostat, R&D Statistics

Figure 4-17: Distribution of manufacturing R&D expenditure in EU member state by high-tech and medium to high-tech industries (2014 or latest year available)



* "other C" includes C29 in EL; C30 in IE; C29 and C30 in LV; and C20, C29 and C30 in SE.
Source: Eurostat, R&D Statistics

4.6 Innovating Firms

Christian Rammer

4.6.1 Concepts and Definitions

The number of innovating firms and their share in the total firm population are a frequently used indicator to capture the ability and readiness of the business enterprise sector to improve competitiveness through an innovation-based business strategy. Following international standards laid down in the Oslo Manual (OECD and Eurostat, 2005), innovation is defined as the implementation of a new or significantly improved product, process, organisational method or marketing method. Implementation includes the introduction of a product to the market (i.e. making it available to potential buyers) and the use of processes or methods within the firm.

The higher the number and share of firms that engage in innovation, the more widespread and the faster new products, processes and methods will be used in an economy. Since innovations by definition represent a higher level of utility or efficiency compared to existing offerings and techniques, innovations can contribute to a competitive advantage. Whether the competitive advantage of an innovation can actually be transferred into better market performance of the innovating firm will depend on the success of the innovation. For product innovation this relates to the sales volume and the profit margin which will depend on the price-performance ratio. While performance characteristics of innovations are usually superior to non-innovative products, the price will usually be higher too, representing higher development and production costs of innovations. For innovations relating to processes and methods, the higher performance of the innovations may also be offset by higher implementation and operating costs. If innovations remain unsuccessful, a higher share of innovating firms does not imply higher revealed competitiveness in the market.

Interpreting the share of innovating firms as a competitiveness indicator is further complicated by the two faces of innovation. On the one hand, innovation denotes a novel way of doing business by the innovator—in terms of products offered or processes and methods applied—that has not been followed by anyone else before. These innovations are often called “new to the market” since the innovator is the first one to use the innovation in the innovator's market. Such innovations are usually associated with a high potential for positive impacts on competitiveness owing to the superior characteristics of the innovation. On the other hand, innovation also includes the diffusion of new products, processes and methods among firms in the same market. If other firms copy or adopt an original innovation, the copying/adopting firm will improve its own products, processes or methods. By doing so, it can improve its own competitiveness at the expense of the competitiveness of the original innovator and of firms that copied/adopted the innovation earlier to which it catches up. In open markets, a high share of innovating firms in one country may not imply a higher competitiveness than a low share of innovating firms in another country if the market position of the firms in the former

country is challenged by a rapid diffusion of their innovations in other countries and an increased competition by these suppliers from abroad.⁷³

4.6.2 Data Sources

The usual approach for collecting innovation data for official innovation statistics is to run dedicated surveys and ask firms, amongst others, whether they did introduce innovations in a given period of time, and how successful these innovations were. In the EU, the survey instrument for this purpose is called the Community Innovation Survey (CIS) which is conducted in all member states biennially. Similar surveys are conducted in many other countries across the world, including most other European countries as well as Japan, South Korea, China, Canada and Australia, but excluding the US.⁷⁴ Since 2005, innovation statistics in the EU is subject to an EU Regulation (currently regulated by the same Regulation as R&D statistics, Commission Implementing Regulation (EU) 995/2012). The Regulation defines variables and breakdowns to be reported by member states, but not the details of the survey instrument as such.

Innovation statistics include a large variety of variables on inputs, outputs and the organisation of innovation activities in firms. With respect to data on innovating firms, the following variables are of particular relevance:

- Number of firms that have introduced a product innovation
- Number of firms that have introduced a process innovation
- Number of firms that have introduced an organisational innovation
- Number of firms that have introduced a marketing innovation

The data refer to innovations introduced in a three year reference period, including the two years prior to the reference year of the survey, and the survey's reference year. For each of the four types of innovation, data can further be differentiated by the area of innovation (product innovation: goods, services; process innovation: production, logistics, supporting activities; organizational innovation: business practices, work organization, external relations; marketing innovation: design/packaging, product promotion, product placement, pricing). Innovation statistics offer several aggregations of the four types of innovation:

- firms with both product and process innovation;
- firms with either product or process innovation;

⁷³ An example for this situation is the solar technology industry in Europe. While the share of innovating firms in this industry is most probably very high, their competitiveness is rather low as their innovations have been rapidly adopted by firms in Asia. These firms now serve the European markets, causing market shares of European firms to fall, as well as prices for solar technology.

⁷⁴ In the US, a „Business Research and Development and Innovation“ survey is conducted that contains questions on product and process innovation. These questions are presented only to a small fraction of the firms in the sample, however, namely firms with at least 1m US-\$ R&D expenditure in the previous year.

- firms with product innovation;
- firms with process innovation;
- firms with marketing innovation;
- firms with organisational innovation;
- firms with either organisational or marketing innovation;
- firms with both organisational and marketing innovation;
- firms with either product or process innovation activity⁷⁵, but no organisational or marketing innovation;
- firms with either organisational or marketing innovation;
- firms with either organisational or marketing innovation, but no product or process innovation activity;
- firms with either product, process, organisational or marketing innovation (only for 2014).

Product and process innovations are sometimes referred to as 'technological innovations' (and organisational and marketing innovations to 'non-technological innovations') because historically, the Oslo Manual labelled these two types as 'technological product and process innovation', and the definition of the two types implicitly makes some reference to the use of technology (e.g. new features with respect to components or sub-system, production process). Nowadays, this terminology is not used anymore.

The most useful indicators for in the context of competitiveness studies are probably the following three indicators on innovating firms:

- Share of firms with product innovation ('product innovators')
- Share of firms with either product or process innovation ('product/process innovators')
- Share of firms with either product, process, organisational or marketing innovation, including firms with ongoing/abandoned product/process innovation activities ('innovating firms')⁷⁶

For product innovators, and additional indicator that is widely used (e.g. in the European Innovation Scoreboard) is the share of sales generated from product innovation. This share is often further differentiated by novelty characteristics of product innovation into

- Share of sales from new-to-the-market product innovations

⁷⁵ These category includes firms with ongoing or abandoned product or process innovation activity that did not introduce a product or process innovation.

⁷⁶ Data on innovating firms excluding firms with ongoing/abandoned product/process innovation activities is available only for 2014. Data including firms with ongoing/abandoned product/process innovation activities is available for all years from 2008 onwards.

- Share of sales from product innovations that were only new to the innovating firm

This indicator often produces quite different results as compared to the share of firms with product innovation since the latter is strongly driven by small firms (since they constitute the majority of firms) while the sales share is strongly driven by larger firms (since they represent a large proportion of total sales). There are no similar indicators for the other three types of innovations.

CIS data do not cover the entire business enterprise sector but are confined to certain size classes and industries:

- CIS data only includes firms with 10+ employees
- CIS data covers NACE sections B to E (mining, manufacturing, utilities), H (transport), J (information and communication) and K (financial services) as well as divisions 46 (wholesale) and 71 to 73 (engineering, R&D, advertising).⁷⁷

Some countries do provide data for other industries, including sections A (agriculture, forestry, fishing), F (construction), G (retail, car repair), I (restaurants, accommodation), L (real estate), M (legal, accounting, consultancy, other professional, scientific and technical, and veterinary activities) and N (administrative and support services).

Results from the CIS are also available at the firm level. Eurostat provides both anonymised data and original data (the latter can only be accessed through the safe centre of Eurostat). Micro data are currently available for the surveys (reference years) 2000, 2004, 2006, 2008, 2010 and 2012. For the most recent year 2012, 20 EU member states provided original micro data for the safe centre and 13 member states provided anonymised data which are distributed through CD-Rom. New micro data release normally takes place two and half years after the end of the reference period (i.e. in mid-2017 for the 2014 survey).

4.6.3 Data Quality

Innovation data are usually based on weighted results of sample surveys. Only a few countries collect innovation data based on a census. Participation of enterprises in innovation surveys is mandatory in some EU member states and voluntary in others. Sample size, drawing quotas and response rates vary widely across member states. While Eurostat provides member states with a harmonised questionnaire for each round of CIS, national questionnaires in several countries deviate from the harmonised questionnaire, e.g. by adding or omitting questions, changing the order of questions, altering explanatory notes or changing design features of the questionnaire.⁷⁸ In addition, some member states conduct innovation surveys as online surveys only while others only use paper version or both. The design of online surveys also varies, e.g. with respect to filtering, forcing answers or applying

⁷⁷ Divisions 59 (motion picture), 60 (broadcasting) and 73 (advertising) have been included to the core industries of CIS in 2010.

⁷⁸ See national CIS quality reports.

consistency checks while a questionnaire is filled in. A further issue for data quality is translation. Innovation surveys apply a variety of concepts and definitions that are not harmonised internationally in the business world and require careful translation in national languages in order to be properly understood by respondents. All these factors add to some concerns about comparability and reliability of innovation data.

In addition, there is no harmonised concept of innovation that would be consistently used in the business world on an international level. In contrast to R&D, innovation is not a standard concept in accounting or taxation, nor is it a clearly defined and reported business function. Firms hence face significant difficulties in providing the data that is being collected through innovation surveys.

Completeness

Innovation data as provided by Eurostat for EU member states is almost complete at the country level as long as the sum of the core industries covered by EU innovation statistics is concerned. Out of the five indicators suggested in section 4.6.2, there were data for all 28 member states for three indicators in 2014 (innovating firms, new-to-market sales, only new-to-firm sales) whereas data for one country was missing for the indicators "product/process innovator" and "product innovators" (Table 4-7: Percentage of missing data for innovation indicators at the industry and economy level: EU-28, 2008-2014). Only few countries provided data for the entire economy (sections A to N). At the NACE section level (for the core industries), the share of missing data is about 20%, with a rather low share of missing data for the indicator "innovating firms" (15% in 2014) and higher for "product/process innovators" (22% in 2014). Over time, the share of missing data went slightly down for "product/process innovators" and "product innovators" between 2008 and 2014 while it slightly went up for the indicators on sales from product innovation. There is no clear trend for the indicator "innovating firms".

At the division level, the share of missing innovation data is very high even when only the core industries are analysed. In 2014, for 42% of all possible combinations of NACE divisions and member states, no data on "innovating firms" were available. For product innovators, the share of missing data was 41%. Slightly smaller shares of missing data is reported for the sales from product innovation while the share of firms with product/process innovation shows the highest figure of missing data (46%). The share of missing division level data is lower, however, if information from different years is combined. Combining 2008, 2010, 2012 and 2014 data results in a share of missing data for "innovating firms" at the division level of 20%. If one excludes the divisions of NACE section B (mining) which show missing data for most member states, the share of missing data falls to 15%. For the sales share indicators, the missing share excluding divisions of section B is only 12%.

Table 4-7: Percentage of missing data for innovation indicators at the industry and economy level: EU-28, 2008-2014

	Maximum no. of data cells per year		2008		2010		2012		2014	
	Core ^{a)}	All ^{b)}	Core	All	Core	All	Core	All	Core	All
	a) Economy level^{c)}									
Product/process innovators	28	28	7	89	4	93	4	93	4	89
Product innovators	28	28	7	89	4	93	4	93	4	89
Innovating firms	28	28	7	89	4	93	0	93	0	93
Sales share new-to-market	28	28	4	93	4	93	4	93	0	93
Sales share only new-to-firm	28	28	4	93	4	93	4	93	0	93
b) Industry level (sections)^{d)}										
Product/process innovators	7x28	14x28	26	46	25	46	22	46	22	45
Product innovators	7x28	14x28	25	45	22	45	21	46	19	44
Innovating firms	7x28	14x28	15	39	19	43	13	42	15	41
Sales share new-to-market	7x28	14x28	18	41	20	43	21	46	20	44
Sales share only new-to-firm	7x28	14x28	15	39	17	42	17	43	19	44
c) Industry level (divisions)^{e)}										
Product/process innovators	52x28	68x28	48	56	42	52	42	53	46	56
Product innovators	52x28	68x28	46	54	39	50	38	50	41	52
Innovating firms	52x28	68x28	42	51	38	49	38	50	42	52
Sales share new-to-market	52x28	68x28	38	48	37	48	39	51	38	50
Sales share only new-to-firm	52x28	68x28	36	47	37	48	38	50	37	49

a): NACE divisions 5-39, 46, 49-53, 58-66, 71-73. b): NACE sections A to N. c) for CIS core industries.

d) Sections B, C,D,E, H, J, K for Core, all sections A to N for All. e) No division level foreseen for sections F and I.

Source: Eurostat, innovation statistics

Timeliness

The EU Regulation defines that innovation data have to be submitted by member states 18 month after the end of the reference year latest, e.g. by end of June 2016 for data referring to the reference year 2014. The actual publication of the data by Eurostat usually takes place several months later owing to data quality checks and data processing. For example, data for 2014 have been released in January 2017. Timeliness does not vary by the level of industry disaggregation since innovation data are currently published at once for all breakdowns.

Innovation data are produced only for every second reference year. The next data publication is expected for autumn 2018 for the reference year 2016.

Representativeness

Innovation data do not cover the entire business enterprise sector but are restricted both in terms of enterprise size and industry coverage. Enterprises with less than 10 employees are not included in innovation statistics. Industry coverage is restricted to a core set of industries (NACE rev. 2 sections B to E, H, J and K, and divisions 46 and 71 to 73) though some countries report data for additional industries.

Innovation surveys to collect innovation data are based on random sampling techniques. Some countries use stratified sampling with disproportional drawing probabilities to consider differences in the variance of key target variables (share of

innovating firms, innovation expenditure) across strata. All in all, sampling methods guarantee a representativeness of samples.

A more serious source for limited representativeness are low response rates and a potential bias between responding and non-responding firms with respect to innovation. In some EU member states response rates are close to 100% owing to the mandatory character of the survey. In other member states, response rates are below 50%. Eurostat recommends conducting a non-response survey if the response rate is below 70%. The non-response survey should target at least 10% of the non-responding firms and collect information on the introduction of innovations (particularly product or process innovation) and whether a firm performs R&D, preferably through telephone interviews. The results of the non-response survey should be used to re-calculate weights in case there is a significant difference in the innovation/R&D behaviour of non-responding firms compared to the responding ones. Results of non-response surveys may have a significant impact on innovation statistics. At the same time there are some doubts about the comparability of responses obtained from telephone interviews and from paper or online questionnaires (see Hoskens et al., 2016).

Reliability

Reliability of innovation data is generally viewed as being not very high. There are basically two major concerns:

- The way innovation is defined and measured is subject to assessments by firms (i.e. the respondents in firms that answer a questionnaire), which are subjective in nature. The definition of an innovation – the implementation of a new or significantly improved product or process, a new marketing method, or a new organisational method – requires respondents to identify such innovations in their organisation, depending on their assessment of novelty and significant improvement. There may be both intra-organisational subjectivity (i.e. one respondent would regard something as an innovation which would not be regarded as innovation by another respondent from the same enterprise) and inter-organisational subjectivity (i.e. the same change would be regarded as an innovation in one enterprise, but not in another). One factor that may contribute to subjectivity is the innovative attempt of a firm. Firms with a distinct innovation strategy and aiming at a high level of novelty of their innovative activities will often apply a higher threshold for considering a certain change an innovation compared to firms for which innovation is of a low priority in their competitive strategy. Another factor is the respondent's position in the organization. Respondents who are directly engaged in innovation activities may have a different view on what constitutes an innovation compared to respondents working in other business functions (e.g. accounting, human resource management).
- The use of mandatory and voluntary surveys in different countries may add to limited reliability. If firms are forced to respond to a survey this may have an

impact on the response behaviour. This may be particularly the case for innovation surveys such as the CIS as these surveys apply filtering, resulting in different response burdens depending on the responses given. For the CIS, the main filtering applies to product or process innovation activity (including the introduction of product or process innovation). Firms stating not to have such activities do not have to respond to a large set of questions. This questionnaire design provides some incentives to firms for reporting no innovation activity since this significantly reduces the effort of completing the survey. This may be particularly relevant when firms are obliged by law to complete the questionnaire. Given the subjective nature of innovation, there is certainly room for opportunistic behaviour.

In addition, innovation statistics are produced by weighting data from sample surveys. Sample surveys are usually subject to sampling errors. There is no information available on the likely size of this error.

Revision history

The definition of innovation in the business enterprise sector has been changed in 2005 in the context of the second revision of the Oslo Manual.⁷⁹ Two types of innovations had been added (organisational innovation, marketing innovation) which previously were not regarded as business enterprise innovation. The consequences for innovation statistics was very limited, however, since innovation surveys still separate between the two types of innovations used for the definition of innovation prior to 2005 (product and process innovation) and the two new types introduced in the 2005 revision. In addition, a series of innovation variables (including innovation expenditure, innovation co-operation, public funding of innovation) are collected only with reference to product or process innovation.

At the time of writing this report, a third revision of the Oslo Manual was under way. A new edition of the Oslo Manual is expected to be published in 2018, potentially contained changes to the definition and measurement of innovation in the business enterprise that would constitute a more significant change for innovation statistics than the previous revision in 2005.

4.6.4 Data Validity

With respect to data validity, there are several issues that somewhat limit the adequacy of innovation indicators for measuring the underlying conceptual considerations, i.e. the ability and readiness of the business enterprise sector to improve competitiveness through an innovation-based business strategy. First, the share of innovating firms is by and large driven by small firms. Out of all innovating firms (product, process, marketing or organisational innovation) in the core industries of the CIS, 72 percent (2014) had between 10 and 49 employees, 22 percent

⁷⁹ The first revision in 1997 only adapted the Manual to refer also to the service sector.

between 50 and 249 employees and 6 percent 250 or more employees.⁸⁰ These shares correspond to the share of these size classes in total firm population (within the core industries of the CIS). In the EU28 in 2014, 79 percent of firms (with 10 or more employees) in the core industries of the CIS had 10 to 49 employees whereas only 4 percent had 250 or more employees. At the same time, the share of small firms (10 to 49) in total turnover was only 19 percent, compared to 56 percent for large firms.

The indicator on innovating firms hence mainly represents the innovation strategies of firms that have limited impact on the economy's total activities. While the strategies of small firms are important for the diffusion of innovations, their role for the competitiveness of an entire economy may be limited. This is particularly true if one takes into account that a large fraction of small innovating firms operate in industries where innovation plays a minor role for competitiveness. In addition, innovation in small firms often takes place at a small scale, frequently involving a single innovation project (see Crass et al., 2016) with limited impact for the innovating firm. Whether these firms do or do not innovate tends to have minor impacts on an economy's competitiveness.

Secondly, changes in the share of innovating firms are strongly driven by 'marginal innovators' (often from less innovation-oriented industries). For these firms, entry and exit costs to innovation are often quite low as their innovations more frequently represent imitations or adaptations of others' innovation or minor improvements to existing products, processes or methods. Switching from non-innovator to innovator or back may hence involve limited impacts on the firms' competitiveness. Given the smallness of the firms, impacts on the economy-level are even more limited.

The share of sales from product innovation is an indicator that overcomes some of the limitations of the share of innovating firms as it is a measure of the economic significance of innovation. While 72 percent of innovators in the EU 28 in 2014 were small firms, 72 percent of sales with product innovations in the EU 28 in 2014 were made by large firms. These figures show that different groups of firms determine the results of the two indicators. It is hence not a surprise if levels and changes of the two indicators go in different directions.

The main disadvantage of the sales share indicator with respect to validity is the fact that the indicator only represents one type of innovation, product innovation. The other three types of innovation can be very important in certain industries, however. Particularly if price competition is fierce and industries are in rather saturated stages of product life cycles, process, organisational and marketing innovation become more important as innovative strategies (Klepper, 1996; Vives, 2008). Using only the sales share from product innovation as a key innovation indicator may result in an incomplete and biased picture of innovation-related competitiveness. This is particularly the case for a comparison between countries as countries show different

⁸⁰ The share of small firms (10-49 employees) in all innovators at member state level ranges from 58% (Poland) to 83% (Greece).

industry specialisations and firms in different countries are faced with different types of competition.

Another disadvantage of the sales share indicator is its strong dependence on the length of the product life cycle in a particular industry. If life cycles are short, products will have to be replaced in short intervals, resulting in a high share of newly introduced products in total sales. In innovation statistics, the indicator on the sales share from product innovation refers to new or significantly improved products that have been introduced in the past three years. In some industries such as electronics, product life cycles tend to be not much longer than this reference period, causing high sales share from product innovation. In other industries such as pharmaceuticals, product life cycles tend to be very long (20 years and beyond), partly reflecting the fact that developing a new product requires a long time (usually several years) and high costs, necessitating a long market presence of the product in order to secure sufficient earnings to refund the development costs. Cross-industry comparison of the sales share indicator can hence be misleading.

The sales share indicator allows for differentiating by the degree of novelty of a product innovation. The share of sales from new-to-market product innovation should in general represent a higher level of novelty than the share of sales from product innovation that were only new to the innovating firm. However, the new-to-market sales share strongly depends on the definition of the market, which is up to the reporting firm. New-to-market may either refer to a local or regional market, to the national market or to the world market, depending on the reach of a firm's sales activities. In addition, markets may be curtailed to a certain group of customers or user industries. In case new-to-market refers to local or regional markets, the sales share may represent the diffusion of innovations developed and introduced elsewhere into this local/regional market.

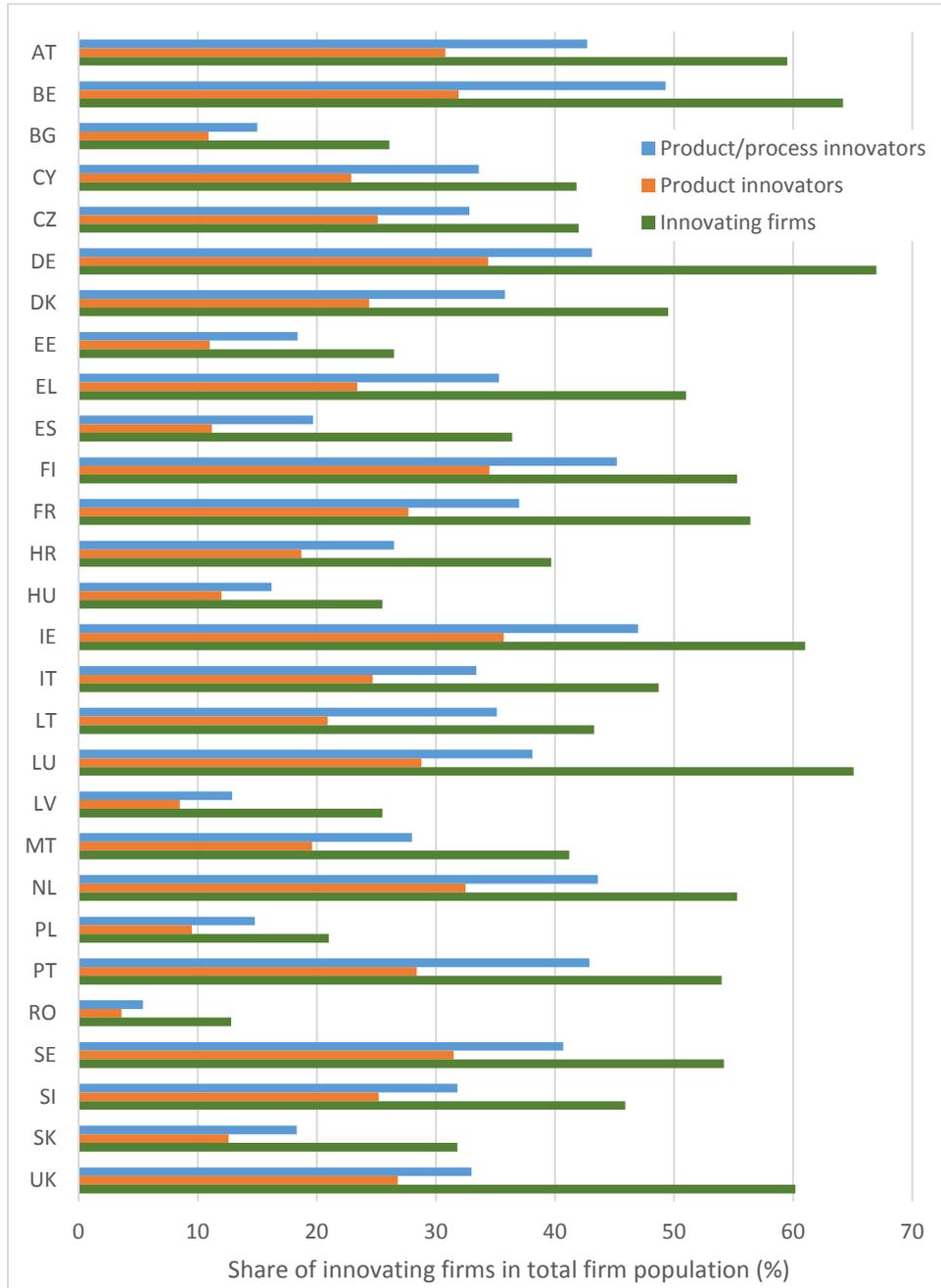
4.6.5 Data Analysis

The share of firms with innovations varies considerably among EU member states (Figure 4-18). In 2014, the share of innovating firms (product, process, marketing or organisational innovation) was between 13% (Romania) and 67% (Germany). The unweighted mean of the EU 28 states was 45%, the median value 47%. For product/process innovators, country shares were between 5% (Romania) and 49% (Belgium). For product innovators, the lowest value was again reported by Romania (4%), the highest one by Ireland (36%).

The country ranks for each of the three indicators on the share of firms with innovations are very consistent. The only country showing a high dispersion of ranks is the UK. While the share of innovating firms was 60% in 2014, putting the country on rank 5 among the EU 28, the share of product/process innovators was rather low (33%), resulting in rank 16. Member states with high shares for all three indicators include Ireland, Germany, Belgium, Finland, the Netherlands, Luxembourg, Austria and Sweden. Member states with low share for all three indicators include Romania, Latvia, Bulgaria, Hungary, Estonia, Slovakia, Spain, Croatia and Malta. All in all, the

results on the country level are consistent with other indicators on the innovative capabilities of EU member states derived from, for instance, R&D data or patent data.

Figure 4-18: Share of firms with innovations by EU member state (2014)

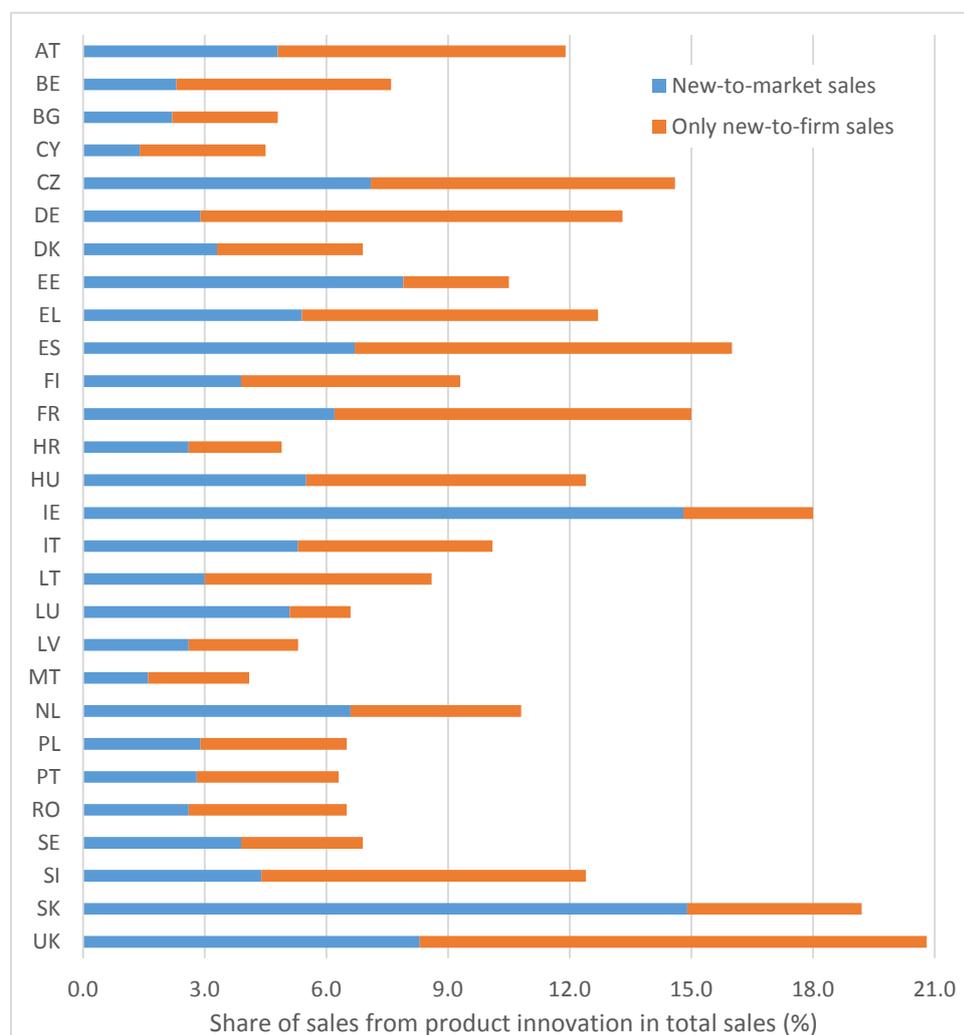


Source: Eurostat, Innovation Statistics

The indicators on the sales share of product innovation also show a high variation across member states (Figure 4-19). In 2014, the lowest share for new-to-market sales is 1.4% (Cyprus), the highest 14.9% (Slovakia). For only new-to-firm sales, the lowest value is 1.5% (Luxembourg), the highest 12.5% (UK). For the sum of both shares, the UK reports the highest figure (20.8%) while Malta reports the lowest (4.1%). Other

member states with a high sales share from product innovations include Slovakia, Ireland, Spain, France and the Czech Republic.

Figure 4-19: Share of sales from product innovations by EU member state (2014)



Source: Eurostat, Innovation Statistics

The country rankings for the two sales share indicators are less consistent compared to the rankings for the three indicators on the share of firms with innovations. Member states with large differences between their ranks based on new-to-market and based on only new-to-firm sales from product innovation include Estonia, Ireland, Luxembourg and Slovakia (all showing a much better rank for new-to-market) as well as Germany and Belgium (both showing a much better rank for only new-to-firm). Member states with high ranks for both indicators include the UK, Spain, the Czech Republic and France while Malta, Cyprus, Bulgaria, Latvia, Portugal, Romania and Poland show low ranks for both indicators. Interestingly, also Sweden and Denmark report rather low values for both sales shares.

The results for the sales share indicators differ significantly from those for the share for firms with innovations. The correlation between the country ranking results is rather

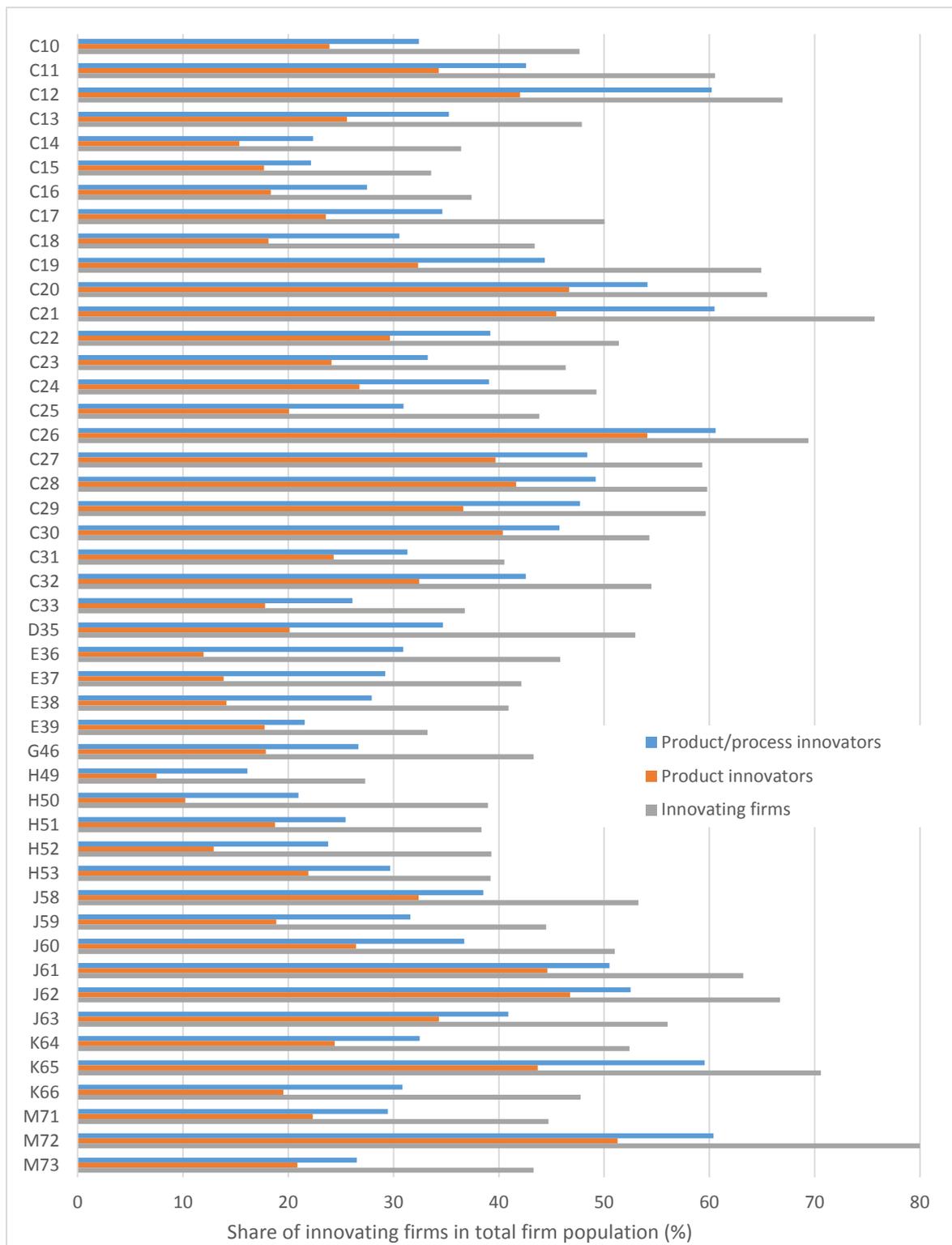
low ($r=0.26$). Large differences between the two groups of indicators are found for Spain, Belgium, Slovakia, Hungary, Luxembourg and Portugal. Member states that get similar rankings in both groups include Lithuania, Bulgaria, Italy, France, Denmark, Austria, Croatia and Slovenia. These differences are not astonishing since the sales share indicators are mainly determined by the activities of large firms while the shares of firms with innovations are driven by small firms.

At the industry level, differences between industries (NACE divisions) with lowest and highest values are at a similar magnitude as at the country level (Figure 4-20). For the share of innovating firms, NACE 49 shows the lowest share (27%) and NACE 72 the highest (80%). NACE 49 also reports the lowest share of product/process innovators (16%) and product innovators (8%). The highest shares are found in NACE 21 (product/process innovators, 61%) and NACE 26 (product innovators, 54%). Note that all percentages are the unweighted average of industry values across the EU 28 member states. This procedure is preferred over a weighted average since competitiveness analysis are usually performed at the country level so that the distribution of indicator values by country is important.

The results for all three indicators on the share of firms with innovations are highly consistent. Industries with high shares for all three indicators include (in descending order) NACE divisions 26, 72, 21, 65, 62, 20, 12, 61, 28, 27 and 29. Most of these industries are often classified as high-tech and medium to high-tech manufacturing or knowledge-intensive services (IT, telecommunication, insurances, R&D). Industries with low shares for all three indicators include (in ascending order) NACE divisions 49, 50, 39, 15, 14, 52, 33, 38, 16, and 37 (i.e. transport services, waste management, manufacturing of clothes, leather products and wood products, repair). A few industries show divergent results, including NACE divisions 35 and 36 (utilities: low share of product innovators, rather high share of innovating firms) as well as 31 and 53 (manufacture of furniture, postal services: rather high share of product innovators, low share of innovating firms).

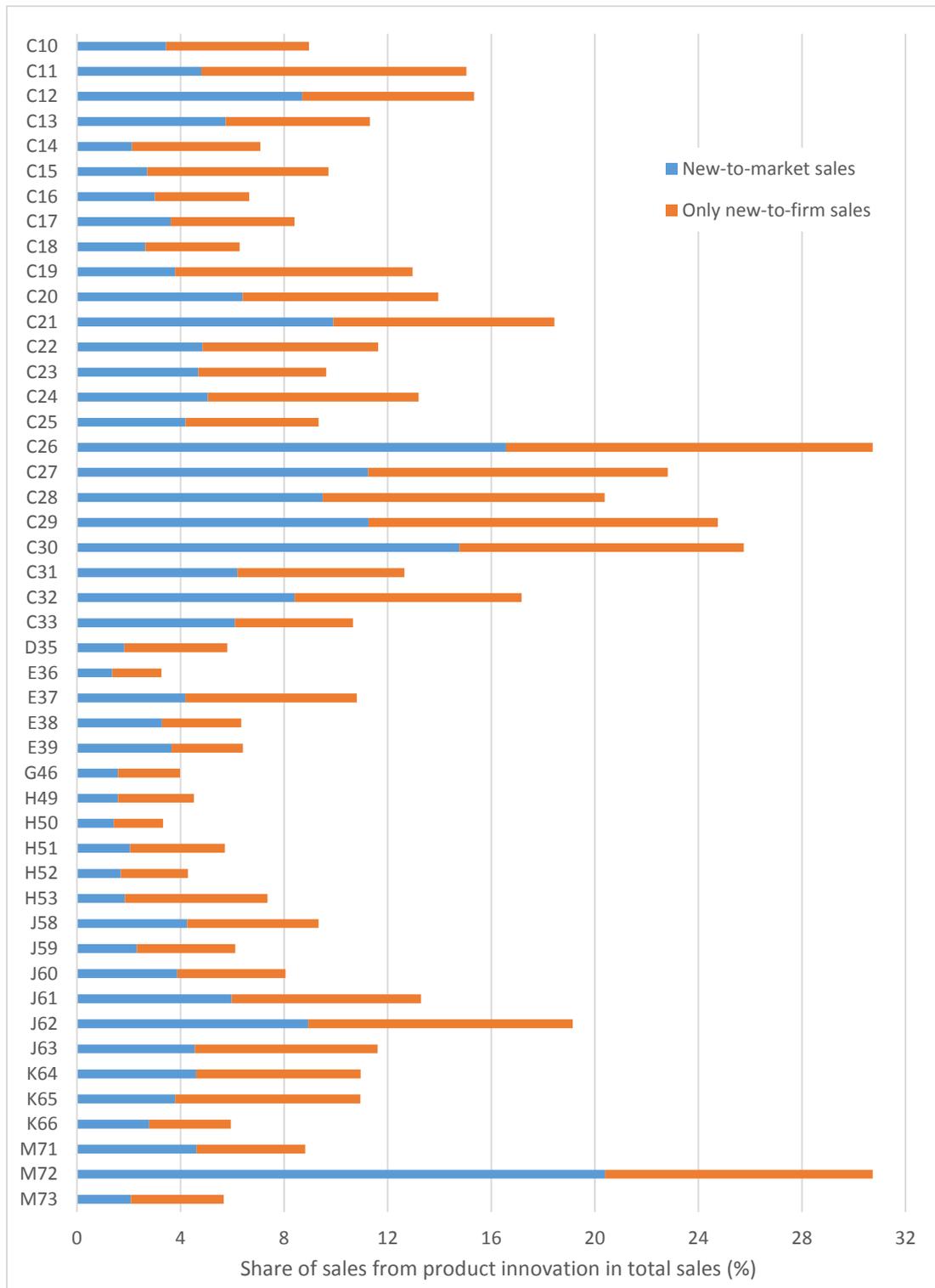
With respect to the sales share indicators, there is also a strong variation across industries (Figure 4-21). Most industries reporting a high share of new-to-market sales also report a high share of only new-to-firm sales, and vice versa. NACE divisions with high values for both indicators include (in descending order) 26, 72, 30, 29, 27, 28, 62, 21 and 32. These are again high-tech and medium to high-tech manufacturing sectors and IT and R&D services. Industries with low shares for all three indicators include (in ascending order) NACE divisions 36, 50, 46, 52, 49, 73, 51, 35, 66 and 18, i.e. transport services, wholesale, utilities, financial services, and advertising. Industries that perform significantly better in terms of new-to-market sales than in terms of only new-to-firm sales include NACE divisions 33, 39 and 71, while NACE divisions 15, 19, 53 and 65 are clearly higher ranked for only new-to-firm sales compared to new-to-market sales.

Figure 4-20: Share of firms with innovations by NACE division (2014 or latest year available) - unweighted average of EU 28 country values



Source: Eurostat, Innovation Statistics

Figure 4-21: Share of sales from product innovations by NACE division (2014 or latest year available) - unweighted average of EU 28 country values



Source: Eurostat, Innovation Statistics

In contrast to the country level analysis, industry results for the three indicators on the share of firms with innovations and the two sales share indicators are highly correlated ($r=0.83$). This results implies that there are incentives for both small and

large firms within a sector to engage (or not engage) in innovation. For competitiveness analysis at the industry level, the results suggest that both groups of indicators will provide similar results. The fact that there is a much lower correlation at the country level suggests that the role of SMEs and large firms for innovation, as well as the role of SMEs versus large firms in more innovative and in less innovative industries, differs substantially across countries.

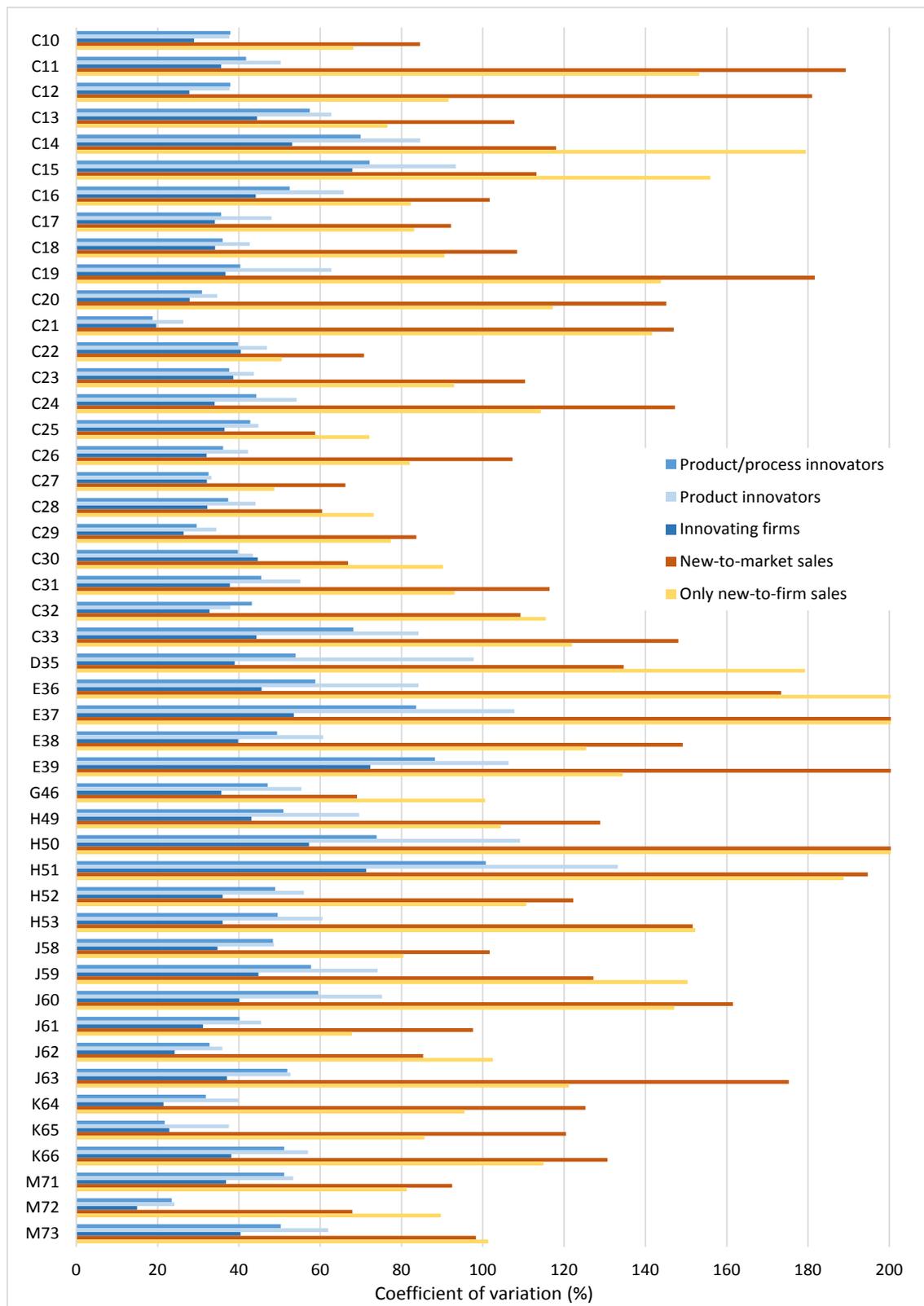
When using innovation indicators at the industry level for country comparisons, one should be aware that the variation in innovation indicators across countries for a given industry can be very high. In general, variation is lower for indicators on the share of firms with innovation and much higher for indicators on sales shares. This difference reflects the fact that the latter are driven by large firms. In many small and medium-sized countries and in many industries, there are often only a few dominating firms that strongly influence the indicator result. As their innovation activities may be very specific and may change across time, innovation indicators may vary accordingly.

With respect to the three indicators on the share of firms with innovations, a few sectors show low coefficients of variation, indicating a rather consistent innovation behaviour of firms in these sectors across countries (Figure 4-22). This is particularly true for NACE divisions 21 and 72 (manufacture of pharmaceuticals, R&D services), but also for 65, 29, 62, 64, 20, 12 and 10 (banking, insurances, IT services, manufacture of motor vehicles, chemicals, tobacco and food products). The manufacturing industries are characterised by rather strong international competition and a high share of large companies. For the service industries one may assume that all facing similar technological changes that lead to a similar innovation behaviour of firms across countries.

Industries with a high cross-country variance in the share of firms with innovations include NACE divisions 51, 39, 37, 50, 15 and 14 (water and air transport, environmental services, sewage, manufacture of clothes and leather products). A high variation in innovation activities suggests that countries show different specialisation within those industries. Some tend to focus on more innovative approaches or more innovative segments while other countries compete through other factors.

With respect to the two sales share indicators, industries with rather low cross-country variation include mainly manufacturing sectors (NACE divisions 27, 22, 25, 28, 10, 30, 29) and R&D services (NACE division 72). Very high variation across countries is reported for NACE divisions 37, 50, 36, 51, 11, 19, 35, 60, 53 and 63. These are mainly service industries (water and air transport, utilities, broadcasting, information services) as well as two manufacturing industries (beverages, petroleum products). One reason for the high variation may be the fact that in many countries these industries comprise only a small number of larger firms.

Figure 4-22: Variation of innovation indicators across EU member states by NACE divisions (2014 or latest year available)



Source: Eurostat, Innovation Statistics

4.7 Openness

Michael Peneder and Stefan Weingärtner

4.7.1 Concept and definitions

Indicators of openness relate to the degree of integration in world trade. As a structural driver of competitiveness it is expected to enhance productivity via various mechanisms emphasised in international economics. For instance, mutual gains from trade may stem from

- economies of scale and specialisation fostering the international division of labour,
- larger sales areas and a broader supply base for intermediate goods, or
- knowledge spillovers and dynamic learning effects from fiercer rivalry on international markets.

In principle, the concept of openness applies to individual enterprises, sectors and countries. Empirically, however, it is most often used at the macro level, since data on imports and exports are readily available. For individual industries, the allocation of trade flows requires trade-linked input-output data, which implies a considerable publication lag. In addition, dynamics of industrial specialisation or spatially clustered and integrated value chains can interfere with a straightforward interpretation in the meaning mentioned above. Finally, at the micro level one would hardly find data about inputs, which the individual firm sources from other countries. Hence, the only dimension covered in many econometric studies using enterprise surveys is typically exports, e.g.

- whether a firm is exporting,
- the share of exports in total turnover, or
- whether a firm sells to other firms producing for foreign markets (indirect exports).

For the meso and macro levels of analysis, the United Nations and World Trade Organization (UN-WTO, 2012) lists several indicators. The general and most common measure of **trade openness** TO of country i is given by the ratio of the sum of exports X and imports M to total GDP :

$$TO_i = \frac{M_i + X_i}{GDP_i}$$

A major advantage of this indicator is that it relies exclusively on data from foreign trade statistics and the national accounts, which are available for many countries at timely intervals.

Among specific information systems that combine detailed information on rules and regulations that affect trade openness, the *European Union's Single Market*

Scoreboard⁸¹ covers, for instance, the openness to imports and particularly those from other EU Member States as an indication of EU market integration. Another particularly comprehensive example is the OECD's *Services Trade Restrictiveness Index (STRI)*⁸², which covers regulatory barriers to services trade for 22 sectors in 44 countries. Going beyond our current focus on measures of competitive performance, both are valuable tools for the detailed study of barriers and hence the drivers and determinants of trade openness in individual sectors and countries.

With trade-linked input-output data one can define alternative measures that focus on an economy's integration into **global value chains**. For example, one can compute Feenstra and Hanson's (1996) measure of *offshoring* as the ratio of imported goods in an industry's total use of intermediate inputs. Hummels et al. (2001) introduced the value share of imported intermediate goods that are embodied in exports as an index of *vertical specialisation*; or Foster-McGregor and Stehrer (2013) offer a generalised measure of vertical specialisation. Similarly, the OECD (2017a) defines backward linkages as the *import content of exports* given by the share of foreign value added in gross exports (OECD, 2017a).

4.7.2 Data sources

The standard indicator of trade openness *TO* relies on a measure of GDP from the *national accounts* as well as exports and imports from *foreign trade statistics* at current prices. For alternative measures of an economy's integration into global value chains, one needs trade-linked input-output data such as the World Input-Output Database (WIOD) or the OECD's Trade in Value Added (TiVA) database.

4.7.3 Data quality

With regard to data quality, Table 4.8 attempts a broad characterisation of the above data sources in terms of representativeness, completeness, timeliness, reliability and patterns of revisions. If we also think of indicators at the level of individual firms (e.g. the share of exports in total sales), these depend on the particular sample and method of the enterprise survey at hand. The only general characterisation is that such surveys offer no scope for data revisions.

For the other indicators, *representativeness* and *completeness* are generally high as they draw exclusively upon official sources such as the national accounts, foreign trade statistics, or supply-use and input-output tables. Aiming for a comprehensive coverage, proper methods of stratification and imputation (where needed), the national statistical institutes contribute much experience and effort in order to achieve a full representation of the economy.

Since each data source faces its particular challenges in terms of concepts and accurate measurement, the characterisation is more nuanced with regard to data

⁸¹ http://ec.europa.eu/internal_market/scoreboard/index_en.htm

⁸² <http://www.oecd.org/tad/services-trade/services-trade-restrictiveness-index.htm>

reliability. The most striking problems with foreign trade statistics, such as difficulties arising from the EU's INTRASTAT system, or general inconsistencies in the valuation of traded goods (*cif* vs. *fob*) have been discussed in Section 3.3. Egger and Wolfmayr (2017) provide further details. Trade-linked input-output data such as WIOD apparently must overcome numerous difficulties in producing a consistent matching of information from different data systems, such as foreign trade statistics, national accounts or the supply-use and input-output tables. Dietzenbacher et al. (2013) and Timmer et al (2015) provide further methodological discussions on them. Finally, the national accounts must deal with numerous difficulties and critical choices. One example is the determination of what constitutes real output net of nominal price effects in certain (non-market) services. Furthermore, in recent years the public debate has highlighted many caveats and the importance of societal objectives beyond GDP.

Table 4-8: Summary of main characteristics of data sources on openness indicators

<i>Data sources</i>	<i>Dimensions</i>	<i>Representativeness</i>	<i>Completeness</i>	<i>Timeliness</i>	<i>Reliability</i>	<i>Revisions</i>
Enterprise surveys	Micro	Limited (depends on size/method: sampling, imputation, etc.)	Limited (depends on size/method)	Limited (potentially high)	Limited (depends on size/method)	None
Trade-linked input-output	Meso & macro	Full	Full	Low (extrapolation, infrequent updates)	Limited (connecting different systems)	Limited (discrete financing)
Foreign trade statistics	Meso & macro	Full	Full	High: t+2/6 months	Limited (INTRASTAT, cif/fob, etc.)	About t+6 months for long-term indicators
National Accounts	Meso & macro	Full	Full	High: t+3/9 months	Limited (e.g., beyond GDP)	Few years backward

The need for *timely* publication reflects the overall importance of national accounts and foreign trade statistics within the national system of economic statistics. In the Eurostat system, first estimates of GDP for EU Member States become available at the year t+3 months and final values at t+9 months. These are frequently *revised* during the follow-up years, whereby the probability and scope of revisions tends to decline with the passage of time. For foreign trade statistics, yearly data of exports and imports are first published at t+2 months, and once revised at t+9 months. Supply-use and input-output tables have a considerably longer publication lag. The most recent tables of EU Member States have been published in early 2017 but for many countries cover only the year 2013. Official input-output data generally are not revised, but those generated for analytical purposes often include extrapolations that ought to be revised with the release of new official data.

4.7.4 Data validity

Indicators of trade openness depend negatively on the size of a country. *Ceteris paribus*, large and integrated economies show lower values of openness, because economic transactions are more likely to take place within the same territory. Conversely, the standard indicators of openness tend to be higher for small countries, since closer borders imply a greater probability of cross-border transactions.

A simple comparison of the total trade of EU Member States with that of the European Union as an integrated economy illustrates the point. For example, in the year 2016 the trade of Member States with partners outside the EU (i.e., extra-EU trade) accounted only for 36 % of their total trade (i.e., if intra-EU trade is included).

In econometric analyses, one can handle the problem by including, e.g., a country's GDP or population among the independent variables and thus control for size dependent effects. However, if standard indicators of openness are used for the monitoring of a country's export competitiveness, one ought to correct directly for its size dependence in order to improve the comparability between large and small countries.

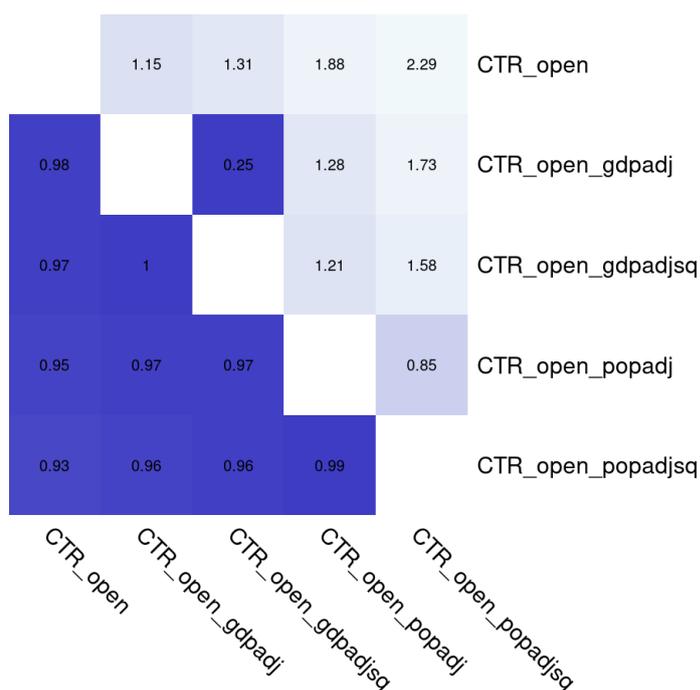
For the purpose of illustration, we determine a **size adjusted** measure of trade openness TO_i^{adj} for country i as the residual of either of two simple regression models. The first (univariate) model uses only the logarithm of the selected indicator of country size ($size$) as independent variable (besides the constant β_0). To test for a possible nonlinear relationship, the second model also adds the logarithm of the quadratic term of the independent variable to the first model. The residuals ε_i serve as our size corrected indicator for openness:

$$\begin{aligned}\ln TO_i^{adj} &= \beta_0 + \beta_1 \ln(size_i) + \varepsilon_i \\ \ln TO_i^{adjsq} &= \beta_0 + \beta_1 \ln(size_i) + \beta_2 \ln(size_i)^2 + \varepsilon_i\end{aligned}$$

To begin with, we focus only on the trade of goods and use the logarithm of either GDP or total population as measures of country size. In addition to the conventional measure of trade openness (CTR_open) we thus have four different alternative indicators referring to the indicator adjusted for country size by GDP with either the linear (CTR_open_gdpadj) or the quadratic model ($CTR_open_gdpadjsq$) or adjusted for the size of its total population with either the linear (CTR_open_popadj) or quadratic model ($CTR_open_popadjsq$).

The quadratic heat map in Figure 4-23 shows a strong similarity between the indicators as far as the ranking of the EU Member States is concerned. The residuals from the linear and quadratic specifications are almost identical. Whereas the Manhattan distance reveals some minor differences, the correlation coefficient is close to one. We consequently can ignore the residual from the quadratic model in the further analysis. Among the two remaining indicators from the linear model, adjustment by population has a somewhat stronger effect on the country ranking.

Figure 4-23: Quadratic heat map – openness, EU28, 2005-2015



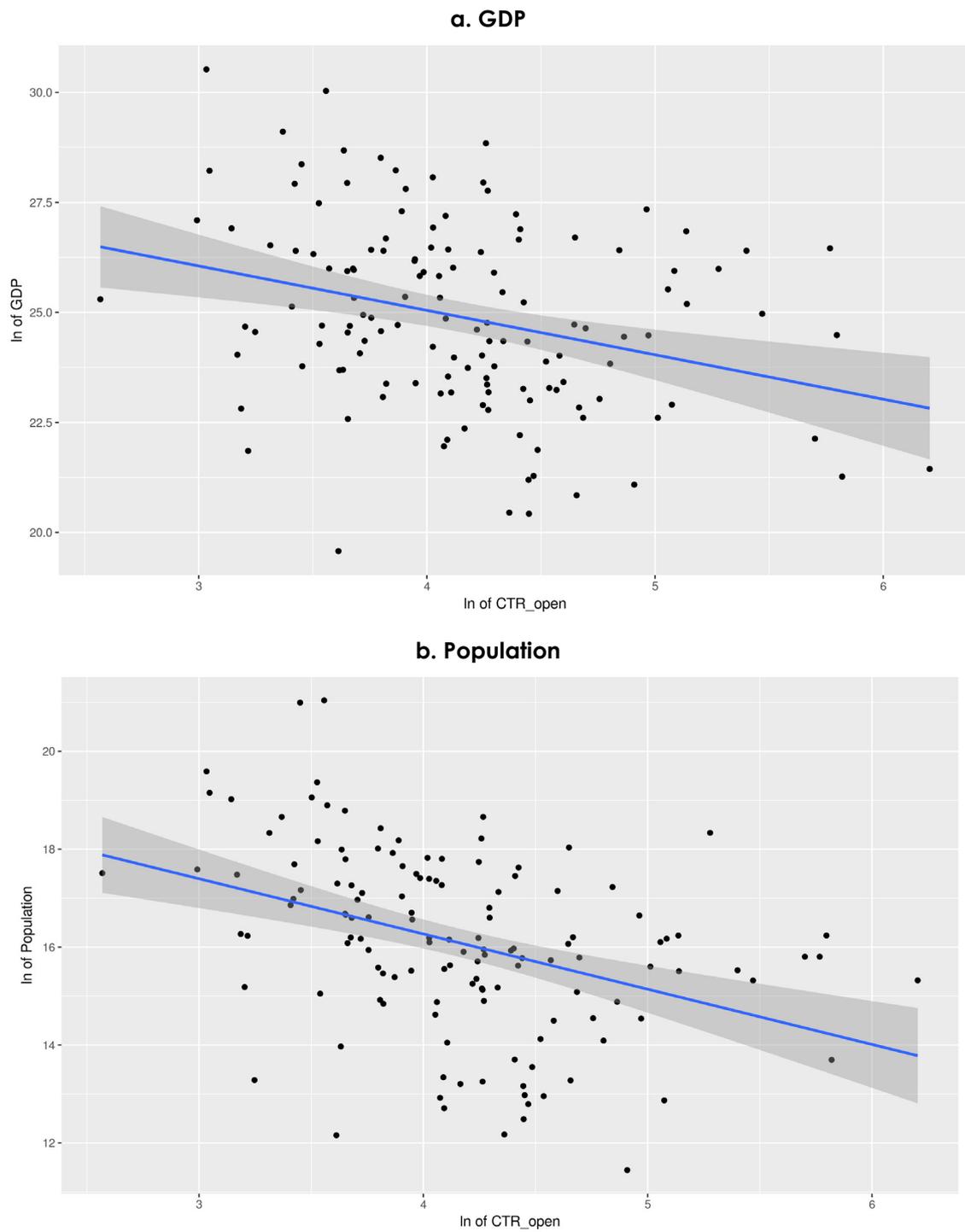
Source: Comtrade and WDI, WIFO calculations.

Despite their general similarity in terms of country rankings, the indicators show an important difference: The scatter plots in Figure 4-24 confirm the suspected size dependence of the conventional measure of trade openness without size adjustment for both the logarithm of GDP and the logarithm of total population. In contrast, the plots in Figure 4-25 demonstrate that our adjusted measures of trade openness estimated from the linear model are size independent and no longer correlated with the total population of an economy.

4.7.5 Data analysis

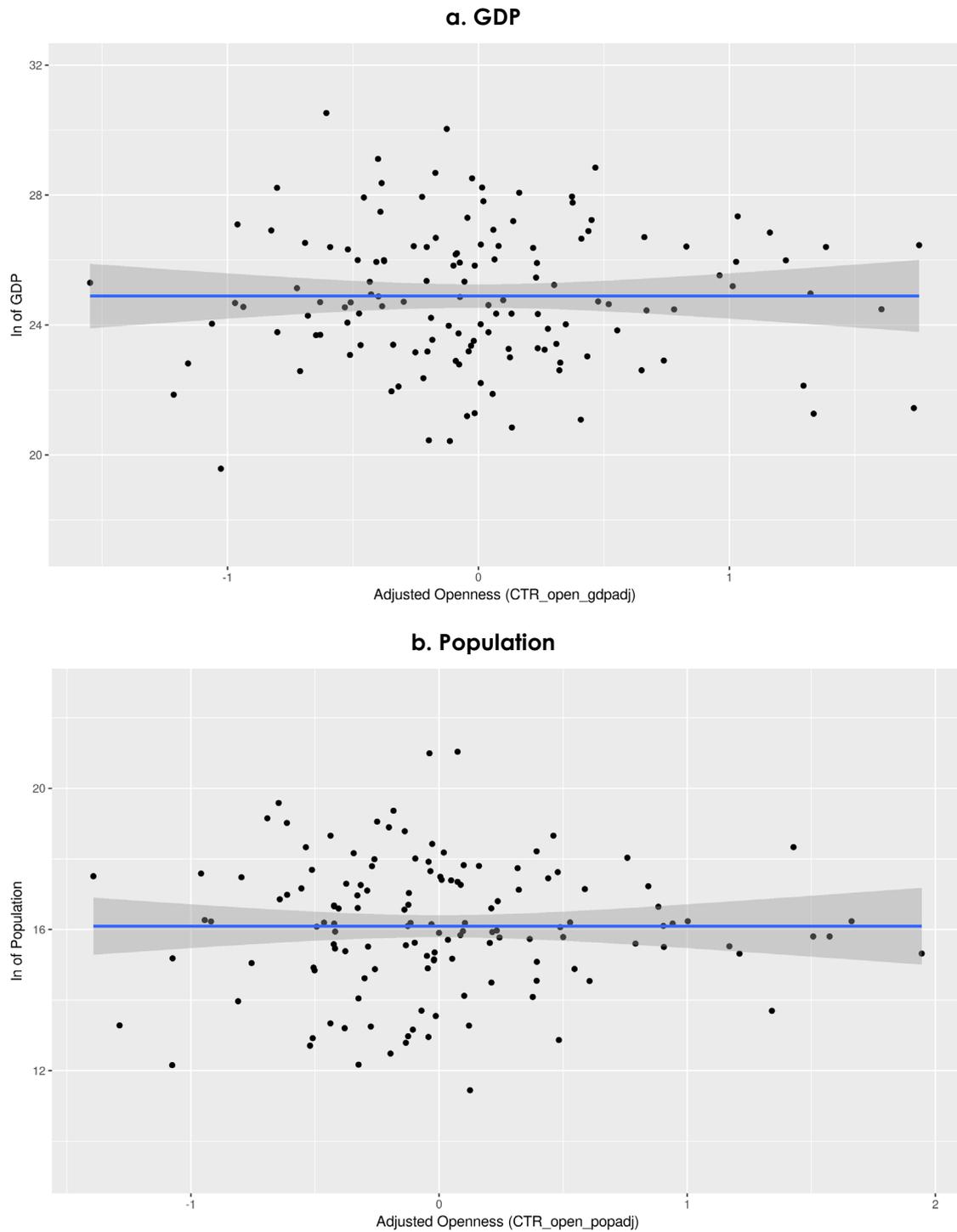
For a first empirical example, Figure 4-26 plots the adjusted measure of trade openness for goods and services (*BOPgs_open_popadj*) against the logarithm of GDP per capita. It confirms the expected positive statistical association between the two variables (as does the standard measure of openness).

Figure 4-24: Openness and country size, 2015 (n=136 countries)



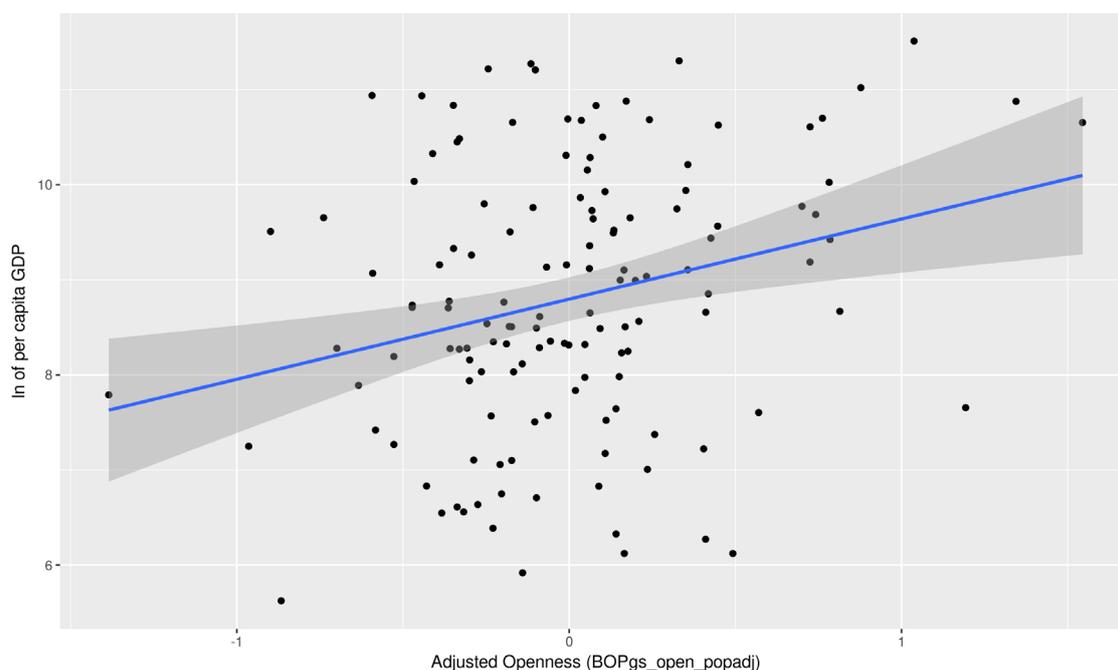
Note: GDP, population and openness are measured in natural logarithms.
Source: Comtrade and WDI, WIFO calculations.

Figure 4-25: Country size and the size adjusted measures of openness, 2015 (n=136 countries)



Note: GDP, population and openness are measured in natural logarithms.
Source: Comtrade and WDI, WIFO calculations.

Figure 4-26: Trade openness (adjusted) and GDP per capita (n=136)

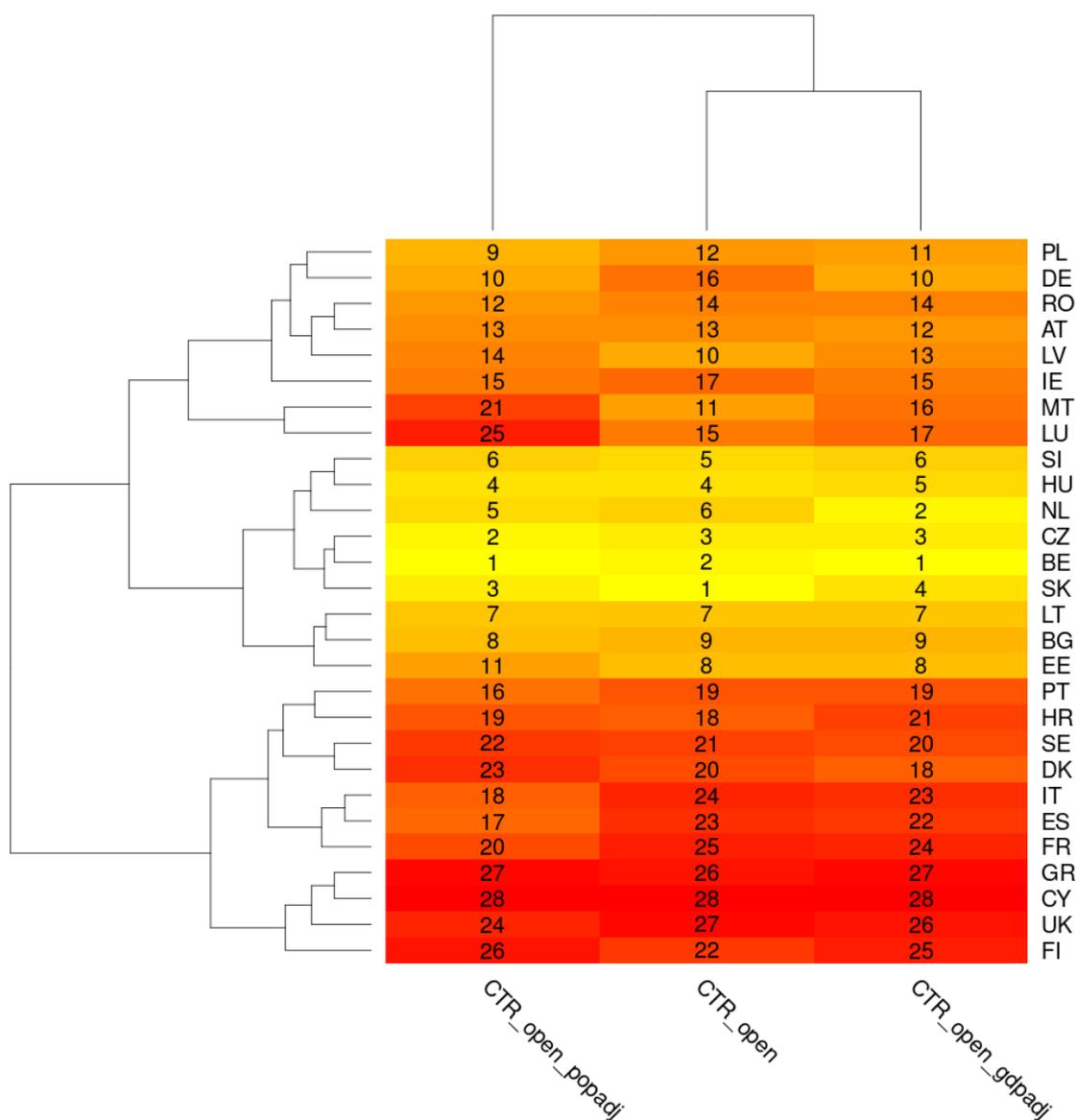


Note: Per capita GDP and openness are measured in natural logarithms.
Source: BOP and WDI, WIFO calculations.

Finally, with Figure 4-27 we turn to the method of cluster heat maps as introduced in Section 3.3 (thereby complementing the other indicators of export competitiveness at the macro level). In accordance with the high similarity/low dissimilarity reported in Figure 4.23 the overall pattern is relatively consistent across the three different variables. Nevertheless, the adjustment by estimating the residual of the traditional measure of trade openness (CTR_open) regressed on either total GDP (CTR_open_gdpadj) or the total population of a country (CTR_open_popadj) makes some significant differences for the country rankings. Most notably, Belgium is the most open economy among EU Member States according to both size adjusted measures of openness. In contrast, Slovakia drops from first to either the second or third place, if one uses total GDP or population for the adjustment.

If we turn to openness in the trade of **goods and services**, Figure 4-28 presents the joint cluster structure for three variables taken from the IMF's balance of payments database (BOP). Combining the country rankings in the trade of goods ($BOPg_open_popadj$), trade of services ($BOPs_open_popadj$) and total trade of goods and services ($BOPg_open_popadj$) produces a varied pattern.

Figure 4-27: Cluster heat map – openness in the trade of goods, EU28, 2015

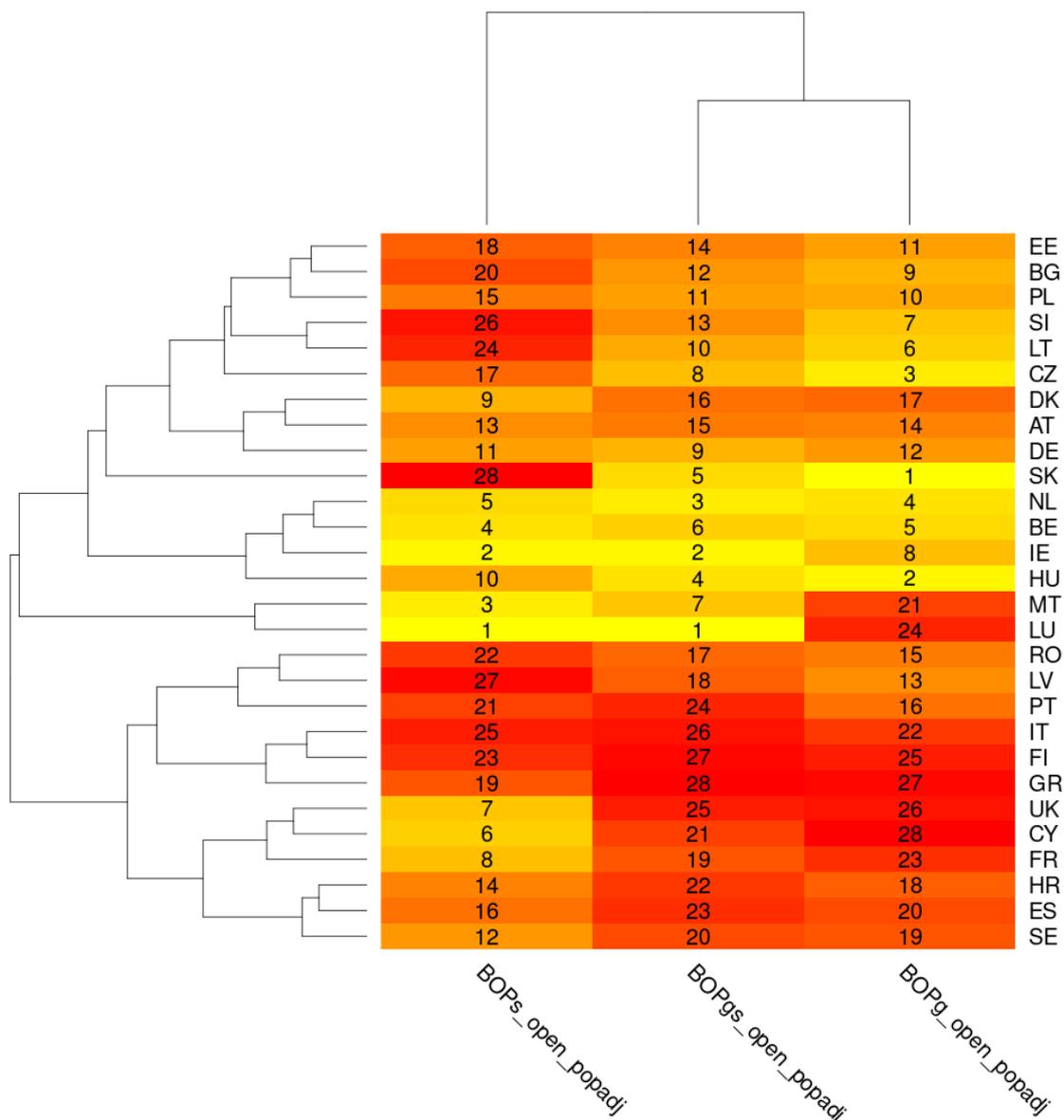


Source: Comtrade and WDI, WIFO calculations.

Investigating the joint cluster structure in Figure 4.28 produces a **taxonomy** of three different groups that are defined by characteristic differences in their openness in the **trade of goods** (in alphabetical order of their ISO codes):

- *High* trade openness: Belgium, Bulgaria, Czech Republic, Estonia, Hungary, Lithuania, Netherlands, Slovenia and Slovakia
- *Intermediate* trade openness: Austria, Germany, Ireland, Luxembourg, Latvia, Malta, Poland and Romania
- *Low* trade openness: Cyprus, Denmark, Spain, Finland, France, Croatia, Italy, United Kingdom, Greece, Portugal and Sweden

Figure 4-28: Cluster heat map – openness in the trade of goods and services, EU28, 2015



Source: BOP and WDI, WIFO calculations.

As for all other country rankings that are based on one particular dimension of competitiveness, one must emphasise that this is only indicative and for the purpose of an empirical illustration. It inevitably neglects explanatory factors, such as geography, particular historical and cultural ties with other economies, or differences in the country-specific institutional setting. Also one must emphasise that the trade of goods is generally more open and that national differences are smaller than in the trade of many services. Since ordinal rankings cannot imply an equidistance in performance either within or between indicators, the difference of one rank in the openness to the trade of goods may reflect much smaller barriers than the same difference in the trade of services.

4.8 Terms of Trade

Andreas Reinstaller

4.8.1 Definition

Terms of trade (TT) are the relative price, on world markets, of a country's exports compared to its imports. If the price of a country's exports rises relative to that of its imports, the country improves its purchasing power on world markets. The two most common indicators are barter terms of trade and income terms of trade.

The Barter Terms of Trade or BTT of country c in year t are defined as

$$BTT_{c,t} = \frac{P_{c,t}^X}{P_{c,t}^M}$$

where $P_{c,t}^X$ and $P_{c,t}^M$ are price indices over the range of exported $N_{c,t}^X$ and imported goods $N_{c,t}^M$. The Income Terms of Trade ITT is defined as the barter terms of trade multiplied by its export volume index:

$$ITT_{c,t} = BTT_{c,t} * Q_{c,t}^X,$$

where $Q_{c,t}^X$ is country c 's export volume index (i.e. the ratio between export quantities in years t and t_0). The ITT show a country's changing import capacity in relation to changes in its exports. Usually, official statistics from Eurostat, the OECD, the World Bank, UNCTAD or the IMF report Barter Terms of Trade. Income Terms of Trade are generally considered being more pertinent to study questions of economic development.

The terms of trade indicators are constructed from import and export price indices. Export price indices measure changes in the prices of goods and services provided by the residents of a country used by non-residents. The import price index in turn measures changes in prices of goods and services provided by the rest of the world and used by residents of a country.

These price indices are weighted averages of the price relatives of its components (product lines, services) where the weights are the share of each component in the total value of exports covered by the index. It is therefore necessary to identify appropriate price relatives and weights, and to choose specific methods for aggregation. Aggregation then follows a two-stage process. At the lower level values and quantities of units are aggregated without weights from customs data into aggregate commodity classes. This will be discussed in the following two sections.

Unit value indices and price indices

The price relatives may take the form of price ratios between two dates t and t_0 of representative items that are comparable over time in terms of their product characteristics. Such prices are generally obtained from establishment surveys. More common is however the use of unit value ratios between two dates t and t_0 for

specific commodity groups obtained from customs declarations as a substitute for survey data which are very costly to obtain.

Unit values $uv_{c,i,t}$ for a commodity class i in country c at time t measure the total value of shipments divided by the corresponding total quantity. These commodity class level unit values are subsequently aggregated across commodity classes using weighted index number formulas discussed later.

The unit value $uv_{c,i,t}$ is defined as

$$uv_{c,i,t} = \frac{\sum_{k=1}^K p_{k,c,t} q_{k,c,t}}{\sum_{k=1}^K q_{k,c,t}},$$

where $p_{k,c,t}$ is the price of the k items, $k=1,\dots,K$, classified under commodity class i in country c , and $q_{k,c,t}$ are the corresponding quantities. The unit value ratio between dates t and t_0 is then given by

$$uv_{c,i,t/t_0} = \frac{\sum_{k=1}^K p_{k,c,t} q_{k,c,t}}{\sum_{k=1}^K q_{k,c,t}} \bigg/ \frac{\sum_{l=1}^L p_{l,c,t_0} q_{l,c,t_0}}{\sum_{l=1}^L q_{l,c,t_0}},$$

where the indices in the base year indicate that the items classified under commodity class i may vary over time.

Aggregation and basic index number theory of aggregation:

To construct aggregate unit value indices based on customs data typically Laspeyeres or Paasche indices are used. The Laspeyeres index ($LI_{c,t/t_0}$) measures changes of price relatives or unit values ($uv_{c,i,t}$) of products exported or imported between two dates t and t_0 for an export basket held constant with regard to reference data t_0 and with constant quantities q_{c,i,t_0} ,

$$LI_{c,t/t_0} = \frac{\sum_i uv_{c,i,t} q_{c,i,t_0}}{\sum_i uv_{c,i,t_0} q_{c,i,t_0}}.$$

The Paasche index ($PI_{c,t/t_0}$) alternatively weights unit value index changes with the current quantities,

$$PI_{c,t/t_0} = \frac{\sum_i uv_{c,i,t} q_{c,i,t}}{\sum_i uv_{c,i,t_0} q_{c,i,t}}.$$

These indices come with two systematic measurement errors. On the one hand, they do not allow considering substitution effects induced by changes in prices, on the other hand, by keeping export or import baskets constant these indices do not consider changes in the composition of these baskets.

With regards to the neglect of substitution effects, the Laspeyeres index overestimates price changes if price increases have also led to a reduction of quantities through substitution effects. The problem in this case results from keeping the product basket fixed to the reference date. The Paasche index instead tends to

underestimate price changes. It gives higher weight to products for which consumption has increased following a relative price drop.

This problem can be in part addressed by using geometric rather than arithmetic means, the former implying a unit elasticity of substitution between goods. Alternatively, it is possible to use composed indices that use the information on quantities traded in both the reference and the current date with an implicit assumption of substitution elasticities lying between zero and one. In addition, it has also been shown empirically (Feenstra 1997) that the Paasche and Laspeyres indices are lower and upper bounds respectively of real price evolutions. The literature therefore argues in favour of the Fisher index ($FI_{c,t/t_0}$) as an alternative. By computing the geometric mean between the Laspeyres and Paasche indices the Fisher index is a good approximation of the unobserved real price index, and has been shown to be an ideal price index insofar as it satisfies all reasonable tests required of index numbers (see Feenstra, 2004, p.415; IMF 2009, Chapter 17):

$$FI_{c,t/t_0} = \left(PI_{c,t/t_0} \cdot LI_{c,t/t_0} \right)^{\frac{1}{2}},$$

With regards to the second measurement error of Laspeyres and Paasche indices that is due to the neglect of changes in the composition of export and import product baskets, the literature proposes chained indices. With chained indices, the reference period changes over time which allows accounting for changes both in the composition and in the array of goods. Changes in the extensive margin (i.e. the array of goods) at date $\tau - 1$ will enter the index at date τ . The chained Laspeyres ($cLI_{c,t}$) and den Paasche indices ($cPI_{c,t}$) are then defined as follows:

$$cLI_{c,t} = \prod_{\tau=1}^t LI_{c,\tau/\tau-1},$$

$$cPI_{c,t} = \prod_{\tau=1}^t PI_{c,\tau/\tau-1}.$$

The higher precision as to what concerns the composition of the import and export baskets comes however at a cost. The multiplication of the price changes over time increases the variation of the series. The chained Fisher index which accommodates substitution and composition effects is then defined as follows:

$$cFI_{c,t/t_0} = \left(cPI_{c,t/t_0} \cdot cLI_{c,t/t_0} \right)^{\frac{1}{2}},$$

Because of these favourable properties international organisations and statistical offices normally report chained Fisher indices. This is the case for Eurostat.

Eurostat calculates elementary unit-value indices are then aggregated over countries and commodities, by using the Laspeyres, Paasche and Fisher formulae. The Fisher unit-value indices are chained back to the reference year (2010=100).

4.8.2 Data Sources

The primary data source to construct import and export price indices is customs statistics that show the value of exports and imports and give also information on the quantities traded such as tonnage, number of units, etc. – for a highly-detailed list of products (customs classifications typically contain several thousand items). This information is used in the national accounts to calculate export and import prices by dividing the values by quantities leading to “unit value indices” as shown in the introduction. Some countries have also developed special price surveys covering exporters and importers to replace these imperfect “unit value indices”. These surveys typically cover only a limited range of items and the data therefore sometimes consist of both establishment-level surveys and unit value indices. While combined survey and customs data unit values are more reliable, they are often only available at country level.

Figures for imports of goods are valued at “cif” prices, which include “cost, insurance, freight” when they enter the frontier of a country. Exports are valued at “fob” or “free on board” prices, signifying that the prices of the goods include transport and insurance costs when they arrive at the exporting country’s frontier but not the transport and insurance costs further to the importing country’s frontier. Therefore, so-called “cif-fob adjustments are needed to make unit values of imports by partner countries and exports to partner countries consistent. To facilitate comparison with the balance of payments in the national accounts all import and export prices or unit values are reported fob.

In addition, in customs statistics export data are less reliable than import data, as the former are typically not part of the tax base and are therefore monitored less carefully by customs administrations. To obtain consistent bilateral import and export flows it is therefore often necessary to “mirror” import data from partner countries with export data to partner countries. This may be a source of bias if for instance traders try to avoid tariffs by declaring products under commodity classes with a lower tariff. In addition, it is necessary to carry out “cif-fob” adjustments. In unit value indices freight costs are typically not observable and cif costs should be estimated.

In the European Union, intra-EU trade data are collected through the INTRASTAT system for collecting information on the trade in goods between EU Member States. Natural and legal persons engaging in a cross border transaction beyond a certain threshold have the obligation to report this flow. Thresholds are set in such a way as to cover more than 95% of dispatches and arrivals.⁸³ Extra-EU trade statistics are collected based on Customs declaration.⁸⁴ These data are collected and compiled according to a harmonised methodology by the national statistical offices of the Member States and transmitted to Eurostat. Using monthly raw data at the most detailed level Eurostat then calculates elementary unit-values defined by trade

⁸³ See Regulation (EC) No 222/2009 of the European Parliament and of the Council of 11 March 2009,

⁸⁴ See Regulation (EC) No 471/2009 of the European Parliament and of the Council, Commission Regulation (EC) No 92/2010 and Commission Regulation (EC) No 113/2010.

value/quantity. These unit-values are divided by the average unit-value of the previous year to obtain elementary unit-value indices, from which outliers are detected and removed.^{85,86}

4.8.3 Data Quality

In its meta-information on International Trade in Goods statistics, Eurostat highlights the relevance, the timeliness and punctuality, the accessibility, the clarity and the coherence as principal strengths and *accuracy and the comparability as important weaknesses. This carries over to the terms of trade statistics at the country level available through Eurostat's website. We cite directly from Eurostat's meta-information with some omissions and rearrangements:*⁸⁷

Completeness

The EU trade statistics are based on the EU legislation which is directly applicable in the Member States. The legislation includes a clear and precise list of all the statistical variables to be provided by the Member States to Eurostat. All the mandatory variables are provided by all the Member States.

Timeliness

The international trade in goods statistics benefit from the well-established data collection and compilation procedures and as well from the INTRASTAT and EXTRASTAT regulations which include deadlines for data transmission to Eurostat.

Representativeness

EU trade statistics are based on the INTRASTAT system for the intra-EU trade and on the customs clearance system for the extra-EU trade. Thus, international trade in goods statistics are not affected by errors specifically applicable to sample surveys.

Extra-EU trade statistics data are collected by using customs declaration. Trade operators fulfilling their reporting obligations to the Customs authorities in a Member State are providing at the same occasion the statistical data. The statistical information depends, therefore, very much on customs practices, definitions and policies and only few dimensions are collected purely for statistical purpose. The dependence on customs procedures entails to a high quality and nearly total coverage of data on trade with non-EU countries.

⁸⁵ Outliers are removed using the so-called TRAMO procedure. Seasonal adjustment is also carried out.

⁸⁶

<http://ec.europa.eu/eurostat/tgm/refreshTableAction.do?tab=table&plugin=1&pcode=tet00028&language=en>

⁸⁷ Full meta-data are available here: http://ec.europa.eu/eurostat/cache/metadata/en/ext_go_esms.htm

Intra-EU trade statistics are collected directly from trade operators because of the abolishment of customs control at the borders between the Member States. The reporting burdens are simpler, compared with the Extrastat system and private individual and small scale traders are excluded. However, any taxable person in a Member State carrying out intra-EU trade and being above a certain threshold is obliged to report monthly on its intra-EU trade to the competent national statistical authorities. The national authorities use data on the total taxable amount of intra-EU acquisitions and deliveries provided by the fiscal authorities to identify the target population and maintain registers on trade operators.

Reliability

The international trade in goods statistics benefit from well-established data collection systems supported by efficient validation and compilation tools. Nevertheless, there is still a place for improvement especially in the intra-EU trade statistics which suffer from non- or late responses from some of the enterprises asked to report their trade in goods. In addition, the confidentiality impact the data accuracy at very detailed level, i.e. at the level of about 10,000 8-digit codes of the product nomenclature.

The comparability across countries could be improved through further harmonisation in the Member States' practices regarding specific goods or movements. In addition, trade statistics offer a unique possibility to scrutinise data through a "mirror" comparison of trade flows between the two countries involved. This kind of examination indicates problems in the comparability and may consequently reveal problems in the accuracy.

Revisions

Data are revised frequently according to national needs and practices. They become normally final from six months up to more than one year after the reference year. Revisions to older data are also possible. Eurostat makes the revisions available in its monthly updates as soon as they were transmitted by the Member States.

Potential measurement error related to unit value indices and related terms-of-trade statistics

Next to the aspects of data quality related to the collection of trade data for the computation of terms of trade indices cited from Eurostat's meta-information on International Trade in Goods statistics, several potential measurement issues related to unit value indices should be highlighted as well (see International Monetary Fund (2009), p. 280 ff. for a complete account).

- Unit value indices represent price changes. They work well for the aggregation of homogeneous items but are biased if items classified under a commodity class are heterogeneous. Potential issues arise from compositional changes in both qualities and quantities. In this case only establishment-based surveys where

respondents are asked to price a commodity with specific fixed characteristics each period would allow appropriately dealing with this issue.

- Another source of measurement error is that information on quantities in customs returns and the choice of units in which quantities are measured continues to be problem, even though units are typically expressed in tons and for other types of commodities conversion factors have been developed. They cannot be aggregated (tons of potatoes cannot be added to tons of carrots), and they are not well monitored by customs for this reason as well.
- Customs union countries may have limited intra-area trade data. In the case of the European Union, intra-EU trade data are collected through the Intrastat system as discussed earlier.
- Missing values and outlier detection and deletion are another source of measurement error. Very often commodity classes with zero trade are omitted by national customs rather than reported with a zero value, which makes it easy to overlook them. In case zero values are reported, it is difficult to tell true zero trade from unreported trade or entry errors. Missing data can be complemented by mirroring, as discussed earlier.
- Unit value indices rely also heavily on outlier detection and deletion (see for instance Silver 2007). Such deletions run the risk of excluding potential price catch-ups when they take place thereby understating inflationary developments.
- Most countries that produce export or import price indices publish them only for trade in commodities. However, services make up an increasing amount of international trade. Given the importance these data for the Balance of Payments statistics they are collected through surveys by the National Banks and national statistical institutes following the Extended Balance of Payments Services Classification (EBOPS).⁸⁸ In services the intangible nature of the commodities traded make the measurement of services difficult. Indeed, it is often difficult to define the service traded. Transactions are often unique and no stable commodity can be identified over time. In addition, the classifications used to classify are not compatible with trade in goods classifications. The calculation of unit value price indices is therefore strongly biased. Survey data are needed to compute export and import price indices.

4.8.4 Data Validity

The (barter) terms of trade are a valid indicator for the competitiveness of a country insofar as they indicate to what extent a country is able of financing its imports through its own exports. If a country exports products that experience a long-run

⁸⁸See Regulation (EU) No. 184/2005 of 12 January 2005 on Community statistics concerning balance of payments, international trade in services and foreign direct investment; ECB's Guideline of 16 July 2004 on the statistical reporting requirements of the European Central Bank in the field of external statistics (ECB/2004/15).

decay in prices relative to its imports it will need to export more and more to obtain the same or even lower amount of imports. Especially, for developing countries that in the past heavily relied on capital goods from industrialised countries for their own development this was an unwanted consequence of unfavourable trade specialisations (mostly in primary commodities). This view is enshrined in the Prebisch-Singer Hypothesis (Prebisch 1950; Singer 1950).

The key idea carries over to industrialised countries, if they have an unfavourable industrial and trade specialisation. If industries, in which a country is specialised experience a persistent decline in prices of their manufactured products this can have negative impacts on domestic welfare as an increasing amount of domestic resources needs to be spent for any given level of imports. Persistent declines in prices can be the result of processes of commodification or standardisation, which make products less unique and transform them into inferior goods. This is especially the case if the rate of international imitation in an industry is considerably higher than the rate of invention (at the technological frontier). Such developments can be observed in low tech industries.

Using developments in the unit values of exports and imports at either the product or sectoral level it is possible to construct a measure of the sectoral terms of trade. International organisations and statistical offices however do not report sectoral terms of trade as their meaning is contested. The terms of trade at the country level capture the relationship between export and import prices and allows examining the amount of imports a country can buy per unit of exports. Some authors argue that the meaning of what terms of trade mean at the sectoral level is not clear and how relevant relative export and import prices are at this level. However, in the presence of product differentiation within industries and resulting strong intra-industry trade, sectoral terms of trade acquire a clear meaning.⁸⁹ If say, electrical machinery manufactured in the US is not a perfect substitute for electrical machinery in Germany then Germany will export to the US and vice versa. If in addition different price tags are associated to German and US machines, then sectoral terms of trade clearly indicate how much electrical machinery the US needs to export to buy one unit of machinery from Germany and vice versa. The relative development of these prices over time then indicates how the exports of a country in a specific sector move relative to the imports the country demands in global markets. Sectoral terms of trade can therefore be interpreted as a sectoral measure of competitiveness in quality relative to the markets from which the country imports similar products. Differences in import and export price indices at the sector level therefore reflect also differences in the pace of technological upgrading between the exporting sector and the sector in countries from which the country imports.

Alternatively, some authors compare export unit values at the sectoral level to the unit value of a representative basket of imports (across all sectors for a country or

⁸⁹ Most of trade flows take place between countries of approximately similar income levels. In addition, intra-industry trade is strongly driven by similar GDP per capita levels as well as similar capital-labour ratios (see Helpman 1987, Cieslik 2005, Debaere 2005).

country group), which then tells whether a unit of exports in a sector allows for an increasing or decreasing amount of imports over time. In both instance, the indices must be constructed from bilateral trade data such as Comtrade, Comext or BACI data by the analyst.

1 Data Analysis

Terms of trade for the European Member states are shown in Figure 4-29. The figure compares the time series on terms of trade published by Eurostat with the time series that can be obtained from the OECD.⁹⁰ The difference between the two series is that Eurostat uses monthly data on trade between Member States as well as Member States and non-member countries in terms of arrivals and dispatches of goods. The data for the OECD series are instead based the 2008 System of National Account (SNA), and therefore include also trade in services consisting mainly in travel, transport services, and insurance.⁹¹ The terms of trade of the OECD data are therefore based on import and export price indices that are consistent with other consumer and produce price indices obtained from and used in the National Accounts.

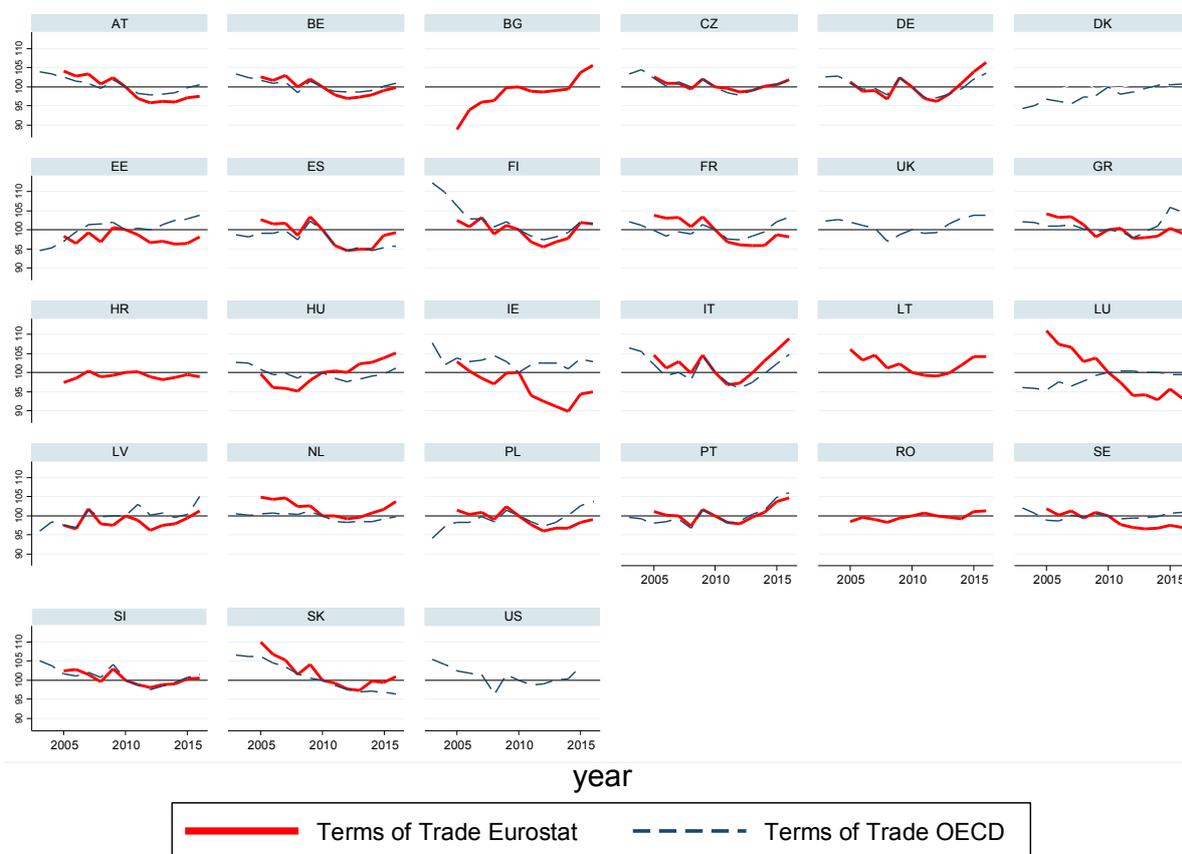
For smaller service-driven economies or economies with strong FDI flows through special purpose entities (such as Ireland, the Netherlands, or Luxemburg) these differences in measurement may lead to considerable deviation between the terms of trade figures based on trade in goods and SNA based indices. For countries with a strong manufacturing base such as Austria, Germany, Slovenia or Czech Republic the two indices in turn strongly correlate, and follow also the same overall time pattern.

If the goal is to assess the competitiveness of the entire economy, SNA based terms of trade statistics should be preferred over purely commodity based ones, however, in this case it is important to be aware of the circumstance that calculating price indices for services comes with considerable methodological issues.

⁹⁰ Information on OECD meta data are available from: [http://stats.oecd.org/OECDStat_Metadata/ShowMetadata.ashx?Dataset=NAAG&Lang=en&Coords=\[INDICATOR\].\[TOT\]&backtodotstat=false](http://stats.oecd.org/OECDStat_Metadata/ShowMetadata.ashx?Dataset=NAAG&Lang=en&Coords=[INDICATOR].[TOT]&backtodotstat=false).

⁹¹ The OECD meta data underscore however, that outsourcing, merchanting, goods sent abroad for processing, and transactions in intellectual property increase the difficulties inherent in the measurement of trade in services.

Figure 4-29: Development of the terms of trade for the European Countries, 2005-2016. Comparison between the Eurostat and OECD country series.



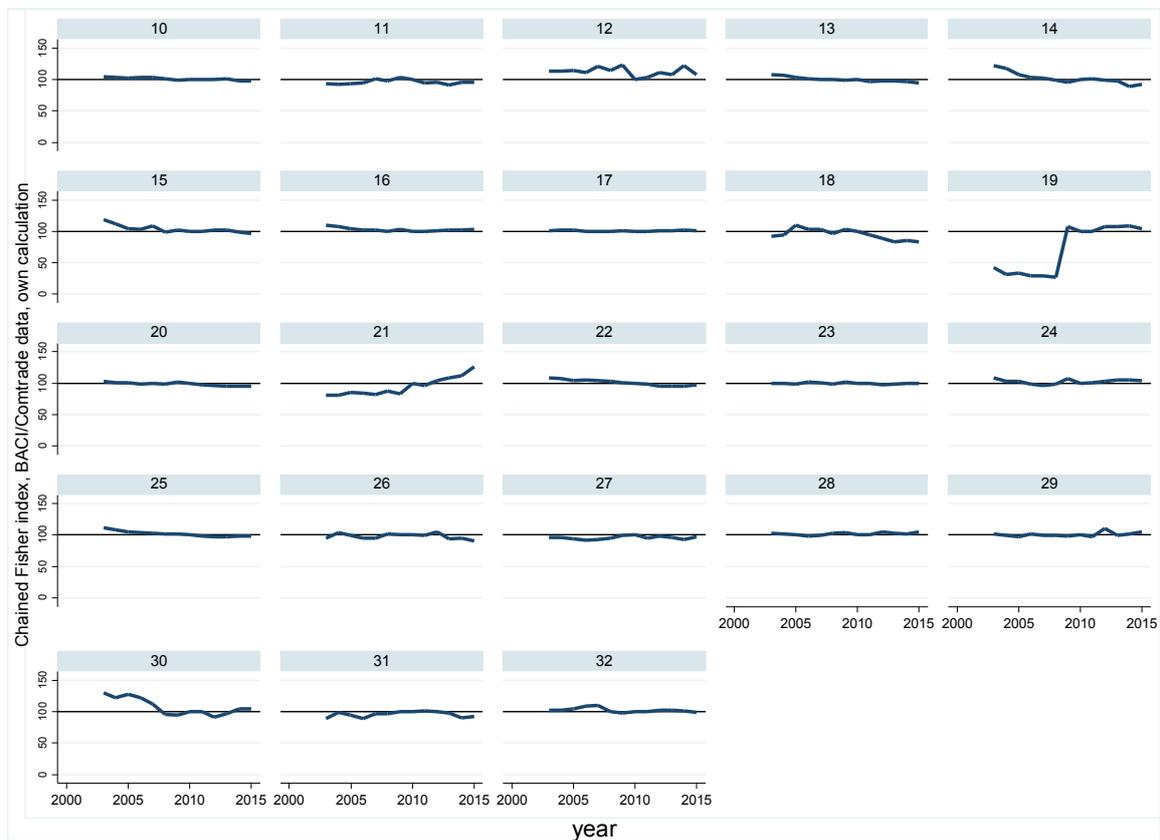
Note: Based on chained Fisher import and export unit value indices. Base year 2010.
 Source: Eurostat, International Trade in Goods Statistics, OECD: "National Accounts at a Glance", *OECD National Accounts Statistics* (database). doi: <http://dx.doi.org/10.1787/data-00369-en> (Accessed on 6 June 2017).

Relying exclusively on customs data it is possible to calculate also sector level terms of trade. These data are typically not available from statistical offices or international organisations as discussed earlier. Figure 4-30 and Figure 4-31 show the example of the sector level terms of trade as well as the import and export unit value price indices for the German manufacturing sector (NACE Rev.2 code 10 through 32) respectively. As can be seen the figure shows for most industries relatively stable values. For instance, in the wearing apparel industry (NACE 14) we observe a decline over time. In the pharmaceutical industry (NACE 21) instead a steep improvement has taken place. For the manufacture of transportation equipment (NACE 30) instead we observe a decline of the terms of trade during the first half of the observation period and a stabilisation from 2008 onwards.

Generally, terms of trade figures are not informative as to the causes of the observed changes. Import and export price indices must be examined more in detail. Figure 4-31 shows that the improvement of the terms of trade in the pharmaceutical industry was driven by both a decline of import unit values and an increase of export unit values. The development in the transportation equipment

industry was instead driven by a relatively faster increase in import unit values relative to export unit values with a relatively balanced development after 2008. A similar development can be observed for the wearing apparel industry.

Figure 4-30: Development of the terms of trade for the German manufacturing sector, 2003-2015.

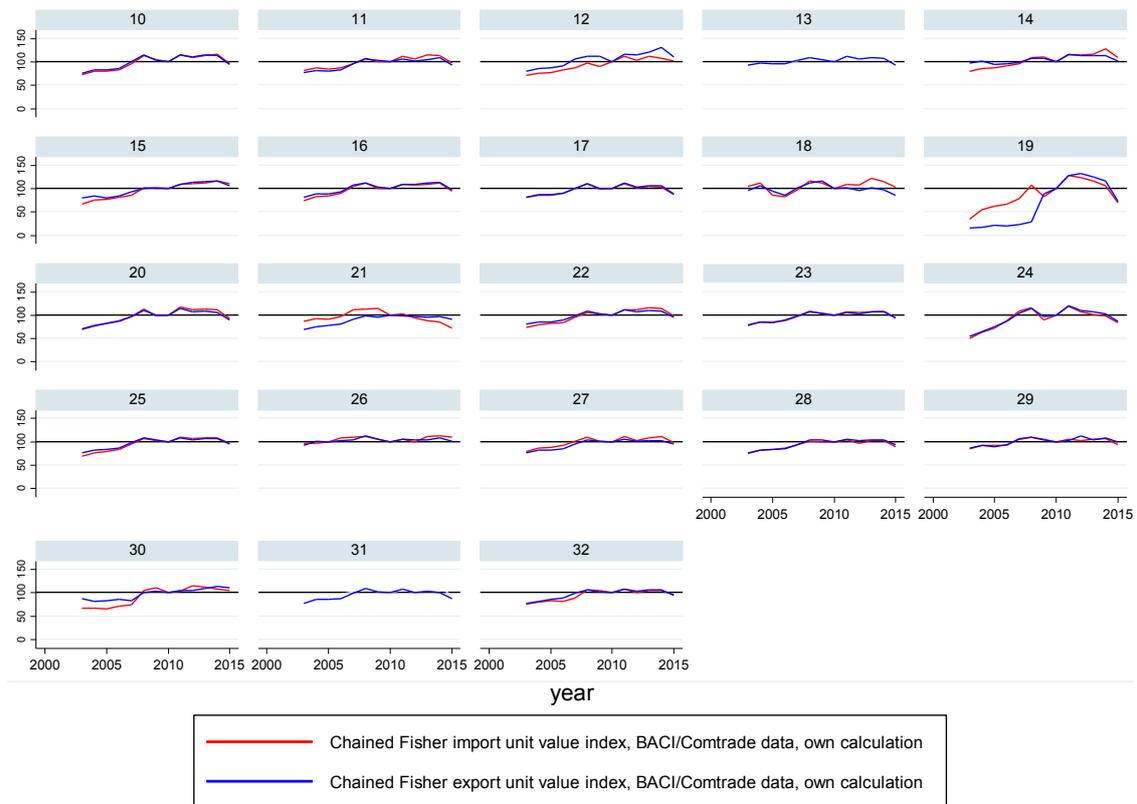


Note: Based on chained Fisher import and export unit value indices. Base year 2010.
Source: WIFO calculations; BACI data.

Developments at the sector level tend to be more volatile than aggregate, country level figures, as is evident from the data presented for instance for the coke and refined petroleum products industry (NACE 19) in Germany. For this reason, the scales of Figure 4-29 and Figure 4-30 show different ranges.

Figure 4-31 also shows that countries tend to import commodities in an industry that follow approximately similar price development patterns than the commodities they export. As argued earlier, as price indices are used that take into account substitution and composition effects, then these relative price developments of imports and exports in a sector of a country are likely to reflect the relative pace of technological upgrading in the sector between the exporting country and the countries from which it imports. However, this interpretation is valid only if at the same time we also observe a balanced or improving trade balance at the sector level, as otherwise the relative increase of export prices may reflect a lack in price competitiveness.

Figure 4-31: Development of the import and export unit value indices for the German manufacturing sector, 2003-2015.



Note: Based on chained Fisher import and export unit value indices. Numbers on top of each panel indicate Nace Rev. 2 two-digit industry codes. Base year 2010.
 Source: WIFO calculations; BACI data.

5 Conclusions

Michael Peneder and Christian Rammer

This report examined indicators for measuring competitiveness both conceptually and empirically, distinguishing three levels of analysis: micro (firm), meso (sector) and macro (economy-wide).

At the **micro** level, competitiveness usually refers to the ability of a firm to sell products in the market and earn a profit, at least in the longer term.

At the **meso** level, competitiveness is a less clear concept as it can either refer to competition between different sectors for attracting scarce resources (such as capital or labour), or to competition between sectors from different national or regional economies. The former should reflect higher growth, though a sector's growth is affected by many other factors, particularly demand. The latter is strongly related to the notion of international competitiveness at the macro level. In contrast to the macro level, a sector's productivity is a less well suited indicator since it is strongly affected by technical characteristics of production.

At the **macro** level, competitiveness refers to an economy's ability to achieve a high standard of living through the combination of income growth and qualitative change (new technologies, social and ecological transformation, etc.). In this sense, GDP per capita is the most comprehensive measure of material well-being ("the tip of the iceberg") and export competitiveness a particularly important determinant of the economy's ability to earn income and create jobs. Conversely, new concepts and measurements "beyond GDP" are needed to cover qualitative transformations towards other societal objectives.

The analysis of competitiveness indicators in this report focussed on three groups of indicators:

- **Cost-related competitiveness** indicators are linked to the ability to sell products (goods, services) in a market at a competitive price. This type of competitiveness is often also called price competitiveness, though this concept may also include some non-cost related quality aspects (ability to enforce a certain price level in the market). Key measures include input cost-related indicators (cost of production factors such as labour, capital, land; cost of intermediaries), productivity-related indicators, and a combination of both (particularly unit labour costs).
- **Innovation-related competitiveness** indicators refer to the ability to limit or avoid price competition by differentiating products in a way that they are not directly comparable to competitors' offers. The most important mechanism is to introduce new products that are superior in some respect to existing products in the market. But innovation may also relate to the way how products are

produced and delivered. Such innovation ('process innovation') can affect productivity and hence improves cost competitiveness. But it may also improve the quality of products and hence contribute to product differentiation.

- **Export competitiveness** relates to the ability to earn income from selling products abroad. This concept is related to a wider concept of external competitiveness which relates to the ability to earn income from any international transactions (e.g. including financial transactions). Export competitiveness has for long been a central part of competitiveness studies at the macro level, and a large number of indicators, mostly based on trade data, have been developed. Widely used indicators include cost and price indicators, external trade balances, export market shares and export structure. Within this dimension, the focus was exclusively on country-wide indicators. For sectoral analyses one can additionally turn to indicators of revealed comparative advantage (RCA).

Based on the conceptual considerations, underlying policy rationales and the results of our empirical analysis, the following general conclusions on the use of competitiveness measures can be made.

- First, a clear reference should be made as to the targeted **level of analysis**. Depending on the chosen level, different indicators and data will have to be used. While analyses at the meso and macro level are facilitated by comprehensive and internationally comparable time series data for a variety of indicators (particularly relating to cost and export competitiveness), no suitable micro-level data base is available that would allow analysis across countries for a larger set of relevant competitiveness indicators.
- Secondly, as competitiveness is a multi-dimensional phenomenon, a **multi-indicator approach** is needed. This particularly refers to combining indicators from different groups (cost, innovation, exports) as these groups not only reflect different aspects of competitiveness, but also a different time dimension. Whereas export-related indicators measure past performance, cost competitiveness indicators measure a current determinant and innovation-related indicators are linked to the future potential for realising competitiveness, though this potential does not necessarily have to materialise (e.g. in case R&D efforts do not result in competitive innovations).
- Thirdly, studies of competitiveness should focus on **structural and medium to long-term analyses** rather than on short-term fluctuations in indicators since the latter may be subject to business cycle effects and idiosyncratic changes. If the monitoring of short-term changes is required, such as in the context of the European Semester, these changes should always be interpreted in the context of longer-term developments.
- Fourthly, **productivity** is perhaps the single best key indicator of competitiveness at the macro level and for structural and long-term analysis. For this purpose, it is also a useful indicator at the meso and micro level. For short-term analysis, productivity is a less suitable indicator owing to its dependence on business cycle

fluctuations. As productivity measures have different limitations, a combination of various indicators (such as labour productivity complemented by TFP/MFP) is advisable. In addition to standard economic measures based on the concept of value added and contributions from the various production factors, other societal objectives (beyond GDP) should also be taken into account, though no standard set of indicators has been developed yet and a further discussion has been beyond the scope of this study.

Based on these conclusions, a set of indicators can be proposed for investigating competitiveness at different levels of analysis. Table 5-1 summarises those indicators that best meet the three key criteria of indicator selection: based on a sound economic concept, being empirical valid (i.e. accurately measuring the underlying concept), and showing a sufficient level of data quality.

Table 5-1: Useful indicators by area of competitiveness and level of analysis

Indicator	Level
Cost-related competitiveness	
Unit labour cost	sector, firm
Quality index	sector
Selling capacity	sector
Equilibrium wage index	economy, sector
Innovation-related competitiveness	
R&D expenditure per GDP	economy
R&D personnel per number of employed persons	sector, firm
R&D expenditure per sales	firm
Patent applications per GDP	economy
Patent applications per number of employed persons	sector (manufacturing), firm
Share of innovating firms	economy, sector
Share of sales from product innovation	economy, sector, firm
Export-related competitiveness	
Real effective exchange rates (REER) based on GDP deflator	economy
Trade balance	economy, sector
Revealed comparative advantage (RCA)	sector
Export market share	economy, sector
Exports as a share of total sales	firm
Export diversity	economy
Export share of advanced products	economy
Comprehensive indicators of competitiveness	
GDP per capita	economy
Labour productivity	economy, sector, firm
Multi factor productivity / total factor productivity	economy, sector, firm
Market share	firm
Profitability	firm

It is important to note that many indicators are not useful for all levels of analysis. In addition, many of the listed indicators are still subject to some data concerns and need to be interpreted with caution particularly when looking at short-term changes.

6 References

- Ackerberg, D.A., Caves, K., Frazer, G. (2015), Identification properties of recent production function estimators, *Econometrica* 83(6), 2411-2451.
- Aghion, P., Howitt, P. (2009), *The Economics of Growth*, Cambridge: MIT Press.
- Altomonte, C., Bekés, G. (eds.) (2016), *Measuring Competitiveness in Europe: Resource Allocation, Granularity and Trade*, Bruegel Blueprint Series, Brussels.
- Altomonte, C., Osbat, C. (2013). *Going beyond labour costs: How and why "structural" and micro-based factors can help explaining export performance?* Compnet Policy Brief 01/2013. Frankfurt: European Central Bank.
- Arellano, M., Bond, S. (1991), Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, *Review of Economic Studies* 58, 277-297.
- Arundel, A. (2001), The relative effectiveness of patents and secrecy for appropriation, *Research Policy* 30(4), 611-624.
- Barney, J. (1991), Firm resources and sustained competitive advantage, *Journal of Management* 17(1), 99-120.
- Barney, J., Hesterly, W.S. (2006), *Strategic Management and Competitive Advantage. Concepts*, 2nd Edition. New Jersey: Prentice Hall.
- Bartelsman, E., Haltiwanger, J., Scarpetta, S. (2009), Measuring and analyzing cross-country differences in firm dynamics, in: Dunne, T., Jensen, J.B., Roberts, M.J. (eds.), *Producer Dynamics: New Evidence from Micro Data*, Chicago: University of Chicago Press, 15-76.
- Bartlett, C.A., Ghoshal, S. (1990), Managing innovation in the transnational corporation, in: Bartlett, C., Doz, Y., Hedlund, G. (eds.), *Managing the Global Firm*, London: Routledge, 215-255.
- Beise, M. (2004), Lead markets: country-specific drivers of the global diffusion of innovations, *Research Policy* 33, 997-1018.
- Benkovskis, K., Wörz, J. (2014), *What Drives Market Share Changes? Price versus Non-Price Factors*, Working Paper No. 1640, Frankfurt: European Central Bank.
- Berlingieri, G., Blanchenay, P., Calligaris, S., Criscuolo, C. (2017), *The Multiprod project: a comprehensive overview*, Paris: OECD.
- Biatour, B., Dumont, M., & Kegels, C. (2011), *The determinants of industry-level total factor productivity in Belgium*. Federal Planning Bureau, Working Paper, 7-11.
- Black, S.E., Lynch, L.M. (2001), Measuring organizational capital in the New Economy, in: Corrado, C., Haltiwanger, J., Sichel, D. (eds.), *Measuring Capital in the New Economy*, Studies in Income and Wealth, Vol. 65. Chicago: The University of Chicago Press, 205-236.
- Blanchard, O.J., Fisher, S. (1993), *Lectures on Macroeconomics*, MIT Press, Cambridge MA.
- Bloom, N., Van Reenen, J. (2007), Measuring and explaining management practices across countries, *The Quarterly Journal of Economics* 122, 1351-1408.
- Bloom, N., Van Reenen, J. (2010), Why do management practices differ across firms and countries? *Journal of Economic Perspectives* 24, 203-224.

- Blundell, R., Bond, S. (2000), GMM estimation with persistent panel data: an application to production functions, *Econometric Reviews* 19, 321-340.
- Breuss, F. (2006), *Monetäre Außenwirtschaft und Europäische Integration*, PeterLang Europäischer Verlag für Wissenschaften, Frankfurt am Main.
- Buckley, P.J., Pass, C.L., Prescott, K. (1988), Measures of international competitiveness: a critical survey, *Journal of Marketing Management* 4(2), 175-200.
- Bureau of Labor Statistics (2012), *International Comparisons of manufacturing productivity and unit labor costs trends*. Geneva: International Labour Organization.
- Cable, J.R., Mueller, D.C. (2008), Testing for persistence of profits' differences across firms, *International Journal of the Economics of Business* 15, 201-228.
- Cárdenas Rodríguez, M., Hašič, I., Shier, M. (2016), Environmentally Adjusted Multifactor Productivity: Methodology and Empirical Results for OECD and G20 Countries, *OECD Green Growth Papers*, No. 2016/04, OECD Publishing, Paris.
- Cassiman, B., Veugelers, R. (2006), In search of complementarity in innovation strategy: internal R&D and external knowledge acquisition, *Management Science* 52(1), 68-82.
- Castellani, D., Koch, A. (2015), *Mapping competitiveness with European data*. Bruegel Blueprint Series, Brussels: Bruegel.
- Cattell, K., Flanagan, R., Jewell, C.A. (2004), Competitiveness and productivity in the construction industry: the importance of definitions. In: Root (ed.), *Proceedings of the Construction Industry Development Board (CIDB) 2nd Conference*, Cape Town: Construction Industry Development Board, 25-35.
- Caves D.W., Christensen L.R., Diewert W.E. (1982), Multilateral comparisons of output, input, and productivity using superlative index numbers, *Economic Journal* 92(365), 73-86.
- Chinn, M.D. (2006), A Primer on Real Effective Exchange Rates: Determinants, Overvaluation, Trade Flows and Competitive Devaluation, *Open Economies Review* 17(1), 115-143.
- Cieslik, A. (2005), Intraindustry trade and relative factor endowments. *Review of International Economics* 13, 904-926.
- Cobbold, T. (2003), *A Comparison of Gross Output and Value-added Methods of Productivity Estimation*. Research Memorandum Cat No: GA511, Australian Government Productivity Commission.
- Coe, D.T., Helpman, E. (1995), International R&D spillovers, *European Economic Review* 39(5), 859-887.
- Cohen, S.S. (1994), Speaking freely, *Foreign Affairs* 73(4), 194-197.
- Cohen, W.M., Levinthal, D.A. (1990), Absorptive Capacity: A New Perspective on Learning and Innovation, *Administrative Science Quarterly* 35(1), 128-152.
- Collignon, S., Esposito, P. (2017), *Measuring European Competitiveness at the Sectoral Level*, ETUI report new 25, Brussels: ETUI.
- Corrado, C., Hulten, C., Sichel, D. (2005), Measuring capital and technology: an expanded framework, in: Corrado, C., Haltiwanger, J., Sichel, D. (eds.), *Measuring Capital in the New Economy*, Chicago: University of Chicago Press, 11-46.
- Crass, D., Garcia Valero, F., Pitton, F., Rammer, C. (2016), *Protecting Innovation through Patents and Trade Secrets: Determinants and Performance Impacts for Firms with a Single Innovation*, ZEW Discussion Paper No. 16-061, Mannheim.

- Dachs, B., Hud, M., Köhler, C., Peters, B. (2016), *Employment Effects of Innovations over the Business Cycle: Firm-Level Evidence from European Countries*, ZEW Discussion Paper No. 16-076, Mannheim: Centre for European Economic Research.
- Dachs, B., Hud, M., Köhler, C., Peters, B. (2017), Innovation, Creative Destruction, Structural Change: Firm-level Evidence from European Countries, *Industry and Innovation* 2(4), 346-381.
- DC (2001), *Destination Competitiveness: Development of a Model with Application to Australia and the Republic of Korea*, An Australian Government Report.
- D'Cruz, J.R. (1992), *New Compacts for Canadian Competitiveness*. DIANE Publishing.
- de Jong, J.P.J., den Hartog, D.N. (2007), How leaders influence employees innovative behaviour, *European Journal of Innovation Management* 10, 41-64.
- Debaere, P. (2005), Monopolistic competition in trade revisited: Testing the model without testing for gravity, *Journal of International Economics* 66, 249-266.
- Denicolò, V. (1996), Patent races and optimal patent breadth and length, *Journal of Industrial Economics* 44, 249-265.
- Department of Trade and Industry (1994), *Competitiveness*, White Paper, Cm 2867, London: HMSO.
- Di Comite, F. (2012). *Measuring quality and non-cost competitiveness at a country-product level* (No. 467). Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.
- Dietzenbacher, E., Los, B., Stehrer, R., Timmer, M.P., de Vries, G. (2013), The construction of World Input-Output Tables in the WIOD project, *Economic Systems Research* 25, 71-98.
- Diewert, W.E. (1976), Exact and superlative index numbers, *Journal of Econometrics* 4, 115-146.
- Egger, P., Wolfmayr, Y. (2017), International Trade Data and Empirical Patterns, in: Bloningen B., Wilson, W. (eds.), *Handbook of International Trade and Transportation* (forthcoming).
- European Commission (1998), *The Competitiveness of European Industry: 1998 Report*, European Communities, Luxembourg.
- European Commission (2004), *Differences between Balance of Payments and Foreign Trade Statistics*, Working Papers and Studies, European Communities, Luxembourg.
- European Commission (2012), *Scoreboard for the Surveillance of Macroeconomic Imbalances*, European Economy Occasional Papers 92, European Union, Brussels.
- European Commission (2014), *Energy Costs and Competitiveness*. Available at http://ec.europa.eu/economy_finance/publications/european_economy/2014/pdf/e1_1_en.pdf (last accessed June 20, 2017).
- European Commission (2016), *The Macroeconomic Imbalance Procedure. Rationale, Process, Application: A Compendium*, European Union, Brussels.
- Eurostat (2013), *European System of Accounts: ESA 2010*, Luxembourg: Publications Office of the European Union.
- Fagerberg, J. (1988), International competitiveness, *The Economic Journal* 98, 355-374.
- Fagerberg, J. (1996), Technology and competitiveness, *Oxford Review of Economic Policy* 12(3), 39-51.

- Feenstra, R.C. (1997), *U.S. exports, 1972-1994: With State exports and other U.S. data*, NBER Working Papers 5990.
- Feenstra, R.C. (2004), *Advanced International Trade: Theory and Evidence*, Princeton University Press.
- Feenstra, R.C., Hanson, G. (1996), Globalization, outsourcing, and wage inequality, *American Economic Review* 86 (2), 240-245.
- Flanagan, R., Lu, W., Shen, L., Jewell, C. (2007), Competitiveness in construction: a critical review of research, *Construction Management and Economics* 25(9), 989-1000.
- Fleck, S.E. (2009), International comparisons of hours worked: an assessment of the statistics. *Monthly Labour Review* 132, 3.
- Foster-McGregor, N., Stehrer, R. (2013), Value added content of trade: a comprehensive approach, *Economic Letters* 120, 354-357.
- Fraunhofer-ISI (2015), *Electricity Costs of Energy-Intensive Industries. An International Comparison*, Karlsruhe: Fraunhofer Institute for Systems and Innovation Research, http://www.isi.fraunhofer.de/isi-wAssets/docs/x/de/projekte/Strompreiswirkung_330639/Industriestrompreise_englisch.pdf (last accessed June 20, 2017).
- Furman, J.L., Porter, M.E., Scott, S. (2002), The determinants of national innovative capacity, *Research Policy* 31, 899-933.
- Gambardella, A., Harhoff, D., Verspagen, B. (2008), The value of European patents, *European Management Review* 5, 69-84.
- Gaulier, G., Zignago, S. (2010), *BACI: International Trade Database at the Product Level. The 1994-2007 Version*, Document de Travail No 23, CEPIL, Paris.
- Graham, J.R., Harvey, C.R., Popadak, J., Rajgopal, S. (2017), *Corporate Culture: Evidence from the Field*, Discussion Paper, Duke University.
- Grant, R.M. (2013), *Contemporary Strategy Analysis*, 8th edition. London: Wiley.
- Griliches, Z. (1990), Patent statistics as economic indicators: a survey, *Journal of Economic Literature* 28, 1661-1707.
- Griliches, Z. (1992), The search for R&D spillovers, *Scandinavian Journal of Economics* 94, 29-47.
- Griliches, Z. (1998), *R&D and Productivity. The Econometric Evidence*, Chicago: University of Chicago Press.
- Grubel, H.G., Lloyd, P.J. (1971), The Empirical Measurement of Intra-Industry Trade, *Economic Record* 47(4), 494-517.
- Hall, B.H., Harhoff, D. (2012), Recent research on the economics of patents, *Annual Review of Economics* 4, 541-565.
- Hall, B.H., Helmers, C., Rogers, M., Sena, V. (2014), The choice between formal and informal intellectual property: a review, *Journal of Economic Literature* 52(2), 1-50.
- Hamel, G., Prahalad, C.K. (1994), *Competing for the Future*, Boston: Harvard Business Books.
- Harrison, R., Jaumandreu, J., Mairesse, J., Peters, B. (2014), Does Innovation Stimulate Employment? A Firm-Level Analysis Using Comparable Micro Data from Four European Countries, *International Journal of Industrial Organization* 36, 29-43.
- Helfat, C., Martin, J.A. (2015), Dynamic Managerial Capabilities. Review and Assessment of Managerial Impact on Strategic Change, *Journal of Management* 41(5), 1281-1312.

- Helfat, C.E., Finkelstein, S., Mitchell, W., Peteraf, M.A., Singh, H., Teece, D.J., Winter, S.G. (2007), *Dynamic Capabilities: Understanding Strategic Change in Organizations*. London: Blackwell.
- Helpman, E. (1987), Imperfect competition and international trade: Evidence from fourteen industrial countries. *Journal of the Japanese and International Economies* 1, 62-81.
- Hoskens, M., Delanote, J., Debackere, K., Verheyden, L. (2016), *State of the art insights in capturing, measuring and reporting firm-level innovation indicators*, OECD Blue Sky Forum on Science and Innovation Indicators, Ghent (Belgium), 19-21 September 2016.
- Hummels, D., Ishi, J., Yi, K.M. (2001), The nature and growth of vertical specialization in world trade, *Journal of International Economics* 45, 75-96.
- Hussinger, K. (2006), Is silence golden? Patents versus secrecy at the firm level, *Economics of Innovation and New Technology* 15(8), 735–752.
- IMD (2004), *World Competitiveness Yearbook 2003*, Lausanne: IMD.
- International Energy Agency (2016), *Key World Energy Statistics*. Available at <https://www.iea.org/statistics/relateddatabases/worldenergystatistics/> (last accessed June 20, 2017).
- International Monetary Fund (2009), *Export and Import Price Index Manual: Theory and Practice*. International Labour Organization, International Monetary Fund, Organisation for Economic Co-operation and Development, Statistical Office of the European Communities (Eurostat), United Nations Economic Commission for Europe, World Bank, Washington.
- Janger, J., Schubert, T., Andries, P., Rammer, C., Hoskens, M. (2017), The EU 2020 innovation indicator: A step forward in measuring innovation outputs and outcomes? *Research Policy* 46 (1), 30-42.
- Jensen, P.H., Webster, E. (2004), *Examining Biases in Measures of Firm Innovation*, Intellectual Property Research Institute of Australia Working Paper No. 05/04, Melbourne.
- Jones, C.I., Klenow, P.J. (2016), Beyond GDP? Welfare across countries and time, *American Economic Review* 106(9), 2426-2457.
- Klepper, S. (1996), Entry, exit, growth, and innovation over the product life cycle, *American Economic Review* 86(3), 562-583.
- Klingebiel, R., Rammer, C. (2014), Resource allocation strategy for innovation portfolio management, *Strategic Management Journal* 35(2), 246-268.
- Köhler-Töglhofer, W., Url, T., Glauning, U. (2017), Price/cost competitiveness of the Austrian economy comparatively stable over the longer horizon, *Monetary Policy and the Economy* (forthcoming).
- Krugman, P. (1994), Competitiveness: A dangerous obsession, *Foreign Affairs* 73(2), 28-44.
- Krugman, P. (1996), Making Sense of the Competitiveness Debate, *Oxford Review of Economic Policy* 12(3), 17-25.
- Lawrence, R.Z. (2002), *Competitiveness*, Liberty Fund: www.econlib.org/library/Enc1/Competitiveness.html.
- Leiponen, A., Helfat, C. (2011), Location, Decentralization, and Knowledge Sources for Innovation, *Organization Science* 22(3), 641-658.

- Levinsohn, J., Petrin, A. (2003), Estimating production functions using inputs to control for unobservables, *Review of Economic Studies* 70, 317-342.
- Lu, W., Shen, L., Yam, M.C. (2008), Critical success factors for competitiveness of contractors: China study, *Journal of Construction Engineering and Management* 134(12), 972-982.
- Mann, C. (1999), *Is the U.S. Trade Deficit Sustainable?* Institute for International Economics, Washington.
- Mann, C. (2002), Perspectives on the U.S. Current Account Deficit and Sustainability, *Journal of Economic Perspectives* 16(3), 131-152.
- Marschak, J., Andrews, W.H. (1944), Random simultaneous equations and the theory of production, *Econometrica* 12, 143-205.
- Mehrez, G., Vilaseca, L.F., Monteagudo, J. (2014), A Competitiveness Measure Based on Sector Unit Labour Costs, in: European Commission (ed.), *Quarterly Report on the Euro Area* 13(2), Section II.3, 34-40.
- Mohnen, P., Hall, B.H. (2013), Innovation and productivity: an update, *Eurasian Business Review* 3, 47-65.
- Momaya, K. (1998), Evaluating international competitiveness at the industry level, *Vikalpa* 23(2), 39-46.
- OECD (1992), *Technology and the Economy: The Key Relationships*, Paris: Organization for Economic Co-operation and Development.
- OECD (2001), *OECD Productivity Manual: A Guide to the Measurement of Industry-Level and Aggregate Productivity Growth*, OECD, Paris, March 2001, Annex 1 – Glossary.
- OECD (2007), *OECD System of Unit Labour Cost Indicators*, OECD, Paris.
- OECD (2015), *Frascati Manual: Proposed Standard Practice for Surveys on Research and Experimental Development*, 6th edition, Paris: OECD Publishing.
- OECD (2017a), *Import content of exports* (indicator), doi: 10.1787/5834f58a-en.
- OECD (2017b), *OECD compendium of productivity indicators 2017*, OECD, Paris.
- Olley, S., Pakes, A. (1996), The dynamics of productivity in telecommunications equipment industry, *Econometrica* 64, 1263-1295.
- Patel, P., Pavitt, K. (1987), The elements of British technological competitiveness, *National Institute Economic Review* 122(1), 72-83.
- Pavitt, K. (1984), Sectoral patterns of technical change: towards a taxonomy and a theory, *Research Policy* 13(6), 343-373.
- Peneder, M. (2002), Intangible investment and human resources, *Journal of Evolutionary Economics* 12(1-2), 107-134.
- Peneder, M. (2005), Creating industry classifications by statistical cluster analysis, *Estudios de Economica Aplicada* 23(2), 451-463.
- Peneder, M. (2017), Competitiveness and industrial policy: from rationalities of failure towards the ability to evolve, *Cambridge Journal of Economics* 41, 829-858.
- Peteraf, M.A. (1993), The cornerstone of competitive advantage: a resource-based view, *Strategic Management Journal* 14, 179-191.
- Porter, M. (1990), *The Competitive Advantage of Nations*, New York: The Free Press.
- Prahalad, C.K., Hamel, G. (1990), The core competence of the corporation. *Harvard Business Review* 68(3), 79-91.

- Prebisch, R. (1950), *The Economic Development of Latin America and its Principal Problems*. Economic Commission for Latin America, United Nations, Department of Economic Affairs, New York: Lake Success.
- Prestowitz, C.V. (1994), Playing to win, *Foreign Affairs* 73(4), 186-189.
- Reinstaller, A., Hölzl, W., Kutsam, J., Schmid, C. (2012), *The Development of Productive Structures of EU Member States and Their International Competitiveness*, report to the European Commission (Framework Contract No. ENTR/2009/033)
- Schmoch, U., Gauch, S. (2009), Service marks as indicators for innovation in knowledge-based services, *Research Evaluation* 18, 323-335.
- Schmoch, U., Laville, F., Patel, P., Frietsch, R. (2003), *Linking Technology Areas to Industrial Sectors*, Final Report to the European Commission, DG Research, Karlsruhe, Paris, Brighton: Fraunhofer-ISI, OST, SPRU.
- Schumpeter, J.A. (1934), *The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle*, New Brunswick: Transaction Books.
- Schwab, K. (2015), *The Global Competitiveness Report 2015-2016*. Geneva: World Economic Forum.
- Shannon, C. (1948), A Mathematical Theory of Communication, *Bell System Technical Journal* 27(3), 379-423.
- Shapiro, C. (1985), Patent licensing and R & D rivalry, *American Economic Review* 75, 25-30
- Shepherd, W.G. (1972), The elements of market structure, *Review of Economics and Statistics* 54, 25-37.
- Silver, M. (2007), *Do unit value export, import, and terms of trade indices represent or misrepresent price indices?* IMF Working Paper WP/07/121.
- Singer, H.W. (1950), 'The distribution of gains between investing and borrowing countries'. *American Economic Review* 40, 473-485.
- Stehrer, R., Leitner, S., Marcias, M., Mirza, D., Stöllinger, R. (2015), *The Future Development of EU industry in a Global Context*, report to the European Commission (Framework Contract No. ENTR/300/PP/FC-WIFO).
- Susanto, B., Pascali, L., Schiantarelli, F., Serven, L. (2014), *Productivity and the Welfare of Nations*, NBER Working Paper 17971.
- Syverson, C. (2011), What determines productivity? *Journal of Economic Literature* 49(2), 326-365.
- Teece, D.J. (1998), Capturing value from knowledge assets: the new economy, markets for know-how, and intangible assets, *California Management Review* 40, 55-79.
- Teece, D.J., Pisano, G. (1994), The dynamic capabilities of firms: an introduction, *Industrial and Corporate Change* 3, 537-556.
- Ten Raa, T., Shestalova, V. (2011), The Solow residual, Domar aggregation, and inefficiency: a synthesis of TFP measures, *Journal of Productivity Analysis* 36(1), 71-77.
- Thurow, L.C. (1994), Microchips, not potato chips, *Foreign Affairs* 73(4), 189-192.
- Tidd, J., Bessant, J. (2013), *Managing Innovation: Integrating Technological, Market and Organizational Change*, 5th edition. London: Wiley.

- Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R., de Vries, G.J. (2015), An illustrated user guide to the World Input-Output Database: the case of global automotive production, *Review of International Economics* 23, 575-605.
- UN-WTO (2012), *A practical guide to trade policy analysis*, WTO publications, Geneva: United Nations and World Trade Organization.
- Vandenbussche, H. (2014), *Quality in Exports*, European Economy – Economic Papers 528, European Union, Brussels.
- Vives, X. (2008), Innovation and competitive pressure, *Journal of Industrial Economics* 56(3), 419-469.
- Vondra, K. (2017), *Export Market Shares – a Trivial Concept?* FIW Working Paper 177, Vienna: Research Centre International Economics, WIFO.
- Wilkinson, L., Friendly, M. (2009), The History of the Cluster Heat Map, *The American Statistician* 63(2), 179-184.
- Wooldridge, J. (2009), On estimating firm-level production functions using proxy variables to control for unobservables, *Economic Letters* 104(3), 112-114.
- World Economic Forum (2016), *Global Competitiveness Report 2016-2017*, Geneva: WEF.

7 Appendix A: Indicator Sheets for Selected Competitiveness Indicators

Niklas Dür, Michael Peneder and Christian Rammer

7.1 Cost Competitiveness

Unit Labour Costs (ULC)	
Area	Cost Competitiveness
1. Data	
Definition	Personnel Costs / GVA_t Personnel Costs: Personnel costs are defined as the total remuneration, in cash or in kind, payable by an employer to an employee (regular and temporary employees as well as home workers) in return for work done by the latter during the reference period. Personnel costs also include taxes and employees' social security contributions retained by the unit as well as the employer's compulsory and voluntary social contributions. Personnel costs are made up of wages and salaries and employers' social security costs GVA_t : Value added at factor costs is the gross income from operating activities after adjusting for operating subsidies and indirect taxes. Value adjustments (such as depreciation) are not subtracted.
Sources	EU: Eurostat for NACE two digit codes AMECO for NACE one digit codes and country-wide
Data collection	Download from http://ec.europa.eu/eurostat/data/database resp. http://ec.europa.eu/economy_finance/ameco/user/serie/SelectSerie.cfm
Timeliness	Data are collected for every year, data publication about two years after the end of the reference year.
Country coverage	AMECO: EU Member States plus AL, AU, CA, IS, JP, KR, MK, MX, ME, NZ, NO, RS, CH, TK, US Eurostat: EU Member States plus BA, MK, NO, CH, TK
Levels	Eurostat: Sector level: Two-digit-NACE Codes for divisions from sections B, C, D, E, F,G, H, J, L, M, N, S AMECO: sectors C, F, H and economy-wide
2. Conceptual Assessment	
Theoretical background	Lower personnel costs allow firms to produce at lower costs and therefore they can sell and export at a lower final price. Nevertheless, many countries with high labour costs are very successful in economic terms because they compensate high wages with very productive work. ULC allow to compare the personnel costs in a sector or across countries while taking the productivity of workers into account.
Policy relevance	If a policy maker observes that his country has high ULC, he or she might want to consider policy measures that stimulate productivity. It is also an option to tackle the personnel costs which companies have to pay, for instance by reducing ancillary wage costs.
Caveats	a) At the macro level, ULC cover only labour earnings and no other

	<p>components that also lead to added value. In addition, an aggregation bias is likely to occur if firms have heterogeneous ULC. This aggregation bias affects the capability of standard aggregate cost measures to predict export success.</p> <p>b) At the micro level, differences in firm quality that are not reflected by added value may create a bias. As ULC is a compounded measure, caveats of the compounds are often kept when using ULC.</p> <p>c) A major drawback of ULC indices is that they ignore intra-sectoral quality heterogeneity, i.e. differences in quality of the products across countries. However, in reality for most products the concept of monopolistic competition between countries is more appropriate. A further problem when inferring competitiveness trends from ULC indices is that the choice of the benchmark year may affect the interpretation substantially as it assumes that in an arbitrary chosen base year all countries start from supposedly equal conditions. Thus, it is ignored that substantial disequilibria may exist at the moment when the index starts, so that the future evolution might reflect the adjustment of levels toward the equilibrium.</p>
3. Data Assessment	
Stability over time	ULC is the second least stable indicator over time.
Rank stability	ULC is the second least stable indicator over time in terms of ranks as well.
Country size impacts	No specific country-size effects are known that would affect indicator values systematically.
Data quality issues	Generally, personnel cost and GVA are reliable and well established measures. However, if GVA are negative ULC becomes obsolete.

Export Prices	
Area	Cost Competitiveness
1. Data	
Definition	Export Value / Export quantity Export price: The export price is the export value divided by the export quantity. Exports of goods from a given Member State include goods destined for another Member State which are in free circulation; or have been placed in the given Member State, under the customs procedures for inward processing or, until April 2016, for processing under customs control.
Sources	AMECO for NACE one digit codes and country-wide COMEXT Database for export value and quantity.
Data collection	Download from http://epp.eurostat.ec.europa.eu/newxtweb/ resp. http://ec.europa.eu/economy_finance/ameco/user/serie/SelectSerie.cfm
Timeliness	Data are collected for every year, data publication about two years after the end of the reference year.
Country coverage	AMECO: EU Member States plus AL, AU, CA, IS, JP, KR, MK, MX, ME, NZ, NO, RS, CH, TK, US COMEXT: EU Member States plus BA, MK, ME, NO, IS, TK
Levels	Sector level: Eight-digit-NACE Codes for divisions in section C
2. Conceptual Assessment	
Theoretical background	At first glance, export prices may seem as a natural choice to measure competitiveness, as they show at which price a product can finally be exported. A high export price in combination with a high export quantity is likely to signal a high product quality.
Policy relevance	Export prices should be interpreted with caution due to the following caveats. Since different reasons may explain high or low export prices they should be considered in combination with other indicators.
Caveats	a) Due to fluctuations in commodity prices and changes in the composition of trade, export prices have a high volatility. b) Export prices are only available for goods which sell successfully in international markets. Ignoring non-exported goods creates a selection bias. c) It is not clear whether high export prices are a sign of too high costs or just good quality. d) As export prices are measured per kg, they are not available for services.
3. Data Assessment	
Stability over time	Export price is the third most stable indicator over time.
Rank stability	Export price is the third most stable indicator over time also in ranks.
Country size impacts	For countries which export more, the measure is more stable compared to smaller countries with less exports. These little exports in smaller countries could skew the measure. An example is Malta which exports only very limited numbers of products.
Data quality issues	The two parts of export prices export value and export quantity are reliable measures, so that the indicator itself should also be reliable.

Physical Unit Labour Costs (PULC)	
Area	Cost Competitiveness
1. Data	
Definition	ULC*Export price ULC: see above Export price: see above
Sources	Eurostat or AMECO for ULC (see above), COMEXT Database for export prices.
Data collection	Download from http://ec.europa.eu/eurostat/data/database resp. http://ec.europa.eu/economy_finance/ameco/user/serie/SelectSerie.cfm and http://epp.eurostat.ec.europa.eu/newxtweb/
Timeliness	Data are collected for every year, data publication about two years after the end of the reference year.
Country coverage	AMECO: EU Member States plus AL, AU, CA, IS, JP, KR, MK, MX, ME, NZ, NO, RS, CH, TK, US COMEXT: EU Member States plus BA, MK, ME, NO, IS, TK
Levels	Sector level: Two-digit-NACE Codes for divisions for section C
2. Conceptual Assessment	
Theoretical background	PULC combine the information from ULC and export prices. Since they have a measurement unit (Euro or US-\$ per kg) they can get interpreted more directly than ULC.
Policy relevance	It is difficult to derive policy conclusions only from looking at PULC. For instance, high PULC could indicate that labour costs and export prices are high. However, this could be just due to a concentration on high-quality products which are also more costly to produce as high-skilled workers are needed. In turn, low PULC could signal low costs and thus a good competitiveness, but it may also reflect that only a low quality is produced.
Caveats	a) Since PULC is a compounded measure, the caveats from both compounds still apply. b) The composition of lighter and heavier products affects the measure.
3. Data Assessment	
Stability over time	PULC is the second most stable indicator over time behind selling capacity.
Rank stability	In terms of ranks PULC is the fourth most stable indicator over time.
Country size impacts	For countries which export more, the measure is more stable compared to smaller countries with less exports. These little exports in smaller countries could skew the measure. An example is Malta which exports only very limited numbers of products.
Data quality issues	Four different measures are needed to calculate the indicator if only one is faulty the entire measure can be misleading. Also if GVA is negative, the PULC become obsolete.

Labour Productivity	
Area	Cost Competitiveness
1. Data	
Definition	GVA/Number of employees, or GVA/hours worked GVA: Value added at factor costs is the gross income from operating activities after adjusting for operating subsidies and indirect taxes. Value adjustments (such as depreciation) are not subtracted. Number of employees: Number of employees is defined as those persons who work for an employer and who have a contract of employment and receive compensation in the form of wages, salaries, fees, gratuities, piecework pay or remuneration in kind. A worker from an employment agency is considered to be an employee of that temporary employment agency and not of the unit (customer) in which they work.
Sources	Eurostat for GVA and number of employees OECD Stan Database for hours worked
Data collection	Download from http://ec.europa.eu/eurostat/data/database resp. https://stats.oecd.org/Index.aspx?DataSetCode=STAN08BIS
Timeliness	Data are collected for every year, data publication about two years after the end of the reference year.
Country coverage	Eurostat: EU Member States plus BA, MK, NO, CH, TK OECD Stan: AU, AT, BE, CA, CL, CZ, DK, EE, FI, FR, DE, GR, HU, IS, IE, IL, IT, JP, KO, LT, LU, LV, MX, NL, NZ, NO, PL, PO, SK, SL, ES, SE, CH, TK, UK, US
Levels	Sector level: Two-digit-NACE Codes for divisions from sections B, C, D, E, F, G, H, J, L, M, N, S
2. Conceptual Assessment	
Theoretical background	If workers are more productive, a higher output can be produced in the same amount of time. By being more productive, a country or sector can acquire a competitive advantage. Labour productivity is closely related to the wealth of a country.
Policy relevance	Policymakers who observe a low Labour productivity can attempt to improve it, for instance by investing in better education and professional training of their labour force.
Caveats	a) To measure Labour productivity, it is necessary to know the actual working time. However, actual working time is not directly observable and proxies like scheduled working hours are imperfect. Obtaining actual working hours by surveys is possible, but there might be biased answers, for instance because workers do not remember how much they worked or because they give socially adequate answers. Data on working hours often excludes some groups, for instance self-employed persons. b) Labour productivity captures only one input factor and is thus a less comprehensive indicator than total factor productivity.
3. Data Assessment	
Stability over time	Labour productivity is the least stable cost competitiveness indicator over time.
Rank stability	Labour productivity is the second most stable cost competitiveness indicator after selling capacity in terms of rank over time. Given a low stability of the index itself over time, a stable rank indicates that the different countries are

	sufficiently far away from each other so that changes in ranks are rather seldom.
Country size impacts	No specific country-size effects are known that would affect indicator values systematically.
Data quality issues	GVA can be negative in some instances and this would result in a negative Labour productivity. Apart from that GVA and number of employees are well established figures that are trustworthy.

Quality Index	
Area	Cost Competitiveness
1. Data	
Definition	Non-Cost Competitiveness measure based on Di Comite (2016) average quality level.
Sources	AMECO for NACE one digit codes and country-wide COMEXT Database for export value and quantity
Data collection	from http://ec.europa.eu/eurostat/data/database and http://ec.europa.eu/economy_finance/ameco/user/serie/SelectSerie.cfm
Timeliness	Data are collected for every year, data publication about two years after the end of the reference year.
Country coverage	AMECO: EU Member States plus AL, AU, CA, IS, JP, KR, MK, MX, ME, NZ, NO, RS, CH, TK, US COMEXT: EU Member States plus BA, MK, ME, NO, IS, TK
Levels	Sector level: Two-digit-NACE Codes for divisions for section C
2. Conceptual Assessment	
Theoretical background	This measure of quality can be seen as the intercept of the inverse demand function in the absence of competition as in reality there is always some degree of competition, this value cannot be observed directly.
Policy relevance	To look at cost competitiveness as the only competitiveness measure can be misleading as the quality of the products can be high leading to high ULC which in turn would misleadingly be interpreted as less competitive. Taking into account the quality produced can therefore be a very important complementary measure.
Caveats	The quality index is complex to calculate and costly in terms of data requirements. Furthermore, it is built upon two assumptions. The degree of substitutability must not change over time and the weighted average quality within a market must not change over time. Finally, as PULC are an important ingredient, the quality index can only be calculated for sectors where an export volume can get assessed. Accordingly, it is not suited for services.
3. Data Assessment	
Stability over time	The quality index is the fourth most stable index over time.
Rank stability	In terms of rank stability, quality index is the least stable indicator. Given medium stability in the measure itself, indicates that the different countries are close and change ranks rather often.
Country size impacts	As PULC play an important role in calculating the index it could be prone to the same country size impacts as PULC.
Data quality issues	The quality index requires a sophisticated calculation and many ingredients, this fact might make the indicator prone to errors.

Selling Capacity	
Area	Cost Competitiveness
1. Data	
Definition	Non-Cost Competitiveness measure based on Di Comite (2016) selling capacity. $1/\text{selling capacity} = \text{Export Quantity}/(\text{Export prices}-\text{PULC})$
Sources	AMECO for NACE one digit codes and country-wide COMEXT Database for export value and quantity
Data collection	from http://ec.europa.eu/eurostat/data/database and http://ec.europa.eu/economy_finance/ameco/user/serie/SelectSerie.cfm
Timeliness	Data are collected for every year, data publication about two years after the end of the reference year.
Country coverage	AMECO: EU Member States plus AL, AU, CA, IS, JP, KR, MK, MX, ME, NZ, NO, RS, CH, TK, US COMEXT: EU Member States plus BA, MK, ME, NO, IS, TK
Levels	Sector level: Two-digit-NACE Codes for divisions for section C
2. Conceptual Assessment	
Theoretical background	The selling capacity is an approach to measure the amount of goods a country was able to export to other countries at a profit maximising level of markups. In this respect, the measure captures all the characteristics of a product attributed to the capacity of exporting except for price and quality.
Policy relevance	The selling capacity measures a third dimension that contributes to competitiveness apart from price and quality. This dimension might reflect export channels, management skills or reputation. In this respect the measure can be very interesting to look at.
Caveats	As PULC are an important ingredient, the selling capacity can only be calculated for sectors where an export volume can get assessed. Accordingly, it is not suited for services.
3. Data Assessment	
Stability over time	The selling capacity is the most stable cost competitiveness indicator from the seven analysed ones.
Rank stability	The rank-stability over time is also most stable for selling capacity within the cost competitiveness indicators. This is compelling as export channels and reputation cannot easily be built within short timeframes.
Country size impacts	Country size could play a role as export channels and reputation might be more easily being built up in larger countries like Germany compared to smaller ones.
Data quality issues	As the measure builds upon several indicators it could be prone to faulty or missing data. If only one of the needed ingredients is not available it cannot get calculated.

Equilibrium Wage Index	
Area	Cost Competitiveness
1. Data	
Definition	Non-Cost Competitiveness measure based on Collignon and Esposito (2017)
Sources	AMECO for NACE one digit codes and country-wide COMEXT Database for export value and quantity
Data collection	from http://ec.europa.eu/eurostat/data/database and http://ec.europa.eu/economy_finance/ameco/user/serie/SelectSerie.cfm
Timeliness	Data are collected for every year, data publication about two years after the end of the reference year.
Country coverage	AMECO: EU Member States plus AL, AU, CA, IS, JP, KR, MK, MX, ME, NZ, NO, RS, CH, TK, US COMEXT: EU Member States plus BA, MK, ME, NO, IS, TK
Levels	Sector level: Two-digit-NACE Codes.
2. Conceptual Assessment	
Theoretical background	The measure aims to capture the difference between the actual and the nominal wage within a sector. By doing so, it is possible to judge whether wages are over- or undervalued.
Policy relevance	The information on whether prices are under- or overvalued in a sector and country could guide upcoming rounds of collective bargaining which makes the equilibrium wage index a valuable information to consider.
Caveats	The main issue for calculating the equilibrium wage index is the requirement of capital stock. This information is very difficult to get on a sector level. Therefore, many missing values occur.
3. Data Assessment	
Stability over time	The equilibrium wage index is difficult to compare with the other indicators as there are many missing values.
Rank stability	The equilibrium wage index rank is difficult to compare with the other indicators as there are many missing values.
Country size impacts	No specific country-size effects are known that would affect indicator values systematically.
Data quality issues	The weak point in this measure is that accumulated capital stock are needed which is difficult to observe and also to assess. Hence, there are many missing values associated with this measure.

7.2 Innovation-related Competitiveness

R&D expenditure as a share in value added / R&D personnel as a share in total employees	
Area	Innovation-related Competitiveness
1. Data	
Definition	RDE_t/VA_t RDP_t/TE_t RDE: expenditure for research and technological development in year t, RDE includes all in-house R&D expenditure (wages and salaries for R&D personnel, costs of purchased materials for R&D, cost of acquisition of tangible and intangible assets required for R&D). RDE may also include purchase of R&D services (extramural R&D or contracted out R&D). RDP: number of R&D personnel (usually measured in full-time equivalents - FTE) VA: value added TE: total number of employees (in FTE if R&D personnel is measured in FTE)
Sources	EU: R&D Statistics (Eurostat) Other countries: OECD (R&D statistics), UNESCO (Science, Technology and Innovation Statistics)
Data collection	Enterprise surveys (census of all R&D performing enterprises, sometimes using sample surveys for small enterprises or sectors with few R&D performing enterprises) by NSI or ONS
Timeliness	Data are collected annually for key indicators and biennial for more differentiated, data publication about two years after the end of the reference year
Country coverage	EU Member States plus all other European countries Non-Europe: most countries provide R&D data (the UNESCO database contains R&D data for 158 countries)
Levels	<ul style="list-style-type: none"> - Firm level: CIS micro data on R&D expenditure, some national R&D micro data are accessible through national data safe centres. - Sector level: All NACE sections - Economy-wide level: all enterprises
2. Conceptual Assessment	
Theoretical background	R&D can contribute to competitiveness by generating new knowledge that can be used to upgrade a firm's products and processes, leading to competitive advantages in terms of products with higher utility, more efficient processes or offerings that address needs that have not been addressed before. The role of R&D as a competitive potential is reinforced at the meso and macro levels by spillovers from R&D. As the main output of R&D is new knowledge which is difficult to exclude others from using it, R&D results can be used by others to improve their competitiveness.

Policy relevance	<p>The level of R&D expenditure is a key indicator of the Europe 2020 strategy. Higher R&D expenditure are generally regarded as transferring into higher productivity and growth, though there may be considerable time lags, and productivity gains may occur in other areas than those where R&D investment took place.</p> <p>Due to spillovers of R&D results, incentives for private actors to invest into R&D may be restricted, leading to private underinvestment in R&D (as compared to the level needed for maximising productivity gains).</p> <p>Government therefore provide incentives for business R&D or organise R&D as a state activity (e.g. through government research labs or basic funding of R&D at higher education institutions).</p>
Caveats	<p>R&D as an input indicator. The competitiveness impacts of R&D depend on the success of R&D activities. First, investment in R&D may not result in new knowledge, either because the R&D did not produce useful results, or because others arrived at useful results earlier. Secondly, even if new knowledge has been generated from R&D activities, the knowledge needs to be transferred into innovation to produce competitiveness impacts. This transfer may be impeded by several barriers, including lack of technological feasibility, changes in demand preferences and competitor actions (e.g. developing a competing innovation design earlier).</p>
3. Data Assessment	
Stability over time	<p>R&D data are rather stable over time in terms of absence of arbitrary fluctuations. Stability is higher for R&D personnel intensity than for R&D expenditure intensity.</p>
Rank stability	<p>Country rankings at the macro level are quite stable over time. At the sector level, particularly smaller countries show substantial changes in the ranks even within a shorter period of time. Rankings are more volatile for R&D intensities based on expenditure data as compared to personnel data.</p>
Country size impacts	<p>Stability of R&D data at the sector level is tends to be higher for large countries than for small countries. In small countries, R&D in many sectors may be driven by a few firms only, and idiosyncratic changes in R&D activities may affect sector totals and sometimes even country totals.</p>
Data quality issues	<p>There are no major data quality issues. R&D data are complete at the macro level while there are many missing data at the sector level.</p>

Share of Innovating Firms	
Area	Innovation-related Competitiveness
1. Data	
Definition	$INN_{jt,t-2}/FRM_t$ INN_{jt} : number of firms having introduced innovation of type j in the reference period starting in t-2 and ending in t FRM_t : total number of firms in year t The share of innovating firms may refer to different types of innovation. According to the current Oslo Manual (OECD and Eurostat, 2005), innovations include product innovation, process innovation, marketing innovation and organisational innovation. The indicator may be built by either looking at firms with any of these types of innovation, or a specific combination of. A commonly used subgroup refers to firms with either product or process innovation (previously often referred to as 'technological innovations'). The ongoing revision of the Oslo Manual, which is planned to be published in 2018, may result in a change of innovation types.
Sources	EU: Innovation Statistics (Eurostat) Other countries: various national sources
Data collection	Enterprise surveys (random sample surveys, mandatory or voluntary, conducted by NSI or ONS)
Timeliness	Data are collected biennial (for even reference years), data publication about two years after the end of the reference year
Country coverage	EU Member States plus CH, NO, IS, TK Non-Europe: several countries provide data at varying levels of comparability to EU data
Levels	<ul style="list-style-type: none"> - Firm level: CIS micro data - Sector level: NACE sections B, C, D, E, H, J, K plus divisions 46, 71, 72, 73 - Economy-wide level: enterprises with 10+ employees in the above listed sectors
2. Conceptual Assessment	
Theoretical background	The higher the number and the share of firms that engage in innovation, the more widespread and the faster new products, processes and methods will be used in an economy. Since innovations by definition represent a higher level of utility or efficiency compared to existing offerings and techniques, innovations can contribute to a competitive advantage. Whether the competitive advantage of an innovation can actually be transferred into better market performance of the innovating firm will depend on the success of the innovation.
Policy relevance	Innovations are the outcome of investment into new knowledge, including R&D. Many governments as well as the EU Commission have committed to strengthen R&D activities, with a view to reap economic benefits through developing, exploiting and diffusing innovations. A high level of innovation in an economy is hence a key policy output indicator.
Caveats	a) The competitive impact of innovations tends to vary by type of innovation. Studies on productivity and employment impacts of different types of innovation (see Harrison et al., 2008, for product and process innovation impacts, and Dachs et al., 2016, 2017, for including also organisational innovations) show that product innovation tend to have

	<p>strong positive impact both on productivity and employment. One also often finds a positive productivity impact of process innovation while the effect of organisational innovation is smaller. Employment effects of both process organisational innovation are often neutral. There is little evidence on productivity effects of marketing innovation (see Mohnen and Hall, 2013). For competitiveness analysis, a focus on product innovation and process innovation seems to be more informative than considering all types of innovation together.</p> <p>b) The share of innovating firms includes both 'real' innovators (i.e. firms introducing an innovation that has not been available on the market before) and 'imitators' (i.e. firms that adopt innovations previously introduced by others, which may be a long time ago).</p> <p>c) The indicator value is strongly driven by small firms. Changes in the indicators often reflect changes in the innovation behaviour of 'marginal' innovators, i.e. firms that stop innovating or enter into innovation while having a low level of innovation expenditure and innovations with a low level of novelty. The impact of these changes on an economy's or sector's competitiveness tend to be very limited.</p>
3. Data Assessment	
Stability over time	The variation of the indicator value at the sector level is rather low and significantly lower than for other innovation indicators. A main reason is that there are significant differences in the share of innovating firms across industries, and these differences remain rather stable over time.
Rank stability	Ranks of countries at the sector level are less stable. This is particularly true for smaller countries.
Country size impacts	No specific country-size effects are known that would affect indicator values systematically.
Data quality issues	<p>As for all CIS indicators,</p> <ul style="list-style-type: none"> - sample surveys are subject to sampling errors; - country questionnaires and surveying methods differ, limiting comparability; - type of survey (mandatory or voluntary) may have an impact on country results. <p>In addition, many firms do not record the volume of sales generated from product innovations and hence have to estimate this value.</p>

Share of Sales from Product Innovation / New-to-the Market Product Innovation	
Area	Innovation-related Competitiveness
1. Data	
Definition	SPI_t/S_t SPI _t : sales generated by product innovations in year t; product innovations are new or significantly improved products (goods or services) introduced during the t-2 and t S _t : total sales of the enterprise sector in year t As a sub-indicator, SPI may be restricted to product innovations that are new to the firm's market, hence excluding product innovations that are only new to the innovating firm and existed in the market before.
Sources	EU: Innovation Statistics (Eurostat) Other countries: various national sources
Data collection	Enterprise surveys (random sample surveys, mandatory or voluntary, conducted by NSI or ONS)
Timeliness	Data are collected biennial (for even reference years), data publication about two years after the end of the reference year
Country coverage	EU Member States plus CH, NO, IS, TK Non-Europe: several countries provide data at varying levels of comparability to EU data
Levels	<ul style="list-style-type: none"> - Firm level: CIS micro data - Sector level: NACE sections B, C, D, E, H, J, K plus divisions 46, 71, 72, 73 - Economy-wide level: enterprises with 10+ employees in the above listed sectors
2. Conceptual Assessment	
Theoretical background	Product innovation represents a main approach of product differentiation and can provide the innovator with a temporary monopoly position in the market. Innovative products typically have superior features over other products offered in the same market and may increase the competitiveness of the innovator. The actual impact of product innovation on competitiveness depends on the innovations of competitors and whether potential buyers value the features of a product innovation. The share of product innovations in total sales is a measure of the economic significance of this type of product.
Policy relevance	Product innovation has the potential to open-up new markets and generate new demand (by addressing new needs), potentially resulting in net growth and new jobs. In some circumstances, a high share of product innovations in an economy can represent an inefficient use of resources if product innovations rapidly substitute earlier product innovations ('product innovation cannibalism').
Caveats	a) The theoretical argument presented above only holds for 'real' innovations (first to market) and depends on the radicalness and disruptive nature of an innovation. Most product innovations are rather small improvements, novelties for fragmented markets (regional markets, niche markets) or imitations of other's innovations. b) Sales share of product innovation strongly depends on product life cycle length which may be driven by non-innovative factors (e.g. fashions),

	<p>though in most sectors short life cycles result from rapid technological change and are hence a sign of a high innovative activity.</p> <p>c) The sub-indicator, new-to-the-market product innovation, depends on the market definition, which is up to the innovating firm and may refer to local, regional or sectoral markets. New-to-the-market product innovation must hence not necessarily represent a higher level of novelty, e.g. if a firm acting on a local market introduces an innovation that has been introduced in other regional markets long before.</p>
3. Data Assessment	
Stability over time	There are significant fluctuations in the indicator value, The average coefficient of variation at the sector level (unweighted average of EU member states for the years 2008, 2010, 2012, 2014) is 42 and higher than for any other innovation indicator analysed in this study.
Rank stability	Ranks of countries vary considerably for considerably (and more than for other innovation indicators).
Country size impacts	No specific country-size effects are known that would affect indicator values systematically.
Data quality issues	<p>As for all CIS indicators,</p> <ul style="list-style-type: none"> - sample surveys are subject to sampling errors; - country questionnaires and surveying methods differ, limiting comparability; - type of survey (mandatory or voluntary) may have an impact on country results. <p>In addition, many firms do not record the volume of sales generated from product innovations and hence have to estimate this value.</p>

7.3 Export Competitiveness

Real effective exchange rate (REER)	
Area	Export Competitiveness
1. Data	
Definition	The index of <i>effective exchange rates</i> (EER) aggregates and weights bilateral exchange rates, typically by the relative importance of trade partners. The <i>real effective exchange rate</i> (REER) results from further deflating the EER series. Various options for deflation include the harmonised consumer price index, the GDP deflator, producer prices, export prices and unit labour costs.
Sources	For instance, Eurostat, DG ECFIN, ECB, IMF, OECD.
Data collection	See for instance Eurostat's metafile: http://ec.europa.eu/eurostat/cache/metadata/en/ert_eff_esms.htm
Timeliness	High; typically recalculated every quarter, as component series are frequently revised (see Eurostat above).
Country coverage	Generally comprehensive for exchange rates, but limited by the availability of internationally harmonised price data.
Levels	Country wide (macro)
2. Conceptual Assessment	
Theoretical background	Appreciation of REERs imply that exports and a country's own production become more expensive relative to imports. Exact interpretations should account for the choice of the particular price deflator used.
Policy relevance	Continuing appreciation may indicate accumulating imbalances in terms of an economy's deteriorating price competitiveness relative to its trade partners.
Caveats	The appreciation of the REER may reflect a strong productivity performance of the tradable sector and hence be a consequence of competitive strength (Balassa-Samuelson effect).
3. Data Assessment	
Stability over time	Variations mainly reflect changes in the nominal exchange rates and international variations of price trends.
Rank stability	There is no agreed method, particularly with regard to the choice of adequate price deflators. Series provided by different organisations can therefore produce different outcomes.
Country size impacts	n.a.
Data quality issues	See above (rank stability); a major limitation can be the lack of internationally harmonised price deflators.

Trade balance	
Area	Export Competitiveness
1. Data	
Definition	Difference between a country's exports and imports
Sources	There are two main sources: the balance of payments (BoP, e.g. by Eurostat or the IMF) and foreign trade statistics (FTS, e.g., Comext, Comtrade, BACI).
Data collection	See for instance Eurostat's online portal: http://ec.europa.eu/eurostat/data/database
Timeliness	High
Country coverage	Very comprehensive
Levels	BoP: country wide; goods and services FTS: aggregate and detailed products; bilateral trade flows; only goods.
2. Conceptual Assessment	
Theoretical background	The difference between exports and imports reflects the difference between a country's domestic production and expenditures. Trade surpluses imply the accumulation of claims or the reduction of debts relative to foreign countries. Conversely, deficits must be financed either by an increase in debt or the sale of assets.
Policy relevance	A trade surplus/deficit is generally interpreted as an indication of a country's competitive strength/weakness. In addition, positive net trade implies additional demand, strengthening domestic jobs and income.
Caveats	Temporary deficits help to smooth domestic consumption and hence growth. Persistent deficits may be consistent with desirable economic transformations with high investments and according imports of investment goods.
3. Data Assessment	
Stability over time	Trade balances may correlate negatively with the business cycle. For example, imports grow faster than exports if domestic demand is more dynamic than foreign demand.
Rank stability	See above; yearly fluctuations in the ranks are likely affected by differences in the business cycle; longer term changes indicate the impact of variations in competitiveness.
Country size impacts	n.a.
Data quality issues	Distortions arise, for instance, from the INTRASTAT system of recording trade among EU Member States ("Rotterdam effect") or inconsistent mirror statistics due to the different valuation of trade flows ("cif" vs. "fob").

Export market share	
Area	Export Competitiveness
1. Data	
Definition	Share of a country's exports in total exports (or imports) of the world, or any other group of countries (e.g. the OECD).
Sources	Balance of payments (BoP, e.g. by Eurostat or the IMF) and foreign trade statistics (FTS, e.g., Comext, Comtrade, BACI).
Data collection	See for instance Eurostat's online portal: http://ec.europa.eu/eurostat/data/database
Timeliness	High
Country coverage	Very comprehensive
Levels	BoP: country wide; goods and services FTS: aggregate and detailed products; only goods.
2. Conceptual Assessment	
Theoretical background	The change of export market share reflects differential success in the selling of goods and services on the international market.
Policy relevance	An increase/decline of export market shares generally indicates growing/declining external competitiveness of an economy.
Caveats	The change in export market shares can reflect differences in the business cycle or general growth trends of a country's main export destinations. Causes other than competitiveness thus affect its development in the short run. In the longer run an economy's ability to deal with such fluctuations and its ability to sell in major growth poles is a relevant dimension of its export competitiveness.
3. Data Assessment	
Stability over time	Cyclical fluctuations among major export destinations create variations, which in the short run do not necessarily associate with a country's own competitiveness.
Rank stability	The change of market shares tends to be volatile.
Country size impacts	n.a.
Data quality issues	Distortions can arise, for instance, from the INTRASTAT system of recording trade among EU Member States ("Rotterdam effect") and inconsistent mirror statistics arising from the different valuation of trade flows ("cif" vs. "fob").

8 Appendix B: Micro-level Analysis of Competitiveness Indicators

Christian Rammer

8.1 Introduction

Analysing competitiveness indicators at the micro level is substantially limited by restricted data availability. At the European level, no accessible firm-level data base exists that would allow to analyse a set of core competitiveness indicators as discussed in section 2.1. Eurostat offers access only to a two firm-level data sets, the Community Innovation Survey (CIS) and the Continuing Vocational Training Survey (CVTS). Both data sets contain almost no relevant data for competitiveness analysis. The CIS offers data on innovation-related activities of firms, but no detailed data on profits, productivity, trade, market shares of other variables that would inform about a firm's performance in the market and its efficiency in conducting business.⁹²

In order to carry out some micro-level analysis for this study, a unique data set from Germany has been used. The Mannheim Innovation Panel (MIP) is the German contribution to the CIS. In contrast to the CIS of most other member states, the MIP is a panel survey conducted annually which contains a large number of additional data, including most of the competitiveness indicators discussed in section 2.1. The drawback of using this data set is of course that it only represents one member state which clearly limits any generalisation of the findings.

The main purpose of the analysis is to identify correlations among different competitiveness indicators at the firm level. Following section 2.1, two groups of indicators are distinguished, competitive performance and competitive potential. For competitive performance, four groups of indicators are used: profitability, productivity, market share and export share. For competitive potential, three groups of indicators are used: expenditure for R&D and innovation, sales from new products, and cost savings from process innovation.

8.2 Data

The Mannheim Innovation Panel (MIP) is a representative survey of enterprises in Germany having 5 or more employees and operating in any of the CIS core sectors (NACE B to E, 46, H, J, K, 71 to 73) or in a further group of services sectors (69, 70, 74, 78 to 82). The data set also includes firms from other sectors (F, 45, 47, L, 77) as these

⁹² Another potential database for competitiveness-oriented analyses is Eurostat's Micro-Moment Dataset (MMD). MMD is a linked micro-aggregated data set on ICT usage, innovation and economic performance in enterprises. The data set covers 12 member states. Its main purpose is to enable studies of the economic impact of ICT at the firm level across Europe. Its usefulness for evaluating competitiveness indicators is highly limited due to a restricted set of indicators and the aggregation of firm-level data.

have been part of the target population of the MIP in earlier years. The MIP allows to measure the following competitiveness indicators at the firm level:

- Profit margin (net): earnings before taxes as a percentage of total sales (PMN); this variable is measured in categories (<0%; 0 to <2%; 2 to <4%; 4 to <7%; 7 to <10%; 10 to <15%; 15% or more).
- Profit margin (gross): sales minus intermediaries and minus wages and salaries, as a percentage of sales (PMG)
- Productivity (net): sales minus intermediaries (in m€) per employee (full-time equivalents - FTE) (PDN)
- Productivity (gross): sales (in m€) per FTE employee (PDG)
- Market share: a firm's sales as a percentage of total sales within the applicable sales market (total sales = the firm's sales plus sales of all competitors) (MKT)
- Export share: exports, as a percentage of sales (EXP)
- Innovation expenditure: expenditure for product or process innovation activities, as a percentage of sales (INN)
- R&D expenditure: in-house and extramural expenditure on research and technological development as a percentage of by sales (RDT)
- New-product sales share: sales from product innovations, as a percentage of sales (NPS)
- New-to-market sales share: sales from product innovations that were new-to-the-market, as a percentage of sales (NMS)
- Unit cost reduction share: reduction in a firm's average unit costs due to process innovations (UCR)

Note that for four indicator groups, alternative measures are used. Profitability is measured by net profit margin (based earnings before taxes) and by gross profit margin (based on earnings before taxes, interest, depreciation and other expenses not included in cost of intermediaries or personnel). Productivity is measured as value added (incl. depreciation and other costs not part of intermediaries) per full-time equivalent and as sales per full-time equivalent. Innovative expenditure is measured as R&D intensity (R&D expenditure per sales) and as innovation intensity (the latter including all R&D expenditure). For sales from product innovations we also use a narrower indicator that focuses on product innovations that were new-to-the-market.

The analyses are carried out for the years 2006 to 2015 since this is the period for which data on all eleven indicators are available. The total number of firm-year observations available in the data set is 110,726 (i.e. about 11,000 per year), representing 25,597 different firms (i.e. about 4 observations per firm). Due to missing data, not all observations can be used for all competitiveness indicators. This is particularly true for indicators that rest on information on the volume of

intermediaries (PMG, PDN). The market share indicator, which is directly requested from firms, also shows a high share of missing values. Table 8-1 reports descriptive statistics for the eleven competitiveness indicators.

Table 8-1: Descriptive statistics for competitiveness indicators at the firm level (German CIS) for the observation period 2006-2015

<i>Variable</i>	<i>Unit</i>	<i>No. obs.</i>	<i>Mean</i>	<i>Std.dev.</i>	<i>Minimum</i>	<i>Maximum</i>
PMN	Category ^{a)}	52,368	3.80	1.93	1	7
PMG	%	34,584	21.77	16.34	-19.4	64.1
PDN	m€	31,339	0.08	0.05	0.0	0.3
PDG	m€	77,343	0.16	0.12	0.0	0.7
MKT	%	35,524	17.09	27.72	0	100
EXP	%	85,321	14.77	24.48	0	100
INN	%	65,126	4.47	12.33	0	100
RDT	%	63,558	2.34	9.24	0	100
NPS	%	72,022	8.74	19.09	0	100
NMS	%	72,668	2.07	8.95	0	100
UCR	%	70,738	1.17	4.52	0	100

a) 1: <0%; 2: 0 to <2%; 3: 2 to <4%; 4: 4 to <7%; 5: 7 to <10%; 6: 10 to <15%; 7: 15% or more.

Source: Mannheim Innovation Panel

8.3 Results

Table 8-2 shows correlation coefficients for each pair of indicator. For most indicators, we find a statistically significant positive correlation with other the indicators. The main exception is R&D and innovation intensity. Both indicators are negatively correlated with profitability and productivity. R&D intensity is also negatively correlated with the market share. This results hints to the fact that R&D and innovation expenditure are basically investment into future potential earnings. At the time when made, these expenditure reduce profitability and have no positive immediate productivity effects. Shifting resources from production to R&D and innovation may rather lower productivity due to a lower level of scale economies associated to R&D and innovation activities.

In addition, the gross profit margin is negatively correlated with gross productivity, market share and export share. This result suggests that gross profit margin is an imprecise measure of a firm's profitability. Heterogeneity across firms for this indicator may not only reflect differences in profitability, but also differences in sector, size and other structural characteristics (e.g. capital intensity, share of administrative and other expenses not included in intermediaries).

Table 8-2: Correlation of competitiveness indicators at the firm level

	PMN	PMG	PDN	PDG	MKT	EXP	INN	RDT	NPS	NMS
PMG	0.34									
PDN	0.23	0.38								
PDG	0.04	-0.08	0.60							
MKT	0.05	-0.02	0.08	0.09						
EXP	0.02	-0.04	0.22	0.22	0.07					
INN	-0.01	-0.02	-0.04	-0.09	-0.01	0.16				
RDT	-0.03	-0.03	-0.03	-0.07	-0.02	0.15	0.84			
NPS	0.04	-0.01	0.06	0.02	0.02	0.26	0.39	0.34		
NMS	0.01	0.00	0.04	0.01	0.06	0.18	0.33	0.31	0.57	
UCR	0.02	0.01	0.03	0.01	0.01	0.11	0.15	0.10	0.23	0.17
		1% confidence level positive correlation					5% confidence level negative correlation			

PMN: profit margin (net); PMG: profit margin (gross); PDN: productivity (net); PDG: productivity (gross); MKT: market share; EXP: export share; INN: innovation intensity; RTD: R&D intensity; NPS: new product sales; NMS: new-to-market sales; UCR: unit cost reduction from process innovation.

Source: Mannheim Innovation Panel

Differentiating the correlation between indicators by size classes (Table 8-3) reveals that the negative correlation between innovation intensity on the one hand and profitability and productivity on the other is confined to small firms up to 50 employees.⁹³ For large firms (500 and more employees), there is a positive correlation. This result can be read that small firms often conduct innovation discontinuously. Times of investing into innovation alter with times when firms try to reap the benefits from prior innovation. Correlating the two indicators with not time lag yield to a negative correlation. For large firms, no such relation is found since large firms usually innovate continuously and run innovation projects of different level of maturity at the same time in order to ensure a steady introduction of innovations.

For all size classes, there is a strong correlation between exports on the one hand, and innovation-related indicators on the other. This results suggests that export performance of German firms is strongly driven by innovation. For other countries, the relation between these two aspects of competitiveness may be different.

The market share tends to correlate with other competitiveness indicators only for medium-sized firms. For very small firms and for large firms, neither a positive correlation with profitability or productivity nor with the export share can be observed. Very large firms even show a significant negative correlation between market share and export share. This results is likely to be driven by firms from the utility sector. These firms often operate under a regional monopoly and only serve their regional market, hence export shares are often zero while market shares are very high.

⁹³ In order to simplify the presentation, we only show one indicator for indicator groups with alternative measures, i.e. PMG, PDG, RTD and NMS are omitted.

Table 8-3: Correlation of competitiveness indicators at the firm level, by size class (no. of employees)

Correlation between ...		0 to 4	5 to 9	10 to 19	20 to 49	50 to 99	100 to 249	250 to 499	500 to 999	1,000 to 2,499	2,500+
PMN	PDN	0.20	0.19	0.19	0.25	0.29	0.30	0.26	0.39	0.34	0.18
PMN	MKT	0.01	-0.01	0.06	0.05	0.09	0.15	0.07	0.15	0.08	0.04
PMN	EXP	-0.06	-0.03	-0.01	0.03	0.05	0.09	0.06	0.04	0.13	0.18
PMN	INN	-0.07	-0.06	-0.06	-0.03	0.01	-0.01	0.01	0.05	0.13	0.17
PMN	NPS	-0.02	0.00	0.02	0.04	0.05	0.06	0.05	0.11	0.12	0.12
PMN	UCR	0.04	0.03	0.03	0.03	0.01	0.04	0.03	0.04	0.03	-0.01
PDN	MKT	0.05	-0.01	0.02	0.10	0.08	0.09	0.04	0.14	0.08	-0.02
PDN	EXP	0.06	0.15	0.17	0.18	0.19	0.18	0.19	0.20	0.16	0.11
PDN	INN	-0.05	-0.10	-0.06	-0.06	-0.02	0.00	0.01	0.02	0.07	-0.02
PDN	NPS	0.04	0.02	0.01	0.01	0.04	0.05	0.05	0.11	0.15	0.11
PDN	UCR	0.01	0.00	0.00	0.00	0.01	0.03	0.02	0.09	0.09	0.00
MKT	EXP	-0.02	0.02	0.03	0.03	0.05	0.08	0.00	-0.01	-0.03	-0.11
MKT	INN	0.00	0.00	-0.02	-0.01	-0.03	0.00	0.01	0.09	0.08	-0.03
MKT	NPS	0.02	0.02	0.00	0.02	0.01	0.02	-0.03	0.04	-0.04	-0.04
MKT	UCR	-0.02	0.00	-0.01	-0.01	0.00	-0.01	-0.02	0.07	0.03	-0.05
EXP	INN	0.10	0.21	0.17	0.20	0.14	0.11	0.18	0.23	0.29	0.44
EXP	NPS	0.12	0.24	0.22	0.22	0.22	0.21	0.20	0.32	0.41	0.52
EXP	UCR	0.05	0.07	0.07	0.07	0.09	0.06	0.09	0.13	0.17	0.20
INN	NPS	0.45	0.44	0.44	0.39	0.30	0.33	0.27	0.36	0.41	0.46
INN	UCR	0.19	0.18	0.17	0.16	0.13	0.10	0.12	0.15	0.21	0.35
NPS	UCR	0.19	0.21	0.21	0.21	0.22	0.22	0.25	0.25	0.33	0.43

1% conf. level 5% conf. level 10% conf. level

positive correlation negative correlation

Source: Mannheim Innovation Panel

This interpretation is supported by Table 8-4 which reports the correlation between competitiveness indicators for different sector groupings. A negative correlation between market share and export share is found for utilities and construction, as well as for the transport and trade sectors. The utilities and construction sectors also show a negative correlation between market share and product and process innovation outcomes while there are only few significant correlations between profitability, productivity and other competitiveness indicators.

The negative correlation between profitability and productivity on the one hand, and innovation intensity on the other can be found in most industries, including manufacturing sectors classified as medium-to-high and high technology ('equipment/pharmaceuticals' in Table 8-4) as well as for knowledge intensive services sectors (creative services, IT services, engineering, financial services, consulting).

The positive correlation between exports and innovation-related indicators holds for all sectors except for producer services where no significant correlation with product and process output indicators is found.

Table 8-4: Correlation of competitiveness indicators at the firm level, by industry

Correlation between ...		Consumer pr.	Basic materials	Processed mat.	Equipment/pharmac.	Logistics/trade	Creative serv.	IT serv./engineer.	Financial serv./consult.	Producer serv.	Utilities/construction
PMN	PDN	0.04	0.27	0.26	0.34	0.05	0.18	0.33	0.07	0.15	0.28
PMN	MKT	0.07	0.12	0.10	0.10	0.02	0.08	0.05	-0.04	0.13	0.05
PMN	EXP	0.01	0.00	0.08	0.07	0.02	-0.05	0.01	-0.03	0.00	-0.01
PMN	INN	0.06	0.05	0.06	-0.02	0.04	0.03	-0.17	-0.04	0.06	0.00
PMN	NPS	0.04	0.06	0.04	0.04	0.05	0.09	-0.02	-0.03	0.02	0.00
PMN	UCR	0.04	0.07	0.07	0.01	0.01	0.05	-0.01	-0.04	-0.03	0.03
PDN	MKT	0.01	0.15	0.11	0.13	-0.02	0.18	0.04	0.16	0.01	0.01
PDN	EXP	0.26	0.22	0.35	0.32	0.20	0.04	0.17	0.17	0.19	0.06
PDN	INN	-0.03	-0.03	-0.04	-0.06	-0.02	-0.10	-0.13	-0.06	0.11	-0.01
PDN	NPS	0.08	0.04	0.06	0.08	0.06	0.00	0.01	0.01	0.12	0.00
PDN	UCR	0.03	0.03	0.04	0.00	0.03	0.04	-0.01	0.06	0.14	0.01
MKT	EXP	0.11	0.18	0.12	0.17	-0.06	-0.01	0.03	0.01	0.02	-0.06
MKT	INN	-0.02	0.01	-0.02	-0.01	0.03	-0.02	0.01	0.02	0.01	0.00
MKT	NPS	0.03	0.10	0.02	0.08	0.03	0.02	0.03	-0.02	0.06	-0.07
MKT	UCR	0.00	0.05	0.04	0.04	-0.02	-0.04	0.00	0.04	-0.01	-0.05
EXP	INN	0.10	0.04	0.09	0.14	0.02	0.05	0.25	0.05	0.08	0.06
EXP	NPS	0.17	0.16	0.17	0.21	0.06	0.08	0.26	0.18	0.01	0.08
EXP	UCR	0.08	0.09	0.08	0.08	0.03	0.06	0.08	0.06	0.01	0.06
INN	NPS	0.27	0.25	0.29	0.35	0.18	0.31	0.43	0.30	0.17	0.18
INN	UCR	0.19	0.20	0.19	0.13	0.09	0.13	0.14	0.09	0.16	0.13
NPS	UCR	0.21	0.23	0.19	0.22	0.17	0.19	0.21	0.21	0.27	0.24

Consumer pr.: NACE 10-12, 14, 15, 31, 32
 Basic materials: NACE 5-9, 16, 17, 23, 24
 Processed mat.: NACE 13, 19, 20, 22, 25
 Equipment/pharmac.: 21, 26-30, 33
 Logistics/trade: 45-47, 49-53
 Source: Mannheim Innovation Panel

Creative serv.: 18, 58-60, 73, 74
 IT serv./engineer.: 61-63, 71, 72
 Financial serv./consult.: 64-70
 Producer serv.: 78-82
 Utilities/construction: 35-43

The final examination looks at the correlation between competitiveness indicators when controlling for firm heterogeneity in terms of size and sectors. For this purpose, simple regression analyses are performed for each of the eleven indicators. Each regression includes a set of dummy variables for a firm's size and sector, time dummies and one of the other ten indicators. The results of this exercise are presented in Table 8-5. The main finding is that the results of pairwise correlations by and large hold if size and sector effects are controlled for. Interestingly, the negative correlation between exports and market share disappears, confirming that this correlation is strongly driven by size and sector differences. The negative correlation between R&D and innovation intensity on the one hand, and profitability and productivity on the other remains however. We find no significant correlation between gross profit margin and gross productivity, suggesting that these 'gross' measures (i.e. based on less precise measures of productivity and profitability) may be less reliable. In addition, we find no correlation between market share and innovation/R&D intensity.

Table 8-5: Estimated parameters of regressions models on the mutual relation of competitiveness indicators when controlling for structural firm characteristics (size, sector)

		Right-hand ('independent') variables										
		PMN	PMG	PDN	PDG	MKT	EXP	INN	RDT	NPS	NMS	UCR
Left-hand ('dependent') variables	PMN		0.13	35.72	5.35	0.02	0.01	-0.02	-0.04	0.01	0.00	0.03
	PMG	2.70		172.40	0.84	0.01	0.03	-0.05	-0.09	0.02	0.02	0.08
	PDN	5.25	1.22		0.25	0.06	0.38	-0.25	-0.30	0.06	0.12	0.00
	PDG	5.01	0.04	1.44		0.10	0.89	-0.79	-0.87	0.09	0.17	0.00
	MKT	0.98	0.03	24.10	6.21		0.06	0.01	-0.01	0.03	0.18	-0.01
	EXP	0.41	0.05	148.22	57.90	0.03		0.26	0.29	0.22	0.35	0.31
	INN	-0.10	-0.02	-12.53	-7.89	0.00	0.08		1.15	0.32	0.44	0.65
	RDT	-0.21	-0.02	-6.53	-4.25	0.00	0.08	0.71		0.25	0.35	0.44
	NPS	1.00	0.10	34.87	8.14	0.04	0.24	0.91	0.90		1.49	1.56
	NMS	0.75	0.11	49.37	9.38	0.13	0.21	0.63	0.67	0.71		1.03
	UCR	0.52	0.05	8.24	0.64	-0.01	0.05	0.28	0.18	0.26	0.29	

Results of cross-section regression models (intervall regression for PMN; OLS for PMG, PDN, PDG, MKT; Tobit for EXP, INN; RDT, NPS, NMS, UCR).

Source: Mannheim Innovation Panel