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Pitfalls of Industry Level Data

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Abstract

In a seminal paper Graetz and Michaels (2018) find that robots increase labor productivity and TFP, lower output prices and adversely affect the employment share of low-skilled labor. We demonstrate that these effects are heavily influenced by the sample composition and argue that focusing on manufacturing and mining sectors mitigates unobserved heterogeneity and is more coherent with an identification strategy that rests on instruments that do not vary by industries. In sum, this leads to more plausible results regarding the overall economic effects of robotization, whereby the focus on robotizing industries leads to a sizable drop of the productivity effects, halving the effect size for labor productivity and insignificant price effects. The most pronounced consequences from the sample choice occur for labor market outcomes, where significant negative employment effects become insignificant and positive wage effects are reversed into the opposite. We show that controlling for demographic workforce characteristics is essential for obtaining significant labor productivity effects and leads to the negative effects of robots on wages. Additionally, investigating only robotizing sectors does not corroborate skill-biased technological change due to robotization, but rather, indicates towards labor market polarization. Finally, we document a non-monotonicity in one of the instruments, which calls for caution in the use of that instrument.

JEL classification: E24, J24, J31, L60, O30

Keywords: Robots, Productivity, Technological Change

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1 Introduction

Fears that automation will lead to mass unemployment are a recurring social and economic issue and in recent decades these fears have been fed by the rapid spread of industrial robots. Economists have been able to dispel these fears on the basis of theoretical models, but due to a lack of data there was also a lack of solid empirical evidence. This changed with the seminal paper by Graetz and Michaels (2018) (henceforth G&M) who analyzed for the first time the economic contributions of modern industrial robots on productivity, prices, wages, and the skill composition of the workforce. Their results suggest that robotization has had a positive impact on labor productivity and total factor productivity (TFP) as well as on wages, while it lowers output prices. With regard to effects on the workforce they conclude that, while no negative effects on total employment are found, the employment share of low-skilled workers is declining with increased robotization. Throughout their analyses they use data from the International Federation of Robotics (IFR), which provides details on robot stocks and deliveries at the two-digit level for manufacturing sectors with a high robotization probability, but also includes sectors with very low robotization probabilities, such as agriculture or education.

In this paper, we demonstrate that the choice of industries included in the sample has serious impacts on the effects of robotization on different outcome variables. By only analyzing the robotizing industries, we find pronounced changes in the above mentioned results. We find that productivity effects are substantially lower, price effects are insignificant, wage effects change sign, and skill-biased technological change due to robotization cannot be corroborated but rather, there is evidence (albeit not significant in all specifications) of labor market polarization. Moreover, we show that the inclusion of demographic workforce characteristics plays an important role, as they are essential to obtain significant labor productivity effects and cause the sign change of the wage effect. On the other hand, controlling for net-import exposure has rather negligible effects on the results. Overall, the substantial changes in results show that researchers should pay attention to the sample composition regarding the industry coverage. The total effects of robotization on productivity derived from the sample reduced to robotizing industries is about a third lower than those for the sample including non-robotizing industries. Finally, reducing the sample to industries with similar characteristics helps to alleviate the influence of unobserved heterogeneity in the results. Whereas manufacturing and mining industries are exposed to global competitive price pressure, the remaining sectors either are subject to regulation in their international activity (Utilities and Agriculture), mainly serve the national market (Education) or compete via quality and not cost (R&D core sector). Usually, these differences could be conditioned on by including industry fixed effects. But since the identification strategy rests on instrumental variables that do not vary by industries, focusing on similar industries and including additional controls is a viable option.

Furthermore, we provide two additional results. First, we find that across all estimations the monotonicity assumption, as formulated in Imbens and Angrist (1994), is violated for one of the instruments used in the original analysis of G&M 2018. This instrument changes the sign of the first-stage coefficient, when we regard only the sample of robotizing industries. This result suggests caution in the use of this instrument for future research. Secondly, we extend the investigation period to the years 2010-2015. For this period, the productivity results show a similar order of magnitude as in the previous period, however the estimates lack precision. With the exception of the hours worked, all other robotization effects are insignificant at conventional levels as well.

Our paper relates to the literature on technological change and automation. Studies in this field face considerable data constraints, as precise and timely measures for automation and digitalization are typically not directly available, neither on an aggregate industry level nor on a more disaggregate firm level. Therefore, the micro-econometric analysis of automation mostly relied on indirect measures. For example, a substantial literature, following the work of Autor, Levy, and Murnane (2003), has explained automation, by using a task based approach, arguing that automation predominantly takes place in routine task intensive jobs.[1]

Against this background, the paper by G&M (2018) provides a considerable improvement, as it uses detailed data on robot stocks and deliveries. Subsequently, this data has become one of the most widely used sources to study automation. For instance, Acemoglu and Restrepo (2020) and Dauth et al. (2021) used the IFR data to examine the labor market consequences of robot adoption in the US and Germany. Both studies find a robust negative impact of industrial robots on manufacturing employment and wages. Thus, our results are in line with this literature, as the effects on wages tend to be negative in our analyses. Our paper also relates to recent studies examining the link between robotization and demographic change (see e.g. Acemoglu and Restrepo (forthcoming)), as taking the demographic workforce structure into account, seems to be crucial for establishing productivity effects on the aggregate industry level. Moreover, also Dauth et al. (2021) point out that detrimental labor market effects of automation mainly concern young workers entering the labor market. Finally, our paper contributes to the literature that analyzes robotization on a country-industry level and uses the instruments developed by G&M. For this kind of research, we urge caution to what kind of variation drives the effects and whether the monotonicity assumption of the instruments is fulfilled. Examples of such studies include papers on routine-biased

[1] Prominent examples of this literature are Spitz-Oener (2006), Autor, Katz, and Kearney (2008), Goos and Manning (2007), Dustmann, Ludsteck, and Schönberg (2009), Autor and Dorn (2013) or Goos, Manning, and Salomons (2014).

technical change by de Vries et al. (2020) or the development of the gender pay gap by Aksoy, Özcan, and Philipp (2021).

The paper is structured as follows: Section 2 substantiates the distinction between robotizing and non-robotizing industries and discusses the data sources and the estimation strategy. Section 3 provides our main results, comparing the results for labor and total factor productivity, prices and labor market outcomes between the full sample of all industries and those including only robotizing industries. Section 4 discuss the non-monotonicity in the reaching and handling instrument and section 6 concludes.

2 Data and Estimation

2.1 Distinguishing robotizing and non-robotizing industries

In principle, one could motivate the sample split into robotizing and non-robotizing industries by a purely data-driven approach.Table 1 shows that following such an approach and defining 'non-robotizing' for instance as "*having less than one robot per 10 Mio. working hours at the end of the investigation period*" would sort industries along established classifications of industries e.g., according to ISIC or NACE into manufacturing and non-manufacturing industries, with the exception of mining. Using the rate of change rather than the ratio of robots to hours worked at the end of the observation period produces a similar industry split. From an economic point of view this result is intuitive, as it corresponds to a division into sectors with a distinct presence of robotizable non-cognitive routine tasks and those sectors with a stronger presence of non-robotizable cognitive non-routine activities. Therefore, we rely on traditional classification schemes and use the manufacturing industries plus mining as our sample, whereby the classification of the latter has no impact on the subsequent regression results, which are qualitatively unchanged for manufacturing alone.

Table 1: Distribution of changes in robot density by economic sector (1993-2007)

	desc_rob 1993	2007	Δ	Mean	Min	Max
Manufacturing Sectors						
Transport equipment	5.36	13.42	8.07	0.87	0.01	1.00
Chemical	1.16	4.50	3.34	0.88	0.64	0.99
Metal	2.37	4.04	1.67	0.79	0.01	0.98
Electronics	0.95	2.26	1.32	0.71	0.01	0.97
Food	0.34	1.55	1.21	0.76	0.25	0.96
Wood products	0.77	1.61	0.84	0.53	0.01	0.97
Other Mineral	0.34	1.15	0.81	0.68	0.04	0.95
Textiles	0.12	0.42	0.3	0.46	0.01	0.95
Paper	0.06	0.20	0.14	0.46	0.01	0.83
Non-Manufacturing Sectors						
Mining	0.07	0.36	0.29	0.35	0.04	0.95
Education, R&D	0.02	0.08	0.06	0.44	0.02	0.75
Agriculture	0.01	0.04	0.03	0.33	0.04	0.74
Construction	0.01	0.03	0.02	0.35	0.03	0.66
Utilities	0.00	0.02	0.02	0.22	0.04	0.69

Note: All values correspond to unweighted mean values over all available countries. The industry classification used in the IFR-data roughly corresponds to the ISIC-Rev. 3 classification. Manufacturing sectors are available at the to 2-digit industry level, while the non-manufacturing sectors are at the 1-digit level.

Investigating the effects of robotization without non-robotizing sectors is useful for several reasons. First, it is informative to know the extent to which overall economic effects of robotization are driven by sectors with virtually no robots, i.e. with observations with hardly any propensity to treatment. Second, from a methodological point of view, as the chosen instrument in the empirical analysis does not allow industry-specific fixed effects, splitting the sample along similar industries helps to assess the influence of unobserved heterogeneity in the results. For instance, the manufacturing and mining sectors are heavily exposed to global competitive price pressure. By contrast, the remaining sectors either are subject to strong regulation and price subsidies in their international activity (Utilities and Agriculture), mainly serve the national market (Education) or compete via quality and not costs (R&D core sector). Finally, G&M (2018) do not use the rate of change of robotization, but a percentile transformation of the rate of change. On the one hand, this transformation does a good job of reducing noise in the data (see Appendix A), but at the same time it means that observations with low robotization are given a much higher weight. The consequences of these artificially assigned higher weights can also be examined with a restriction to actual robotizing sectors.

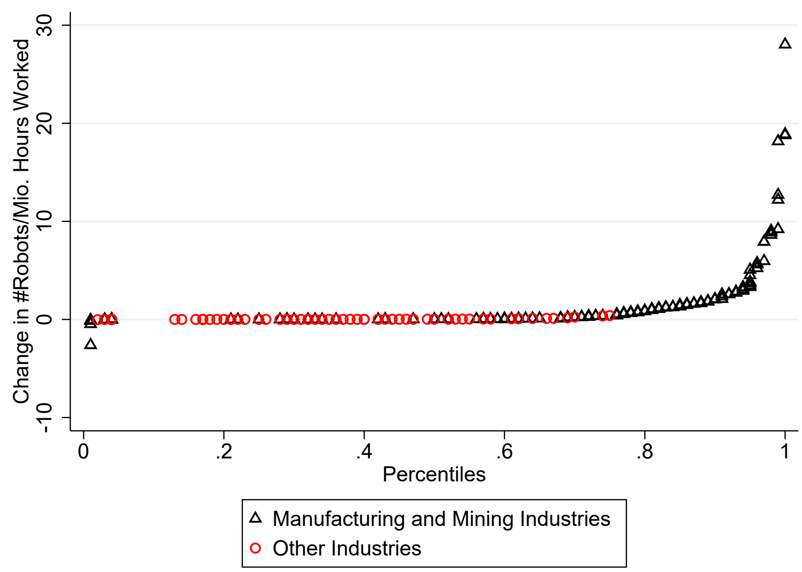
This last point is illustrated in Figure 1, where we plot the percentiles of the change in robots per million hours worked between 1993 and 2007, for all country-industry observations which are also used in the analysis of G&M (2018). It becomes visible that the vast majority of country-industry observations show little to no change, with only industries above the 75th percentile experiencing relevant movements in robotization during this period. Furthermore, the non-manufacturing industries with the exception of mining (represented by the red circles) have almost no robotization between 1997 and 2007 and are therefore not present above the 75th percentile. On average these sectors experienced an increase in robotization of only 0.032 robots per million hours worked, compared to an average increase of 1.799 robots per million hours worked for the manufacturing and mining sectors. This highly skewed distribution affects not only the results of G&M (2018) but, because of the use of a single data source (IFR, see Section 2), all studies of robotization at a country-industry level.

2.2 Data

As in the work of G&M (2018), we take data on robot deliveries from the IFR to measure changes in robot adoption.[2] All other variables are from the EU-KLEMS database, whereby data related to productivity, prices, wages and capital intensity is taken from the March 2011 update and data referring to workforce characteristics (skill,

[2]Data on robot deliveries is used to calculate robot stocks using the perpetual inventory method. For further details see G&M (2018).

Figure 1: Distribution of changes in robot density (1993-2007)



Note: The data shown includes all countries and economic sectors from the main specifications of G&M (2018). Manufacturing and mining industries are represented by the black triangles, while all remaining industries (agriculture, construction, education and R&D, and energy and water supply) are indicated by the red circles. The percentiles of changes in robot density (plotted on the horizontal axis) correspond to the measure of robot adoption used as main explanatory variable in G&M (2018), while the vertical axis plots the actual changes in robot density.

age, gender) comes from the March 2008 release. For estimations on the period 2010-2015, we use the EU-KLEMS September 2017 release. Trade exposure is computed using data from the UN-Comtrade database.

2.3 Estimation

Following G&M (2018) we estimate equations of the form:

$$\Delta Y_{ci} = \beta_1 + \beta_2 f(\Delta robots_{ci}) + \beta_3 controls_{ci} + \epsilon_{ci} \tag{1}$$

where ΔY_{ci} is the change between the initial year (1993 respectively 2010) and the end year (2007 respectively 2015) in the outcome of interest in country c and industry

i. Estimations in sections 3.1, 3.2, 3.3 and 4 use the time-frame 1993-2007, while Section 5 reports estimations for the period 2010-2015. The main variable of interest is $f(\Delta robots_{ci})$, whereby $\Delta robots_{ci}$ indicates the change in robot adoption (defined as robots per million hours worked), while $f(\cdot)$ is a function mapping the raw change in robot adoption to the corresponding percentile rank.

All estimations include a vector of control variables, $controls_{ci}$. The baseline set of control variables is similar to G&M (2018), namely country fixed effects, initial period values of the wage rate and the capital-labor ratio, and changes in the capital-labor ratio and the ratio of ICT-capital to the overall capital stock, as well as (in the wage regression only) changes in the skill composition of the workforce. Additionally, we include the initial period level of the ratio of ICT-capital into the baseline set of controls.[3]

To better control for unobserved heterogeneity, we also include control variables measuring the demographic structure of the workforce, namely the age structure and changes in female labor market participation. Controlling for the age structure of the workforce is motivated by recent work of Acemoglu and Restrepo (forthcoming), who argue that the demographic composition of the workforce impacts robotization. Their argument is based on the observation that automation technologies primarily substitute for jobs of middle aged workers. As the share of middle aged workers decreases through population aging, firms face a relative shortage in labor supply of these workers. Thus, the price for hiring these workers (i.e. their wage rate) increases, which in

[3]This is a first deviation from the approach of G&M, who do not include the initial period level of ICT-capital. We include this variable, because we regard it as a way to more thoroughly control for unobserved heterogeneity in ICT-intensity. Including this variable in the set of baseline controls leads to deviations of our point-estimates from those reported in G&M (2018). These deviations in the baseline regressions for the full-industry sample are however very small, and leave all conclusions from G&M (2018) qualitatively intact.

turn makes investment in automation technologies (like industrial robots) more profitable. In our context, this connection between demographic change and robotization might raise endogeneity concerns, if population aging also affects our outcome variables. Indeed, there is evidence for a connection between aging populations and productivity (Maestas, Mullen, and Powell, 2016), or different labor market outcomes (Goldin and Katz, 2007). Therefore, we include the initial period employment shares of middle aged workers (age 30 to 49) and of older workers (age 50 plus) to mitigate that concern. Additionally, we include the change in the share of female workers in regressions which involve labor market outcomes. This is motivated by concerns that in the presence of gender specific differences in wages and skill-endowment (i.e. education), as well as non-random selection of females into specific sectors, changes in female labor force participation might bias the results. Lastly, we also include controls measuring sectoral net-import exposure (in its initial period value and its change). The computation of net-import exposure follows the approach of Autor, Dorn, and Hanson (2013) and Dauth, Findeisen, and Suedekum (2014).[4]

We estimate OLS regressions, specifications including industry fixed effects and instrumental variable regressions (Two-Stage Least Squares, hencfort 2SLS). In our 2SLS

[4] Dauth, Findeisen, and Suedekum (2014) have shown for Germany that increases in trade integration with countries from Eastern Europe are more informative than the rise in Chinese trade exposure. As our sample contains many European countries as well as the United States and the Republic of Korea (where Chinese trade exposure is more relevant), we regard net-imports from the same group of countries used by Dauth, Findeisen, and Suedekum (2014). Specifically, these countries are China, Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, and the succession states of the former USSR - Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazahkstan, Kyrgyztan, Tajikistan, Turkmenistan and Uzbekistan. The trade data was obtained at the commodity level (according to the SITC Rev. 3 classification), and then aggregated and reclassified to the ISIC-Rev. 3 classification using the `comtradr`-package in R.

estimations we follow G&M (2018) in using their 'replaceable hours' instrument. This instrument is calculated as the fraction of hours in an industry that G&M (2018) classify as replaceable by industrial robots. It utilizes the distribution of working hours across occupations in 1980 US-industries from the 1980 US-census, whereby any occupation is classified as 'replacable' if its title corresponds to at least one of the robot applications described by the IFR. As the instrument is computed for US-industries in 1980 it can be thought of as measuring the industry level potential for future robotization, prior to the emergence of industrial robots. The fact that the instrumental variable is computed entirely from US-values comes with the drawback that it does not vary within industries, i.e. across countries or time. Therefore, in the 2SLS estimations we cannot control for industry fixed effects, as they are collinear with the instrument.[5]

All estimations are weighted by the share of industry i's employment in country c's overall employment in the initial period. Standard errors are two-way clustered by country and industry.

3 Main results

3.1 Productivity

Columns (1) to (4) in Table 2 present the estimation results for the full sample of all industries, while columns (5) to (8) show estimations for the reduced sample (nine manufacturing industries and mining). In table 2 column (1) directly corresponds to the results presented in G&M (2018), with the exception that we additionally control

[5] G&M (2018) also proposed a second instrument - the 'reaching and handling' instrument. We do not use this second instrument in the main part of our analysis, as we regard it as violating the monotonicity assumption of instrumental variable regression. For a detailed discussion of this instrument see section 4.

for the initial period value of ICT-intensity.

Table 2: Productivity Effects of Robotization:

	Full Sample				Reduced Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: △ ln(VA/H)								
OLS								
Robot adoption	0.646*	0.637**	0.650**	0.657**	0.166	0.160	0.289	0.325
	(0.251)	(0.245)	(0.241)	(0.242)	(0.198)	(0.201)	(0.200)	(0.202)
Industry FE								
Robot adoption	0.251	0.253	0.321	0.332	0.262	0.264	0.461	0.490
	(0.172)	(0.172)	(0.223)	(0.226)	(0.231)	(0.224)	(0.371)	(0.361)
IV: Replaceable hours								
Robot adoption	1.032**	1.046**	1.203**	1.207**	0.516	0.522	0.568*	0.614*
	(0.394)	(0.395)	(0.309)	(0.312)	(0.321)	(0.329)	(0.269)	(0.294)
First Stage	1.198**	1.186**	1.258**	1.254**	2.366**	2.358**	2.146**	2.192**
	(0.187)	(0.180)	(0.199)	(0.193)	(0.378)	(0.408)	(0.371)	(0.406)
F-Statistic	34.4	36.2	32.5	33.7	30.5	25.6	25.3	21.6
Observations	224	224	168	168	160	160	120	120
Countries	16	16	12	12	16	16	12	12
Industries	14	14	14	14	10	10	10	10
Panel B: △ ln(TFP)								
OLS								
Robot adoption	0.444*	0.430*	0.442*	0.446*	0.105	0.096	0.272	0.325
	(0.203)	(0.198)	(0.186)	(0.186)	(0.168)	(0.174)	(0.151)	(0.202)
Industry FE								
Robot adoption	0.147	0.147	0.195	0.203	0.139	0.134	0.381	0.403
	(0.154)	(0.155)	(0.192)	(0.194)	(0.167)	(0.168)	(0.312)	(0.317)
IV: Replaceable hours								
Robot adoption	0.762*	0.766*	0.909**	0.905**	0.651**	0.663*	0.672**	0.716**
	(0.334)	(0.332)	(0.216)	(0.217)	(0.251)	(0.262)	(0.212)	(0.230)
First Stage	1.155**	1.148**	1.202**	1.208**	2.343**	2.334**	2.178**	2.171**
	(0.182)	(0.172)	(0.196)	(0.192)	(0.354)	(0.381)	(0.336)	(0.407)
F-Statistic	33.9	37.0	30.3	31.4	34.1	28.8	31.5	20.9
Observations	210	210	154	154	150	150	110	110
Countries	15	15	11	11	15	15	11	11
Industries	14	14	14	14	10	10	10	10
G&M Controls:	x	x	x	x	x	x	x	x
Trade Controls:		x		x		x		x
Demographic Controls:			x	x			x	x

Note: $* < 0.05, ** < 0.01$. Robust standard errors grouped by country and economic sector are shown in brackets. The dependent variables are specified in growth rates. All regressions are weighted by the country specific share of sectoral employment in the initial period (1993). The G&M Controls include country fixed effects, initial period values of the wage rate, the capital-labor ratio, and the ratio of ICT-capital to the overall capital stock, as well as changes in the capital-labor ratio and the ratio of ICT-capital. Trade controls include the initial period value and the change in net-import exposure, and demographic controls include the initial period shares of workers aged 30-49 and 50+.

Panel A of table 2 shows our results for labor productivity. Here the OLS-estimates show a positive relationship between robotization and labor productivity. While the estimate stays relatively stable when including additional control variables, the precision of the point-estimates increases, such that the relationship is significant at the 1%-level in the full specification (column 4). Including industry fixed effects into the OLS regressions leads to a drop in the size of the estimates and to a loss of statistical significance, indicating that there is a relevant degree of unobserved, industry specific heterogeneity not captured by the control variables in the OLS regressions.

Contrasting this to the reduced-sample of robotizing industries in panel A, column (5) shows that the point-estimate for the OLS is markedly reduced in size, while the fixed effects estimate stays relatively stable. Compared to the full-sample, the difference between the OLS and fixed effects estimates is much smaller in the reduced sample of robot using industries. When including the full set of control variables the OLS estimate for the full-sample is about double the size of the corresponding fixed effects estimate (column 4), while the OLS estimate in the reduced sample is about one third smaller than the estimate with industry fixed effects (column 8). This reduced impact of the inclusion of industry fixed effects suggests, that unobserved heterogeneity (while certainly still present in the reduced sample) is less severe, when restricting the analysis to robotizing sectors only.

Regarding the 2SLS estimates we find a similar behavior as in the OLS and fixed effects regressions. In the baseline specifications in columns (1) and (5) the estimate gets roughly cut in half, when restricting the sample to robotizing industries only. As a consequence, the estimate for the reduced sample is less precise. While the inclusion of net-import penetration controls in column (6) leaves the size and precision of the reduced sample estimate unchanged, the inclusion of the age structure of the workforce increases the precision of the estimate, and re-establishes its statistical significance at the 5%-level. In the full specification in column (8) we find an estimate of 0.614 which indicates a positive impact of robotization on labor productivity, also in the reduced sample. However, the size of this effect is only about half as big as in the corresponding regression for the full sample (with an estimate of 1.207). While focusing our analysis on industries that actually experienced relevant increases in robotization confirms the main conclusion posed by G&M (2018), namely a positive effect of robotization on labor productivity, we find this effect to be only about half as strong as previously suggested.

Accordingly, by following the benchmarking procedure of G&M (2018) we estimate that in the absence of changes in robotiziation, productivity in the overall economy would have been on average only around 3.5% lower in 2007, compared to an estimated productivity effect of 5.1% in G&M (2018).[6] This implies that without robotization annual labor productivity growth would have been on average approximately 0.25 percentage points lower during the period 1993-2007. Hence, the estimated annual productivity effect is about 30% smaller than the effect of the steam-engine in Britain during 1850 to 1910, whose annual contribution to labor productivity growth was estimated at around 0.35 percentage points (Crafts, 2004).

Panel B of table 1 presents the results for total factor productivity (TFP). In line with the results for labor productivity in panel A, we find that the OLS and fixed effects

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[6]We followed the benchmark procedure described in the Online-Appendix of G&M (2018). It is based on a coefficient from an OLS estimation controlling only for country and industry specific trends. Using our reduced sample, this estimated coefficient is 0.374, which implies a productivity increase in the overall economy of around 3.5% between 1993 and 2007. If we use our preferred estimate of 0.614 from table 2, column 8 (using the 'replaceable hours' instrument and a full set of controls), we estimate that productivity in the overall economy would have been approximately 4.4% lower without robotization. We want to note that including low-robotization industries in a 2SLS estimation with full controls (which gives an estimate of 1.207 - see table 2, column 4) implies an unreasonably high impact of robotization on the average level of productivity in the overall economy of around 13.5%. We regard this as further evidence, that low-robotization sectors should be excluded, when conducting this type of analysis.

estimates are much more similar in the reduced sample than in the full sample. This signals that the focus on robotizing sectors alleviates concerns arising from unobserved, industry specific heterogeneity. The 2SLS estimates are again reduced in size, when the sample is limited to the manufacturing and mining industries, although not as strongly as in panel A. However, for TFP the point estimates in the reduced sample maintain their statistical significance in all specifications. Gradually including additional control variables once more increases the size of the estimates in both samples. In the full specification for the reduced sample in column (8) we find an estimate of 0.716, which is smaller than the corresponding estimate in the full-sample (0.905 - column 4). The smaller difference between the estimates for the full and reduced sample in panel B (compared to panel A) shows that TFP is more robust to the sample choice. However, including hardly robotized sectors still leads to an overestimation of the effect robotization has had on TFP.

We conclude that analyzing robotizing and non-robotizing sectors jointly leads to a considerable overestimation of the productivity effects of robotization. The appendix tables A1 and A2 demonstrate that this result holds irrespective of the choice of the functional form and a reduction to a sample with all available control variables.[7]

3.2 Prices

We just showed that robotization leads to increases in labor productivity, also when focusing exclusively on robotizing sectors. To some extend these productivity gains might be passed on to consumers via lower prices, as this would result in a competitive advantage for robotizing firms (or industries) in the goods market. This view is corroborated by sizeable and significant negative price effects of the 2SLS estimates from

[7] As data for the demographic controls is not available for Denmark, France, Ireland and Sweden, these countries are excluded in estimations including demographic control variables.

the full sample in table 3. However, focusing only on robotizing sectors cuts the size of these coefficients roughly by half and the estimates lose their significance.

Table 3: Price Effects of Robotization:

	Full Sample				Reduced Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OLS								
Robot adoption	-0.512*	-0.510*	-0.487*	-0.493*	-0.189	-0.190	-0.282	-0.312
	(0.212)	(0.207)	(0.197)	(0.199)	(0.139)	(0.146)	(0.156)	(0.159)
Industry FE								
Robot adoption	-0.212	-0.222	-0.211	-0.224	-0.244	-0.250	-0.400	-0.224
	(0.148)	(0.147)	(0.186)	(0.188)	(0.161)	(0.152)	(0.281)	(0.188)
IV: Replaceable hours								
Robot adoption	-0.728*	-0.741*	-0.876**	-0.879**	-0.415	-0.431	-0.446	-0.496
	(0.356)	(0.354)	(0.287)	(0.289)	(0.336)	(0.362)	(0.271)	(0.298)
First Stage	1.198**	1.186**	1.258**	1.254**	2.366**	2.358**	2.146**	2.192**
	(0.187)	(0.180)	(0.199)	(0.193)	(0.378)	(0.408)	(0.371)	(0.406)
F-Statistic	34.4	36.2	32.5	33.7	30.5	25.6	25.3	21.6
Observations	224	224	168	168	160	160	120	120
Countries	16	16	12	12	16	16	12	12
Industries	14	14	14	14	10	10	10	10
G&M Controls:	x	x	x	x	x	x	x	x
Trade Controls:		x		x		x		x
Demographic Controls:			x	x			x	x

Note: $* < 0.05, ** < 0.01$. Robust standard errors grouped by country and economic sector are shown in brackets. The dependent variables are specified in growth rates. All regressions are weighted by the country specific share of sectoral employment in the initial period (1993). The G&M Controls include country fixed effects, initial period values of the wage rate, the capital-labor ratio, and the ratio of ICT-capital to the overall capital stock, as well as changes in the capital-labor ratio and the ratio of ICT-capital. Trade controls include the initial period value and the change in net-import exposure, and demographic controls include the initial period shares of workers aged 30-49 and 50+.

Regarding the fixed effects estimate we find the same pattern as before. The estimates in the full and reduced sample are very similar, when including industry fixed effects (in the full specifications in columns 4 and 8 they are even identical), while the OLS and 2SLS estimates are generally larger in the full sample. This illustrates once more, how the exclusion of non-robotizing industries alleviates unobserved heterogeneity concerns, arising from fixed industry effects. In sum, restricting the sample to robotizing sectors only, leads to markedly smaller and insignificant effects. Our result regarding prices is consistent with Bonfiglioli et al. (2020), who shows that productivity gains from automation may not be fully passed on to consumers in the form of lower prices. This result is also consistent with Stiebale, Suedekum, and Woessner (2020) who find that advancing robotization is associated with higher markups at robotizing firms.

3.3 Labor Market Outcomes

Table 4 presents the impact of robotization on labor demand, measured by the change in the logarithm of total hours worked, and wages, measured by the logarithm of the average wage rate. Again, we contrast results for the full sample of all available industries (columns 1 to 4) with results for the reduced sample of robotizing industries (columns 5 to 8).[8]

Regarding the results for hours worked in panel A of table 4, we find negative estimates in the full sample in all estimations. For the 2SLS estimations these estimates are statistically significant, when we additionally control for the age structure of the workforce.[9] This negative employment effect in the full-industry sample is contrasted by a positive employment effect when regarding only the reduced sample of robotizing industries. Comparing the 2SLS estimates from the full specification for both sample definitions, we find a significant, negative estimate of -0.682 in the full sample, and positive (albeit insignificant) estimate of 0.617 in the reduced sample. Limiting the sample to actually robotizing industries, thus reverses the sign of the estimate. While the full

[8] To be sure that our results are not driven by the reduced sample size due to the limited availability of the demographic controls, we performed corresponding robustness checks in the appendix table A4.

[9] Accordingly, G&M (2018) do not conclude that there are negative effects of robotization on employment. They in fact argue for no employment effect. As can be seen in the full sample estimations in panel A of table 4, the negative relationship between robotization and the logarithm rate of hours worked only emerges, once one includes the demographic control variables.

Table 4: Robotization effects on labor market outcomes:

	Full Sample				Reduced Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: △ ln(Hours worked)								
OLS								
Robot adoption	-0.177	-0.215	-0.224	-0.252	0.314**	0.265**	0.277**	0.252**
	(0.170)	(0.175)	(0.191)	(0.193)	(0.113)	(0.094)	(0.105)	(0.093)
Industry FE								
Robot adoption	0.008	-0.002	-0.023	-0.030	-0.021	-0.025	0.052	0.056
	(0.114)	(0.110)	(0.124)	(0.123)	(0.090)	(0.094)	(0.061)	(0.063)
IV: Replaceable hours								
Robot adoption	-0.472	-0.492	-0.680*	-0.682*	0.717*	0.629	0.705	0.617
	(0.316)	(0.304)	(0.325)	(0.317)	(0.348)	(0.324)	(0.401)	(0.356)
First Stage	1.198**	1.186**	1.258**	1.254**	2.366**	2.358**	2.146**	2.192**
	(0.187)	(0.180)	(0.199)	(0.193)	(0.378)	(0.408)	(0.371)	(0.406)
F-Statistic	34.4	36.2	32.5	33.7	30.5	25.6	25.3	21.6
Observations	224	224	168	168	160	160	120	120
Countries	16	16	12	12	16	16	12	12
Industries	14	14	14	14	10	10	10	10
Panel B: △ ln(Wages)								
OLS								
Robot adoption	0.033	0.033	0.002	0.001	-0.001	-0.003	-0.020	-0.016
	(0.017)	(0.017)	(0.011)	(0.011)	(0.013)	(0.013)	(0.016)	(0.015)
Industry FE								
Robot adoption	0.007	0.005	-0.017	-0.018	-0.004	-0.002	-0.024	-0.020
	(0.026)	(0.026)	(0.025)	(0.025)	(0.034)	(0.034)	(0.044)	(0.044)
IV: Replaceable hours								
Robot adoption	0.084**	0.083**	0.049	0.049	-0.021	-0.032	-0.052**	-0.054**
	(0.026)	(0.026)	(0.037)	(0.037)	(0.018)	(0.024)	(0.013)	(0.011)
First Stage	1.279**	1.280**	1.190**	1.200**	2.367**	2.345**	2.056**	2.110**
	(0.177)	(0.164)	(0.194)	(0.192)	(0.385)	(0.422)	(0.320)	(0.350)
F-Statistic	43.1	50.0	29.5	30.4	28.7	23.1	29.6	25.6
Observations	224	224	168	168	160	160	120	120
Countries	16	16	12	12	16	16	12	12
Industries	14	14	14	14	10	10	10	10
G&M Controls:	x	x	x	x	x	x	x	x
Trade Controls:		x		x		x		x
Demographic Controls:			x	x			x	x

Note: $* < 0.05, ** < 0.01$. Robust standard errors grouped by country and economic sector are shown in brackets. The dependent variables are specified in growth rates. All regressions are weighted by the country specific share of sectoral employment in the initial period (1993). The G&M Controls include country fixed effects, initial period values of the wage rate, the capital-labor ratio, and the ratio of ICT-capital to the overall capital stock, as well as changes in the capital-labor ratio and the ratio of ICT-capital and (in wage regressions only) initial period values and changes in the employment shares of middle- and high-skilled workers. Trade controls include the initial period value and the change in net-import exposure, and demographic controls include the initial period shares of workers aged 30-49 and 50+, and (in wage regressions only) the change in the share of female workers.

sample shows significant displacement effects of industrial robots, the reduced sample suggests positive but insignificant employment effects.[10] Positive effects of robotization on employment have also been documented by Acemoglu, Lelarge, and Restrepo (2020) and Bonfiglioli et al. (2020) who found similar results on the firm level. Such effects might occur because robotizing firms (or sectors) experience reductions in costs and increases in productivity. Thus, they experience higher employment growth due to an increase in competitiveness. When we additionally control for the change in the logarithm of value added (Δ ln VA) to capture changes in output, as well as for the change in the logarithm of price changes (Δ ln P) to control for changes in competitiveness, the positive employment coefficient in column (8) collapses to 0.055 (see appendix table A5 - column 8). Therefore, the employment estimate in our reduced sample is driven by output expansions and increased competitiveness of robotizing industries. Overall, we do not detect any influence of robotization on employment within the robotized sectors.

In general, in the discussion of labor demand effects of automation, spillover and general equilibrium effects have to be considered. For example, much of the literature on Routine Biased Technological Change (RBTC) argues that the automation of routine-task intensive jobs in the manufacturing industries leads to employment growth in

[10] It is noteworthy however, that between 1993 and 2007 the manufacturing and mining industries in our sample on average experienced a reduction in hours worked of around 16%. Therefore, the positive estimate, which indicates a positive effect of robotization on labor demand in manufacturing and mining shows that stronger increases in robotization are associated with less pronounced declines in employment in these industries, rather than increases. In contrast, the non-robotizing industries, which we removed for the reduced sample, show on average increases in employment of around 2%. This distinction between robotizing industries (which on average experienced employment declines) and non-robotizing industries (which on average experienced employment increases) explains the negative estimates in the full sample, as those two groups of industries form two distinct clusters which are driving the negative relationship.

service sectors. This effect is explained through an increase in aggregate demand, caused by productivity effects of automation technologies. This results in higher demand with subsequent employment growth in the service sectors, which are otherwise unaffected by automation technologies. Empirical evidence for such spillover effects is abundant in the RBTC literature,[11] a literature that is as de Vries et al. (2020) argue closely connected to robotization. Regarding industrial robots, Dauth et al. (2021) find a similar result for Germany. Their analysis shows that increasing robotization has led to employment losses in manufacturing, which are fully offset by employment gains in the service sector (resulting in a net-zero employment effect). Another possible channel for employment spillovers is highlighted by Acemoglu, Lelarge, and Restrepo (2020). While highly robotizing firms or sectors experience employment gains because of increases in their competitiveness, this might in turn lead to employment losses of their competitors. As our sample is comprised of country-industry observations, it is for example possible that employment gains in a highly robotized sector in country A are causally connected to employment losses in the same sector in country B. While spillovers to the service sectors would typically be associated with increases in employment, spillovers to competing industries (e.g. in a different country) would be associated with employment losses.

The estimates in table 4 (panel A) cannot capture these employment spillovers and hence, our estimates do not allow us to draw any conclusions about the economy wide employment effect of robotization. However, our estimates suggest that sectors which are most exposed to robotization experienced no significant employment changes. Importantly, we do not detect any displacement effects within the industries most strongly affected by robotization. This provides some evidence against net-employment losses caused by automation, as such direct employment effects should be strongest in those

[11] See for example Autor and Dorn (2013), Goos and Manning (2007), Goos, Manning, and Salomons (2014), or Dustmann, Ludsteck, and Schönberg (2009).

industries that are most exposed to robotization.

Panel B of table 4 presents the results of industrial robot adoption on average wages. In contrast to employment, wages are less affected by spillover effects, as we are interested in the robotization effect on average wage rates within robotizing industries. To better isolate this effect, these estimations additionally control for changes in the skill-composition of the workforce (included in the G&M controls), as well as for changes in the share of female workers (included in the demographic controls). Once again it is shown that the sample composition has a strong effect on the estimates. Here, the 2SLS estimates in the full sample indicate a significant positive wage effect of robotization, when including only those controls used by G&M (2018) (in column 1), or when additionally controlling for trade exposure (in column 2). This estimate, however, loses its significance once demographic control variables are included (i.e. the initial period age distribution and the change in the share of female workers). Interestingly, the fixed effects estimates for the full sample switch from positive to negative (albeit statistically insignificant) after including the demographic control variables. This hints at the possibility that the positive estimates for the wage effect in columns (1) to (4) are indeed caused by unobserved industry specific heterogeneity, which cannot be controlled for in the 2SLS estimations, as the instrument does not vary within industries. Restricting the sample to robotizing sectors again reduces the problem of unobserved heterogeneity at the industry level. Comparing the fixed effects estimate (including all available controls) for the full sample in column (4) (-0.018) to the corresponding estimate for the reduced sample in column (8) (-0.020) shows that these estimates are very similar in magnitude. Also the fixed effects estimate for the reduced sample in column (8) is much more similar to the corresponding OLS estimate (-0.016), than in the full sample. Hence, the inclusion of industry fixed effects leads to a much smaller movement in the OLS estimates in the reduced sample and leaves the estimate at a very similar magnitude as the fixed effects estimate in the full sample. We again interpret this as an indication that focusing on robotizing sectors alleviates concerns arising from unobserved industry specific heterogeneity.

Turning to the 2SLS estimates in the reduced sample in columns (5) to (8), we find negative estimates across the board. These estimates are significant at the 1% level, when we additionally control for demographic workforce characteristics. In the full specification in column (8) we find a significant negative coefficient of -0.054; indicating negative wage effects of robotization within the robotizing industries. This result contrasts the positive wage effects argued by G&M (2018) (which corresponds to estimates presented in column 1). Our findings are however in line with Acemoglu and Restrepo (2020), who find a similar result for US-commuting zones. Similarly, Dauth et al. (2021) find negative wage effects when analyzing commuting zones in Germany, however this aggregate effect masks heterogeneous effects for workers, who switched firms (or even industries) due to robotization and workers, who manage to stay at their firm. While the first group typically experiences earnings losses, workers who manage to stay at their firm experience earnings gains.

3.3.1 Labor Market Outcomes by Skill-Group

In table 5 we examine the effect of industrial robots on labor demand and average wages for high-, middle-, and low-skilled workers. All estimations contain a full set of control variables.

Panel A shows the results for the change in the share of hours worked by skill-group. Shifts in the skill-composition caused by technological change are known in the literature in two forms. An earlier literature argued that automation technologies primarily substitute for low skilled workers, thus lowering their employment share. This mechanism is known as Skill-Biased-Technological-Change (SBTC - for a detailed

Table 5: Robotization effects on labor market outcomes by skill group:

	Full Sample			Reduced Sample		
	High	Medium	Low	High	Medium	Low
Panel A: △ Share of hours worked						
OLS						
Robot adoption	3.297**	3.578	-6.876**	1.148	-1.574**	0.426
	(1.228)	(2.099)	(1.954)	(0.724)	(0.483)	(0.712)
Industry FE						
Robot adoption	2.620	2.332	-4.952	1.703	-2.559**	0.856
	(1.886)	(2.654)	(2.988)	(1.604)	(0.974)	(0.644)
IV: Replaceable hours						
Robot adoption	4.269*	9.382	-13.651**	0.915**	-0.388	-0.527
	(2.117)	(5.927)	(4.873)	(0.264)	(0.613)	(0.560)
First Stage	1.227**	1.227**	1.227**	2.178**	2.178**	2.178**
	(0.210)	(0.210)	(0.210)	(0.359)	(0.359)	(0.359)
F-Statistic	27.1	27.1	27.1	27.0	27.0	27.0
Panel B: △ ln(Wages)						
OLS						
Robot adoption	-0.025	-0.014	0.063	-0.034**	-0.017	0.031
	(0.019)	(0.021)	(0.038)	(0.012)	(0.022)	(0.019)
Industry FE						
Robot adoption	-0.085*	-0.031	0.009	-0.044	-0.008	0.019
	(0.037)	(0.026)	(0.054)	(0.036)	(0.039)	(0.025)
IV: Replaceable hours						
Robot adoption	0.108	0.024	0.133*	-0.054	-0.060**	0.002
	(0.061)	(0.047)	(0.058)	(0.035)	(0.023)	(0.031)
First Stage	1.200**	1.200**	1.200**	2.110**	2.110**	2.110**
	(0.192)	(0.192)	(0.192)	(0.350)	(0.350)	(0.350)
F-Statistic	30.4	30.4	30.4	25.6	25.6	25.6
Observations	168	168	168	120	120	120
Countries	12	12	12	12	12	12
Industries	14	14	14	10	10	10
G&M Controls:	x	x	x	x	x	x
Trade Controls:	x	x	x	x	x	x
Demographic Controls:	x	x	x	x	x	x

Note: $* < 0.05, ** < 0.01$. Robust standard errors grouped by country and economic sector are shown in brackets. All regressions are weighted by the country specific share of sectoral employment in the initial period (1993). The G&M Controls include country fixed effects, initial period values of the wage rate, the capital-labor ratio, and the ratio of ICT-capital to the overall capital stock, as well as changes in the capital-labor ratio and the ratio of ICT-capital and (in wage regressions only) initial period values and changes in the employment shares of middle- and high-skilled workers. Trade controls include the initial period value and the change in net-import exposure, and demographic controls include the initial period shares of workers aged 30-49 and 50+, and (in wage regressions only) the change in the share of female workers.

overview see Acemoglu and Autor, 2011). More recently, the literature on Routine-Biased-Technological-Change (RBTC) has argued that technological advances primarily substitute for routine tasks, which are predominantly performed by workers in the middle of the skill distribution. This shift away from the middle of the skill distribution toward its tails is generally referred to as job polarization. The task based model underlying RBTC, which was first proposed in the seminal contribution of Autor, Levy, and Murnane (2003), has supplemented the SBTC-model concerning labor market impacts of automation. As Goos, Manning, and Salomons (2014) point out, job polarization (or more general shifts in the skill composition of the workforce) has important between-industry and within-industry components. With regard to the results in table 5, panel A it is important to note that our estimations only capture the within-industry component. Between-industry components, which are related to employment spillovers, are not captured by our analysis.

The full sample in panel A of table 5 shows a significant reduction in the employment share of low-skilled workers and significant employment growth at the top of the skill distribution, while the coefficient for middle-skilled workers is also positive, but statistically insignificant. Thus, the results in the full sample clearly point towards SBTC within industries. This picture is also supported by the OLS and fixed effects estimations. Focusing only on robotizing sectors in the reduced sample estimations gives a different picture. Here, the OLS and fixed effects estimations have sizeable and significant negative estimates in the middle of the skill distribution. This picture is inconsistent with SBTC and instead points towards RBTC. However, the pattern does not pertain in the 2SLS estimations for the full sample. While the estimate in the middle of the skill distribution remains negative, it is no longer statistically significant. Also the estimate for low-skilled workers turns negative, but stays insignificant. Regarding the employment share of high-skilled workers, we find positive and significant effects both in the full sample and the reduced sample. However, the reduced sample estimate is only about 1/4 as large as the full sample estimate. Relative employment gains at the top of the skill-distribution are a result routinely found in automation studies. For industrial robots similar results have been documented by Dauth et al. (2021), Bonfiglioli et al. (2020) or de Vries et al. (2020). Our result confirms these previous findings. Furthermore, our results are more consistent with RBTC than with SBTC, however, due to a lack of precision in some of our estimates, the evidence is inconclusive. In any case, the SBTC-hypothesis no longer finds support, when restricting the sample to the robotizing sectors.

Regarding the effects on the average wage by skill group in panel B of table 5 we find again that focusing on robotizing sectors leads to qualitatively different results. While the full sample indicates positive wage effects for high- and low- skilled workers, the reduced sample estimates point towards negative wage effects in the middle of the skill distribution. Thus, the entire negative aggregated wage effect in column (8) of table 4 stems from earnings reductions in the middle of the skill distribution. This pattern is consistent with the notion of wage polarization as argued by Autor and Dorn (2013).

One important lesson from our estimations in tables 4 and 5 is that the industry composition of the sample has a strong influence on the results of labor market outcomes. While the estimated effects on productivity and prices in sections 3.1 and 3.2 are quantitatively overestimated when including non-robotized industries in the analysis, the quality of the conclusions remains intact. However, this does not hold for the labor market outcomes under investigation. Both for the logarithms of hours worked and average wages, the estimated effects change from a negative employment effect (positive wage effect) in the full sample to an insignificant employment effect (negative wage effect) in the reduced sample. Also for the labor market outcomes by skill group the conclusions markedly changed, when restricting the sample to robotizing sectors. This highlights the importance to limit the analysis to those industries which are actually affected by industrial robots, especially when controlling for unobserved industry trends is not possible (as it is the case with the instrumental variables proposed by G&M, 2018).

Furthermore, the estimation of employment effects using country-industry data is faced with serious constraints arising from possible employment spillovers. This issue is not addressed to full satisfaction, neither in the full sample of all industries, nor by our focus on the reduced sample of robotizing industries. To more thoroughly address the question of economy wide employment effects of robotization more detailed data, either on the firm level (as in Acemoglu, Lelarge, and Restrepo, 2020 or Bonfiglioli et al., 2020), the local-labor market level (as in Acemoglu and Restrepo, 2020 or Dauth et al., 2021), or the worker level is required.

4 Non-monotonicity in the reaching & handling IV

In their work G&M (2018) introduce two instrumental variables to investigate causally the effects of robotization that are used in a number of subsequent research papers. The first instrument ('replaceable hours') computes as the fraction of hours that are replaceable by industrial robots (the instrument we used in sections 3.1, 3.2, 3.3 and 5). The second instrument ('reaching and handling') measures the fraction of tasks performed in an industry that requires reaching or handling, i.e. the kind of tasks that industrial robots typically perform. Both instruments are computed from data of US-industries in 1980, such that they measure the fraction of 'replaceable hours' and 'reaching and handling' tasks prior to the emergence of industrial robots.

While size and sign of the 'replaceable hours' instrument remains stable when restricting the sample exclusively to robot adopting sectors (see tables 2 to 7), the coefficient on the 'reaching and handling' instrument switches sign and thus violates the monotonicity assumption of 2SLS as formulated in Imbens and Angrist (1994).[12] Figure 2 shows this graphically. Here, we plot the first-stage relationships of the two instruments with the decile of change in robot density. This plot is an augmented version of figure A1 from G&Ms (2018) online appendix. To visualize differences between the full sample and the manufacturing and mining sectors, we added separate fit-lines for these two sample definitions.

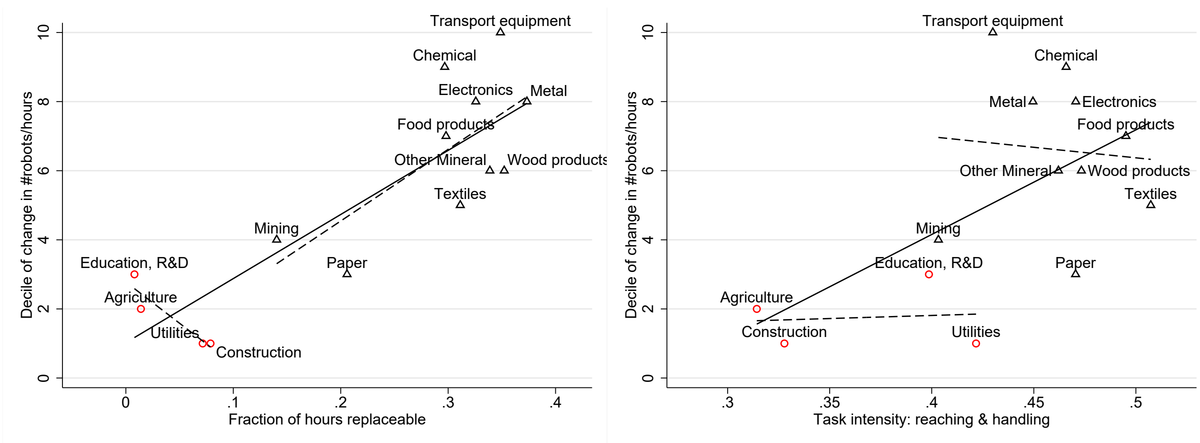
In panel A of figure 2 the first-stage relationship between the 'replaceable hours' instrument and the deciles of change in robotization remains stable when reducing the sample to manufacturing and mining sectors only. While robotoizing sectors (i.e. manufacturing and mining) and non-robotizing sectors appear to form two distinct clusters, the first stage relationship in the full-industry sample and the manufacturing and mining sample is strong and positive in both cases.

This is in stark contrast to the 'reaching and handling' instrument in panel B of figure 2. While the first-stage relationship is positive for all sectors, it becomes negative when restricting the sample to manufacturing and mining sectors only. This sign reversal of the first-stage coefficient, visually depicted in figure 2, carries over to regression analyses using the 'reaching and handling' instrument. To illustrate this, table 6

[12] A large part of the research on the effects of robotization relies on a homogeneous treatment assumption, rather than a classical monotonicity assumption. This kind of studies typically use regional variation across local labor markets, using so-called Shift-Share (or Bartik) instruments for inference (see Goldsmith-Pinkham, Paul, and Swift (2020) for a detailed discussion of Bartik-type instruments and the homogeneous effects assumption in Shift-Share research designs). As noted by Fiorini and Stevens (forthcoming) the monotonicity assumption is always necessary when (i) the gain of treatment is heterogeneous across the population (i.e. the gain of robotization is heterogeneous across industries) and (ii) there is sorting into treatment based on the gain from treatment (i.e. industries with higher gain from robotization sort into robot usage). As we regard both of these conditions to be fulfilled with country-industry-level data, we also regard the monotonicity assumption as necessary in our context.

Figure 2: First-stage relationships between the percentiles of robot adoption and the instruments used in G&M (2018)

(a) (b)



Note: These plots are taken from Figure A1 in the Online Appendix of G&M (2018). Panel (a) shows the first-stage relationship between the replaceable hours instrument and the percentiles of robot adoption, while Panel (b) shows the corresponding first-stage relationship for the reaching & handling instrument. Both panels show cross-industry variation, whereby the industry-level datapoints are calculated as mean values accross all countries used in the subsequent analysis. Manufacturing and mining industries are represented by the black triangles, while all remaining industries (agriculture, construction, education and R&D, and energy and water supply) are indicated by the red circles.

shows estimates for 2SLS-regressions of labor productivity on the deciles of change in robot adoption. Panel A compares the full sample of all available industries with the reduced sample comprised of all 2-digit manufacturing sectors, while panel B includes the mining sector in the reduced sample.

Comparing the baseline estimation for the full sample of all available industries in table 6, panel A, column (1) to the same specification for the manufacturing-sample in column (5), we see that the first-stage coefficient reverses its direction (as in panel B of figure 2). While the full sample in column (1) indicates a positive relationship between the fraction of reaching and handling tasks in 1980 US-industries and robotization in the period 1993-2007, the corresponding first-stage relationship in the manufacturing sample indicates the opposite. This pattern is not only econometrically concerning, as it points to a violation of the monotonicity assumption, but also economically counter

Table 6: Problems with the Reaching & Handling Instrument
(Dependent Variable: $\Delta ln(VA/H)$):

	Full Sample				Reduced Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Reduced Sample: Manufacturing Sectors								
OLS								
Robot adoption	0.663**	0.637**	0.650**	0.657**	0.024	0.108	0.267	0.298
	(0.236)	(0.245)	(0.241)	(0.242)	(0.191)	(0.231)	(0.202)	(0.205)
IV: Reaching & handling								
Robot adoption	1.020*	1.050*	1.290**	1.295**	-0.990	-1.104	-0.637	-0.682
	(0.421)	(0.433)	(0.335)	(0.341)	(0.851)	(0.864)	(0.713)	(0.828)
First Stage	2.141**	2.178**	2.162**	2.175**	-4.466**	-4.076**	-4.522**	-4.077**
	(0.448)	(0.395)	(0.402)	(0.377)	(1.604)	(1.493)	(1.185)	(1.482)
F-Statistic	19.3	25.3	23.5	26.7	5.9	5.6	10.6	5.4
Observations	224	224	168	168	144	144	108	108
Countries	16	16	12	12	16	16	12	12
Industries	14	14	14	14	9	9	9	9
Panel B: Reduced Sample: Manufacturing & Mining Sectors								
OLS								
Robot adoption	0.663**	0.637**	0.650**	0.657**	0.086	0.160	0.289	0.325
	(0.236)	(0.245)	(0.241)	(0.242)	(0.153)	(0.201)	(0.200)	(0.202)
IV: Reaching & handling								
Robot adoption	1.020*	1.050*	1.290**	1.295**	-1.665	-1.286	-0.572	-0.643
	(0.421)	(0.433)	(0.335)	(0.341)	(2.253)	(1.401)	(1.086)	(0.915)
First Stage	2.141**	2.178**	2.162**	2.175**	-1.793	-2.107	-1.885	-1.885
	(0.448)	(0.395)	(0.402)	(0.377)	(2.197)	(1.839)	(1.979)	(1.979)
F-Statistic	19.3	25.3	23.5	26.7	0.5	1.0	0.7	0.7
Observations	224	224	168	168	160	160	120	120
Countries	16	16	12	12	16	16	12	12
Industries	14	14	14	14	10	10	10	10
G&M Controls:	x	x	x	x	x	x	x	x
Trade Controls:		x		x		x		x
Demographic Controls:			x	x			x	x

Note: $* < 0.05, ** < 0.01$. Robust standard errors grouped by country and economic sector are shown in brackets. The dependent variables are specified in growth rates. All regressions are weighted by the country specific share of sectoral employment in the initial period (1993). The G&M Controls include country fixed effects, initial period values of the wage rate, the capital-labor ratio, and the ratio of ICT-capital to the overall capital stock, as well as changes in the capital-labor ratio and the ratio of ICT-capital. Trade controls include the initial period value and the change in net-import exposure, and demographic controls include the initial period shares of workers aged 30-49 and 50+.

intuitive. The negative first-stage estimate in column (5) would suggest that within manufacturing, those sectors with a higher fraction of reaching and handling tasks are *less* probable to robotize than sectors with a lower fraction of such tasks. As these tasks are explicitly chosen for the computation of the instrument, because these are the tasks industrial robots typically perform, this reversal of direction contradicts the intuition underlying the instrument.

Moreover, the negative first-stage coefficient leads to a reversal of the sign for the estimate of the robotization effect on labor productivity within the manufacturing sectors. While the corresponding estimate in the full-sample is positive, indicating a productivity increasing effect of industrial robots, the estimate in the reduced sample becomes negative (albeit statistically insignificant). This is a direct consequence of the negative first-stage coefficient, as the reduced form regression shows a positive estimate (with a coefficient of 4.424). It underscores how a violation of the monotonicity assumption in estimations using the 'reaching and handling' instrument potentially leads to erroneous inference, as negative effects of industrial robots on adopting sectors labor productivity are economically counter-intuitive, and also contradict the results of the existing literature.[13]

The pattern of a sign-reversing first-stage coefficient (accomodated by a sign-reversing second stage coefficient) persist over all following specifications which gradually control for heterogeneity in trade exposure and the demographic composition of the workforce. Additionally controlling for the demographic composition of the workforce (but not for trade exposure) in panel A, column (7) even leads to a first-stage F-statistic greater 10. This might wrongly tempt a researcher to believe that the inference drawn from the 'reaching and handling' instrument is trustworthy, as the instrument seems to be strong (enough) by common standards.

Extending the reduced sample by including the mining sector in panel B of table 6 shows a similar pattern. As when restricting to manufacturing sectors only, the first stage coefficients reverse sign in all specifications, which again leads to reversal of the

[13]See for example Acemoglu, Lelarge, and Restrepo (2020), Bonfiglioli et al. (2020), Cette, Devillard, and Spiezia (2021) or Dauth et al. (2021).

sign in the second stage coefficients. However, in contrast to panel A, the first-stage regression now lacks precision and strength, as the first-stage F-statistic is drastically reduced in size and the first-stage coefficient is statistically insignificant (violating the relevance condition).

Based on the reversal of the sign of the first-stage coefficient documented in figure 2 and table 6, we regard the 'reaching and handling' instrument as violating the monotonicity assumption of instrumental variable regression. We therefore advise caution in using this instrument, as it might lead to erroneous inference.[14]

5 Extended Period: 2010-2015

Finally, we also present results for the more recent time period from 2010 to 2015. We again focus on the 2-digit manufacturing sector and the 1-digit mining sector. Table A6 in the appendix shows that after 2007 robotization remained strongly concentrated within those sectors, as no other sectors are present above the 70th percentile of robot adoption and average increases in robot adoption below the 70th percentile are close to zero. While data is in principle available from 2008 onwards, we focus on the period 2010-2015 to take into account confounding effects of the financial and economic crisis after 2007.[15]

To make the estimates for the period 2010-2015 directly comparable to the estimates in the previous sections, we rescale the dependent variables to 14-year-equivalent-

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[14] The same pattern is also present when regarding the period 2010-2015 (see appendix table A7), or when considering alternative functional forms (see appendix table A8).

[15] Including the years 2008 and 2009 in the estimation indeed leads to much lower estimates e.g. for the effect on productivity. As this is likely caused by crisis effects, we exclude these two years from the analysis. Estimation results including 2008 and 2009 are available upon request.

differences.[16] We include the same control variables as in the previous sections. However, it has to be noted that the demographic controls (age-composition, female labor force participation and skill-composition) in the EU-KLEMS September 2017 release only vary on the 1-digit industry level. As a consequence we adopt for the manufacturing industries the values from the 1-digit level at the individual 2-digit sectors. Therefore, the 2-digit manufacturing sectors show no within country variation in the demographic controls and the entire within country variation stems from the difference between the 1-digit manufacturing sectors and mining. Due to this drastic reduction in variation the demographic controls are not as effective in dealing with unobserved heterogeneity as well as in increasing the precision of the 2SLS estimates, as they were in sections 3.1 to 3.3.

Table 7 reports estimates for the full sample and for the reduced sample (2-digit manufacturing industries plus mining). Comparing the productivity estimates for the reduced sample in columns (2) and (4) of table 7 to the period 1993-2007 in Table 2 reveals that the estimates are of similar magnitude as in the previous period. The estimates are even slightly larger for the period 2010-2015, with an estimate for the effect on labor productivity of 0.749 (compared to 0.614 in 1993-2007) and an estimate of 0.850 for TFP (compared to 0.716). While the size of the estimates hints at continued (possibly even slightly stronger) effects of robotization on productivity, all estimates for the period 2010-2015 remain statistically insignificant.

[16] Rescaling the dependent variables ensures that the estimates are not smaller simply because the time period under investigation (5 years) is shorter than in sections 3.1 to 3.3 (14 years). Notice that this transformation does not affect the percentiles of change in robot density (i.e. the explanatory variable), as the percentile rank is not affected by rescaling changes in robotization to 14-year-equivalent changes.

Table 7: Robotization Effects 2010-2015:

	$\Delta ln(VA/H)$		$\Delta ln(TFP)$		$\Delta ln(P)$		$\Delta ln(H)$		$\Delta ln(W/H)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
OLS										
Robot adoption	0.047	0.178	0.128	0.201	-0.113*	-0.136	0.208	0.286	-0.007	-0.001
	(0.076)	(0.130)	(0.118)	(0.117)	(0.056)	(0.153)	(0.129)	(0.153)	(0.009)	(0.001)
Industry FE										
Robot adoption	0.065	0.232	0.060	0.217	-0.229**	-0.277	-0.083	-0.031	-0.004	-0.000
	(0.072)	(0.122)	(0.089)	(0.135)	(0.059)	(0.155)	(0.105)	(0.112)	(0.015)	(0.001)
IV: Replaceable hours										
Robot adoption	0.899	0.749	1.377*	0.850	-0.524	-0.130	0.324	0.587*	-0.008	-0.003
	(0.582)	(0.562)	(0.683)	(0.685)	(0.501)	(0.335)	(0.456)	(0.265)	(0.018)	(0.005)
First Stage	1.047*	2.755**	1.063*	2.743**	1.047*	2.755**	1.047*	2.755**	1.356**	2.934**
	(0.438)	(0.872)	(0.433)	(0.861)	(0.438)	(0.872)	(0.438)	(0.872)	(0.268)	(0.863)
F-Statistic	4.5	7.1	4.8	7.2	4.5	7.1	4.5	7.1	19.6	7.8
Observations	156	108	155	107	156	108	156	108	156	108
Countries	12	12	12	12	12	12	12	12	12	12
Industries	13	9	13	9	13	9	13	9	13	9
Reduced Sample:	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
G&M Controls:	x	x	x	x	x	x	x	x	x	x
Trade Controls:	x	x	x	x	x	x	x	x	x	x
Demographic Controls:	x	x	x	x	x	x	x	x	x	x

Note: $* < 0.05, ** < 0.01$. Robust standard errors grouped by country and economic sector are shown in brackets. All regressions are weighted by the country specific share of sectoral employment in the initial period (1993). The G&M Controls include country fixed effects, initial period values of the wage rate, the capital-labor ratio, and the ratio of ICT-capital to the overall capital stock, as well as changes in the capital-labor ratio and the ratio of ICT-capital and (in wage regressions only) initial period values and changes in the employment shares of middle- and high-skilled workers. Trade controls include the initial period value and the change in net-import exposure, and demographic controls include the initial period shares of workers aged 30-49 and 50+, and (in wage regressions only) the change in the share of female workers.

However, as the inclusion of the demographic controls has shown to be crucial for re-establishing the productivity effects in the 1993-2007 data and these controls show drastically reduced variation in the 2010-2015 data, we cannot rule out that the lack of statistical significance stems from these data problems. Similar patterns emerge for the effects on prices, hours worked and wages, so the results for the period 2010-2015 are inconclusive.

6 Discussion and Conclusion

This paper reveals pitfalls in the use of the IFR robot data, a prominent source for automation research in economics. We illustrate these difficulties by comparing two different samples: The first sample contains all available country-industry observations from the IFR data, as it has been used in the seminal paper on the economic effects of industrial robots (Graetz and Michaels, 2018). The other sample comprises only country-industry observations that are indeed affected by robotization, i.e. the 2-digit manufacturing industries and the 1-digit mining industry. Investigating the effects of robotization without non-robotizing sectors is important in order to determine the extent to which overall economic effects of robotization are artificially driven by non-robotizing sectors.

By contrasting the effects of robotization between the two samples, the following implications become apparent: The exclusion of non-robotizing industries from the estimation sample leads to a significant drop of the productivity effects of robotization during the period 1993-2007, with a halving of the effect size. The sample choice also influences the effect on prices. Considering all sectors implies a significant reduction in prices, whereas considering only the robotizing sectors no longer reveals any significant effects. The most significant changes due to the sample choice, however, occur in the area of labor market effects. Here, the estimated effects change from a negative employment effect (positive wage effect) in the full sample to an insignificant employment effect (negative wage effect) in the reduced sample. The labor market results by skill group changed in the sense that skill-biased technological change cannot be corroborated, but rather, on the contrary, there is evidence (albeit not significant in all specifications) of labor market polarization.

These drastic changes highlight the importance to limit the analysis to those industries which are affected by industrial robots, especially when controlling for unobserved industry trends is not possible, as it is the case with the instrumental variables proposed by G&M (2018). Excluding the non-robotizing sectors also leads to the economic impact of industrial robots being more in line with the existing literature, especially concerning the labor market outcomes. To interpret the clearly reduced productivity effects and the insignificant price effects, it can be helpful to be aware that robotizing firms have a very low prevalence across all industries,[17] and that it is an open question whether the currently existing industrial robot technology actually represents a break with known automation technologies or is not rather a continuation of them, the greatest effects of which have already passed. (Fernandez-Macias, Klenert, and Anton, 2020).

[17] Deng, Plümpe, and Stegmaier (2020) show for Germany, one of the most robotized countries, that overall only 1.55% of all plants use robots. While this figure rises to 8.22% for manufacturing, even in the most robot-intensive manufacturing industries (motor vehicles and plastics) three-quarters of plants do not use any robots.

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Appendix A Robustness Check: Functional Form

To check whether the pattern from table 2 is specific to the percentile transformation used for computing the robotization measure in equation 1, we also run estimations using other functional forms. For this we use the same functional forms as G&M (2018) (table A5 in their online appendix). We present these estimations in table A1. Specifically, we report estimations using the raw change in the number of robots per million hours worked (panel A) and the change in the logarithm $log(1+\#Robots/Mio.Hours)$ (panel B).[18]

Consistent with the estimations using the percentile transformation in table 2, both alternative measures show similar behaviour. In both cases focusing on robotizing sectors leads to the 2SLS estimates for the impact of robotization on labor productivity being reduced by about half, accomodated by a reduction in precision. The $log(1 + \#Robots/Mio.Hours)$ transformation shows statistically significant estimates in the reduced sample, while the estimates for $\#Robots/Mio.Hours$ are imprecissely estimated.

Notably, table A1 shows that the percentile transformation leads to a clear increase in the precision of the estimates, especially in the first-stage regressions. Here, the percentile transformation is crucial to obtaining a first-stage F-statistic which exceeds the commonly used threshold of 10. This point, which was already thoroughly discussed in the original paper by G&M (2018) provides support for the choice of robotization-percentiles of change, as they markedly reduce the noise in the data.

The estimations reported in table A1 show that the reduced size of the productivity

[18] G&M (2018) also regard a third functional form, namely the change in the price of robot services (normalized by the wage bill). As we do not have access to data on robot prices, we cannot include this third functional form.

estimates, when restricting the sample to robotizing sectors, does not stem from the percentile transformation. This pattern is rather driven by the inclusion of sectors which did not experience relevant changes in robotization during the investigated period.

Table A1: Productivity Effects of Robotization:
Alternative functional forms (Dependent Variable: $\Delta ln(VA/H)$)

	Full Sample				Reduced Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Δ # Robots/Mio. Hours								
OLS								
Robot adoption	0.035*	0.034*	0.034	0.034	-0.001	-0.001	0.007	0.007
	(0.015)	(0.015)	(0.018)	(0.018)	(0.009)	(0.009)	(0.007)	(0.007)
IV: Replaceable hours								
Robot adoption	0.173*	0.176*	0.150	0.151*	0.068	0.064	0.087	0.085
	(0.084)	(0.085)	(0.077)	(0.077)	(0.050)	(0.048)	(0.060)	(0.059)
First Stage	7.145*	7.048*	10.090*	10.036*	17.965*	19.297*	13.992	15.802
	(2.863)	(2.792)	(4.669)	(4.569)	(8.747)	(9.085)	(9.572)	(9.471)
F-Statistic	5.2	5.3	3.8	3.9	3.3	3.5	1.6	2.1
Panel B: Δ log(1+# Robots/Mio. Hours)								
OLS								
Robot adoption	0.438*	0.429*	0.508*	0.511**	0.106	0.104	0.221*	0.239*
	(0.176)	(0.171)	(0.200)	(0.198)	(0.104)	(0.103)	(0.102)	(0.096)
IV: Replaceable hours								
Robot adoption	0.934**	0.943**	0.989**	0.992**	0.565*	0.562*	0.639**	0.681*
	(0.357)	(0.354)	(0.286)	(0.286)	(0.271)	(0.280)	(0.215)	(0.273)
First Stage	1.324**	1.315**	1.531**	1.526**	2.161**	2.191**	1.907*	1.974*
	(0.274)	(0.265)	(0.287)	(0.274)	(0.792)	(0.847)	(0.782)	(0.848)
F-Statistic	19.6	20.5	23.0	24.8	5.8	5.1	4.5	4.0
Observations	224	224	168	168	160	160	120	120
Countries								
Industries								
G&M Controls:	x	x	x	x	x	x	x	x
Trade Controls:		x		x		x		x
Demographic Controls:			x	x			x	x

Note: $* < 0.05, ** < 0.01$. Robust standard errors grouped by country and economic sector are shown in brackets. The dependent variables are specified in growth rates. All regressions are weighted by the country specific share of sectoral employment in the initial period (1993). The G&M Controls include country fixed effects, initial period values of the wage rate, the capital-labor ratio, and the ratio of ICT-capital to the overall capital stock, as well as changes in the capital-labor ratio and the ratio of ICT-capital. Trade controls include the initial period value and the change in net-import exposure, and demographic controls include the initial period shares of workers aged 30-49 and 50+.

Appendix table A2 repeats the estimations from table 2, using only observations with available data on the demographic controls. This reduces the sample size from 160 observations in columns (1) and (5) of table 2 (panel A), to 120 observations in the corresponding regressions in table A2.

Reducing the sample size leaves all previous conclusions unchanged. The 2SLS-coefficient for the effect on labor-productivity (column 1, panel A) in table A2 is of similar magnitude as in table 2 and remains highly significant. Restricting the industries used for the analysis to only the manufacturing and mining sectors (i.e. the sectors in which robotization takes place), again leads to an insignificant estimate and a reduction in the size of the estimate by more than half. The magnitude of the drop between the full sample and the reduced sample is also very similar as in table 2. Successively adding controls for trade exposure and demographic characteristics of the workforce re-establishes the estimates statistical significance and increases the size of the estimate to 0.614 in the full specification. Most notably, comparing columns (6) and (7) in panel A shows, that it is indeed the inclusion of demographic controls that plays a crucial role in re-establishing the estimates significance, rather than the drop in sample size. When regarding the results for TFP in panel B of table A2 the results from table 2 are also confirmed.

Therefore, our results are not driven by the reduced sample size due to limited availability of the demographic control variables, but rather by restricting the sample to industries that show relevant robotization trends during the investigation period.

Table A2: Productivity Effects of Robotization:
Using only observations with available data on demographic controls

	Full Sample				Reduced Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Δ ln(VA/H)								
OLS								
Robot adoption	0.666**	0.668**	0.650**	0.657**	0.231	0.247	0.289	0.325
	(0.253)	(0.253)	(0.241)	(0.242)	(0.247)	(0.252)	(0.200)	(0.202)
Industry FE								
Robot adoption	0.326	0.337	0.321	0.332	0.410	0.440	0.461	0.490
	(0.224)	(0.227)	(0.223)	(0.226)	(0.369)	(0.363)	(0.371)	(0.361)
IV: Replaceable hours								
Robot adoption	1.106**	1.119**	1.203**	1.207**	0.518	0.540	0.568*	0.614*
	(0.381)	(0.389)	(0.309)	(0.312)	(0.321)	(0.348)	(0.269)	(0.294)
First Stage	1.082**	1.066**	1.258**	1.254**	2.219**	2.257**	2.146**	2.192**
	(0.204)	(0.199)	(0.199)	(0.193)	(0.423)	(0.459)	(0.371)	(0.406)
F-Statistic	23.1	23.3	32.5	33.7	21.2	18.3	25.3	21.6
Observations	168	168	168	168	120	120	120	120
Countries	12	12	12	12	12	12	12	12
Industries	14	14	14	14	10	10	10	10
Panel B: Δ ln(TFP)								
OLS								
Robot adoption	0.467*	0.466*	0.442*	0.446*	0.193	0.205	0.272	0.307
	(0.201)	(0.202)	(0.186)	(0.186)	(0.158)	(0.162)	(0.151)	(0.166)
Industry FE								
Robot adoption	0.201	0.209	0.195	0.203	0.341	0.372	0.381	0.403
	(0.200)	(0.202)	(0.192)	(0.194)	(0.304)	(0.308)	(0.312)	(0.317)
IV: Replaceable hours								
Robot adoption	0.827**	0.831**	0.909**	0.905**	0.662**	0.682**	0.672**	0.716**
	(0.310)	(0.313)	(0.216)	(0.217)	(0.211)	(0.243)	(0.212)	(0.230)
First Stage	1.008**	0.999**	1.202**	1.208**	2.182**	2.223**	2.178**	2.171**
	(0.188)	(0.182)	(0.196)	(0.192)	(0.384)	(0.423)	(0.336)	(0.407)
F-Statistic	23.5	24.1	30.3	31.4	24.8	20.7	31.5	20.9
Observations	154	154	154	154	110	110	110	110
Countries	11	11	11	11	11	11	11	11
Industries	14	14	14	14	10	10	10	10
G&M Controls:	x	x	x	x	x	x	x	x
Trade Controls:		x		x		x		x
Demographic Controls:			x	x			x	x

Note: $* < 0.05, ** < 0.01$. Robust standard errors grouped by country and economic sector are shown in brackets. The dependent variables are specified in growth rates. All regressions are weighted by the country specific share of sectoral employment in the initial period (1993). The G&M Controls include country fixed effects, initial period values of the wage rate, the capital-labor ratio, and the ratio of ICT-capital to the overall capital stock, as well as changes in the capital-labor ratio and the ratio of ICT-capital. Trade controls include the initial period value and the change in net-import exposure, and demographic controls include the initial period shares of workers aged 30-49 and 50+.

Table A3: Price Effects of Robotization:
Using only observations with available data on demographic controls

	Full Sample				Reduced Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OLS								
Robot adoption	-0.488*	-0.491*	-0.487*	-0.493*	-0.243	-0.255	-0.282	-0.312
	(0.212)	(0.213)	(0.197)	(0.199)	(0.174)	(0.180)	(0.156)	(0.159)
Industry FE								
Robot adoption	-0.213	-0.227	-0.211	-0.224	-0.359	-0.377	-0.400	-0.224
	(0.186)	(0.189)	(0.186)	(0.188)	(0.279)	(0.272)	(0.281)	(0.188)
IV: Replaceable hours								
Robot adoption	-0.750*	-0.762*	-0.876**	-0.879**	-0.420	-0.446	-0.446	-0.496
	(0.337)	(0.341)	(0.287)	(0.289)	(0.310)	(0.347)	(0.271)	(0.298)
First Stage	1.082**	1.066**	1.258**	1.254**	2.219**	2.257**	2.146**	2.192**
	(0.204)	(0.199)	(0.199)	(0.193)	(0.423)	(0.459)	(0.371)	(0.406)
F-Statistic	23.1	23.3	32.5	33.7	21.2	18.3	25.3	21.6
Observations	168	168	168	168	120	120	120	120
Countries	12	12	12	12	12	12	12	12
Industries	14	14	14	14	10	10	10	10
G&M Controls:	x	x	x	x	x	x	x	x
Trade Controls:		x		x		x		x
Demographic Controls:			x	x			x	x

Note: $* < 0.05, ** < 0.01$. Robust standard errors grouped by country and economic sector are shown in brackets. The dependent variables are specified in growth rates. All regressions are weighted by the country specific share of sectoral employment in the initial period (1993). The G&M Controls include country fixed effects, initial period values of the wage rate, the capital-labor ratio, and the ratio of ICT-capital to the overall capital stock, as well as changes in the capital-labor ratio and the ratio of ICT-capital. Trade controls include the initial period value and the change in net-import exposure, and demographic controls include the initial period shares of workers aged 30-49 and 50+.

Table A4: Robotization effects on labor market outcomes:
Using only observations with available data on demographic controls

	Full Sample				Reduced Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: △ ln(Hours worked)								
OLS								
Robot adoption	-0.215	-0.246	-0.224	-0.252	0.261^{*}	0.231^{*}	0.277^{**}	0.252^{**}
	(0.169)	(0.177)	(0.191)	(0.193)	(0.119)	(0.111)	(0.105)	(0.093)
Industry FE								
Robot adoption	-0.018	-0.027	-0.023	-0.030	-0.002	-0.001	0.052	0.056
	(0.119)	(0.118)	(0.124)	(0.123)	(0.105)	(0.117)	(0.061)	(0.063)
IV: Replaceable hours								
Robot adoption	-0.566	-0.585	-0.680^{*}	-0.682^{*}	0.672	0.584	0.705	0.617
	(0.338)	(0.335)	(0.325)	(0.317)	(0.385)	(0.354)	(0.401)	(0.356)
First Stage	1.082^{**}	1.066^{**}	1.258^{**}	1.254^{**}	2.219^{**}	2.257^{**}	2.146^{**}	2.192^{**}
	(0.204)	(0.199)	(0.199)	(0.193)	(0.423)	(0.459)	(0.371)	(0.406)
F-Statistic	23.1	23.3	32.5	33.7	21.2	18.3	25.3	21.6
Observations	168	168	168	168	120	120	120	120
Countries	12	12	12	12	12	12	12	12
Industries	14	14	14	14	10	10	10	10
Panel B: △ ln(Wages)								
OLS								
Robot adoption	0.012	0.011	0.002	0.001	-0.002	-0.004	-0.020	-0.016
	(0.010)	(0.010)	(0.011)	(0.011)	(0.015)	(0.014)	(0.016)	(0.015)
Industry FE								
Robot adoption	-0.015	-0.016	-0.017	-0.018	-0.010	-0.008	-0.024	-0.020
	(0.026)	(0.026)	(0.025)	(0.025)	(0.040)	(0.041)	(0.044)	(0.044)
IV: Replaceable hours								
Robot adoption	0.086^{*}	0.085^{*}	0.049	0.049	-0.026	-0.041	-0.052^{**}	-0.054^{**}
	(0.037)	(0.038)	(0.037)	(0.037)	(0.024)	(0.032)	(0.013)	(0.011)
First Stage	1.106^{**}	1.104^{**}	1.190^{**}	1.200^{**}	2.202^{**}	2.216^{**}	2.056^{**}	2.110^{**}
	(0.198)	(0.192)	(0.194)	(0.192)	(0.431)	(0.481)	(0.320)	(0.350)
F-Statistic	25.0	26.3	29.5	30.4	19.4	15.4	29.6	25.6
Observations	168	168	168	168	120	120	120	120
Countries	12	12	12	12	12	12	12	12
Industries	14	14	14	14	10	10	10	10
G&M Controls:	x	x	x	x	x	x	x	x
Trade Controls:		x		x		x		x
Demographic Controls:			x	x			x	x

Note: $* < 0.05, ** < 0.01$. Robust standard errors grouped by country and economic sector are shown in brackets. The dependent variables are specified in growth rates. All regressions are weighted by the country specific share of sectoral employment in the initial period (1993). The G&M Controls include country fixed effects, initial period values of the wage rate, the capital-labor ratio, and the ratio of ICT-capital to the overall capital stock, as well as changes in the capital-labor ratio and the ratio of ICT-capital and (in wage regressions only) initial period values and changes in the employment shares of middle- and high-skilled workers. Trade controls include the initial period value and the change in net-import exposure, and demographic controls include the initial period shares of workers aged 30-49 and 50+, and (in wage regressions only) the change in the share of female workers.

Appendix B Further Robustness Checks

Table A5: Robotization effects on labor demand: Include changes in output and prices

	Full Sample				Reduced Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Δ ln(Hours worked)								
OLS								
Robot adoption	-0.177	-0.215	-0.252	-0.145	0.314**	0.265**	0.252**	0.056
	(0.170)	(0.175)	(0.193)	(0.096)	(0.113)	(0.094)	(0.093)	(0.060)
Industry FE								
Robot adoption	0.008	-0.002	-0.030	-0.089	-0.021	-0.025	0.056	-0.013
	(0.114)	(0.110)	(0.123)	(0.086)	(0.090)	(0.094)	(0.063)	(0.052)
IV: Replaceable hours								
Robot adoption	-0.472	-0.492	-0.682*	-0.397**	0.717*	0.629	0.617	0.055
	(0.316)	(0.304)	(0.317)	(0.115)	(0.348)	(0.324)	(0.356)	(0.118)
First Stage	1.198**	1.186**	1.254**	1.154**	2.366**	2.358**	2.192**	1.998**
	(0.187)	(0.180)	(0.193)	(0.189)	(0.378)	(0.408)	(0.406)	(0.402)
F-Statistic	34.4	36.2	33.7	29.4	30.5	25.6	21.6	17.9
Observations	224	224	168	168	160	160	120	120
Countries	16	16	12	12	16	16	12	12
Industries	14	14	14	14	10	10	10	10
G&M Controls:	x	x	x	x	x	x	x	x
Trade Controls:		x	x	x		x	x	x
Demographic Controls:			x	x			x	x
Output & Price Changes:				x				x

Note: $* < 0.05, ** < 0.01$. Robust standard errors grouped by country and economic sector are shown in brackets. The dependent variables are specified in growth rates. All regressions are weighted by the country specific share of sectoral employment in the initial period (1993). The G&M Controls include country fixed effects, initial period values of the wage rate, the capital-labor ratio, and the ratio of ICT-capital to the overall capital stock, as well as changes in the capital-labor ratio and the ratio of ICT-capital. Trade controls include the initial period value and the change in net-import exposure, and demographic controls include the initial period shares of workers aged 30-49 and 50+..

Appendix C Additional Descriptives

Table A6: Distribution of changes in robot density by economic sector (2008-2015)

	#Robots/Mio. Hours			Percentiles of Δ		
	2008	2015	Δ	Mean	Min	Max
Manufacturing Sectors						
Transport equipment	14.96	24.04	9.08	0.97	0.90	1.00
Plastic, Glas	3.96	6.17	2.21	0.88	0.76	0.98
Metal	4.70	6.57	1.87	0.86	0.76	0.96
Food, Beverages	1.66	2.77	1.11	0.76	0.01	0.97
Electrical, Optical	2.12	3.19	1.06	0.72	0.01	0.97
Chemical	0.59	1.25	0.66	0.75	0.33	0.88
Textiles, Leather	0.46	0.97	0.50	0.49	0.01	0.98
Wood, Paper	0.85	1.10	0.25	0.64	0.01	0.80
Non-Manufacturing Sectors						
Mining	0.21	0.30	0.09	0.38	0.01	0.82
Education, R&D	0.08	0.11	0.04	0.47	0.15	0.70
Agriculture	0.05	0.05	0.01	0.27	0.02	0.65
Construction	0.02	0.03	0.01	0.32	0.03	0.61
Utilities	0.01	0.02	0.01	0.24	0.02	0.65

Note: All values correspond to unweighted mean values over all available countries. The industry classification used in the IFR-data are mapped to the ISIC-Rev. 4 classification. Manufacturing sectors are available at the to 2-digit industry level, while the non-manufacturing sectors are at the 1-digit level.

Appendix D Non-monotonicity (Additional Results)

Table A7: Problems with the Reaching & Handling Instrument (Period 2010-2015) (Dependent Variable: $\Delta ln(VA/H)$):

	Full Sample				Reduced Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Reduced Sample: Manufacturing Sectors								
OLS								
Robot adoption	0.056	0.047	0.045	0.047	0.161	0.170	0.167	0.178
	(0.149)	(0.143)	(0.082)	(0.076)	(0.119)	(0.121)	(0.130)	(0.130)
IV: Reaching & handling								
Robot adoption	-0.591	-0.665	-0.811	-0.804	0.958	0.975	0.822	0.811
	(0.327)	(0.416)	(0.531)	(0.556)	(0.666)	(0.703)	(0.593)	(0.614)
First Stage	2.155^{**}	2.031^{**}	1.570^{**}	1.529^{**}	-5.120^{*}	-5.093^{*}	-5.716^{**}	-5.825^{**}
	(0.392)	(0.420)	(0.441)	(0.422)	(2.088)	(2.160)	(2.162)	(2.203)
F-Statistic	25.1	19.0	10.2	10.4	4.6	4.1	5.1	5.0
Observations	169	169	156	156	117	117	108	108
Countries	13	13	12	12	13	13	12	12
Industries	13	13	13	13	9	9	9	9
Panel B: Reduced Sample: Manufacturing & Mining Sectors								
OLS								
Robot adoption	0.056	0.047	0.045	0.047	0.193	0.220	0.185	0.212
	(0.149)	(0.143)	(0.082)	(0.076)	(0.135)	(0.142)	(0.151)	(0.143)
IV: Reaching & handling								
Robot adoption	-0.591	-0.665	-0.811	-0.804	0.799	0.854	0.835	0.877
	(0.327)	(0.416)	(0.531)	(0.556)	(0.543)	(0.543)	(0.552)	(0.557)
First Stage	2.155^{**}	2.031^{**}	1.570^{**}	1.529^{**}	-6.247^{**}	-6.163^{**}	-6.256^{**}	-6.256^{**}
	(0.392)	(0.420)	(0.441)	(0.422)	(2.131)	(2.202)	(2.221)	(2.221)
F-Statistic	25.1	19.0	10.2	10.4	6.3	5.5	5.7	5.7
Observations	169	169	156	156	104	104	96	96
Countries	13	13	12	12	13	13	12	12
Industries	13	13	13	13	8	8	8	8
G&M Controls:	x	x	x	x	x	x	x	x
Trade Controls:		x		x		x		x
Demographic Controls:			x	x			x	x

Note: $* < 0.05, ** < 0.01$. Robust standard errors grouped by country and economic sector are shown in brackets. The dependent variables are specified in growth rates. All regressions are weighted by the country specific share of sectoral employment in the initial period (2010). The G&M Controls include country fixed effects, initial period values of the wage rate, the capital-labor ratio, and the ratio of ICT-capital to the overall capital stock, as well as changes in the capital-labor ratio and the ratio of ICT-capital. Trade controls include the initial period value and the change in net-import exposure, and demographic controls include the initial period shares of workers aged 30-49 and 50+.

Table A8: Problems with the Reaching & Handling Instrument: Alternative functional forms (Dependent Variable: $\Delta ln(VA/H)$)

	Full Sample				Reduced Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Δ # Robots/Mio. Hours								
OLS								
Robot adoption	0.035*	0.034*	0.034	0.034	-0.001	-0.001	0.007	0.007
	(0.015)	(0.015)	(0.018)	(0.018)	(0.009)	(0.009)	(0.007)	(0.007)
IV: Replaceable hours								
Robot adoption	0.300*	0.317*	0.293**	0.301**	-0.058	-0.055	-0.028	-0.036
	(0.119)	(0.125)	(0.099)	(0.101)	(0.062)	(0.058)	(0.049)	(0.047)
robots_dot91_phs	7.366*	7.202*	9.530**	9.357**	-46.239	-49.557	-37.891	-42.196
	(3.628)	(3.502)	(3.535)	(3.355)	(29.944)	(29.122)	(25.265)	(25.230)
F-Statistic	3.5	3.5	5.9	6.2	1.9	2.2	1.7	2.1
Panel B: Δ log(1+# Robots/Mio. Hours)								
OLS								
Robot adoption	0.438*	0.429*	0.508*	0.511**	0.106	0.104	0.221*	0.239*
	(0.176)	(0.171)	(0.200)	(0.198)	(0.104)	(0.103)	(0.102)	(0.096)
IV: Replaceable hours								
Robot adoption	0.994*	1.022*	1.271**	1.281**	-12.412	-5.012	-0.743	-0.768
	(0.436)	(0.446)	(0.400)	(0.397)	(137.404)	(19.268)	(1.884)	(1.342)
robots_dot91_phs	2.226**	2.237**	2.195**	2.199**	-0.215	-0.541	-1.451	-1.982
	(0.677)	(0.626)	(0.553)	(0.506)	(2.428)	(2.121)	(2.741)	(2.303)
F-Statistic	9.1	10.6	12.8	15.1	0.006	0.05	0.2	0.5
Observations	224	224	168	168	160	160	120	120
Countries								
Industries								
G&M Controls:	x	x	x	x	x	x	x	x
Trade Controls:		x		x		x		x
Demographic Controls:			x	x			x	x

Note: $* < 0.05, ** < 0.01$. Robust standard errors grouped by country and economic sector are shown in brackets. The dependent variables are specified in growth rates. All regressions are weighted by the country specific share of sectoral employment in the initial period (1993). The G&M Controls include country fixed effects, initial period values of the wage rate, the capital-labor ratio, and the ratio of ICT-capital to the overall capital stock, as well as changes in the capital-labor ratio and the ratio of ICT-capital. Trade controls include the initial period value and the change in net-import exposure, and demographic controls include the initial period shares of workers aged 30-49 and 50+.