INNOVATIONS AND WORK: ASSESSING THE IMPACT OF AUTOMATION ON LABOR OUTCOMES THROUGH A CROSS-COUNTRY AND CROSS-INDUSTRY ANALYSIS

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Abstract. This paper examines the relationship between technological change and labor market outcomes using cross-country and cross-industry data spanning 25 years (1995–2020). Specifically, it investigates the impact of automation, proxied by total factor productivity (TFP) growth, on two key labor market indicators: aggregate employment and aggregate labor share of value added. The theoretical framework of this paper derives from Autor and Salomons (2018) and delineates four channels—comprising one direct effect and three indirect effects—by which automation influences labor market outcomes. This paper extends A&S' analysis by 13 years and makes methodological changes by revising the lag structure of TFP growth to account for longer, more variable innovation-to-productivity effects and incorporating previously omitted controls to capture the final demand effects of automation. Therefore, the primary goal of this paper is to reassess Autor and Salomons (2018)'s analysis by employing methodologies better suited to the new data. The theoretical framework in this paper is based on the core idea that, while certain technological innovations may displace labor, countervailing responses within the economy can mitigate downward shifts in aggregate labor demand, making it crucial to estimate both the direct and indirect effects of automation. Consistent with Autor and Salomons (2018), this paper finds that for both employment and labor share of value added, there is a negative direct effect of automation on labor outcomes in the industry where the innovation occurs. For employment, this negative direct effect is offset by countervailing forces elsewhere in the economy — including upstream and downstream linkages, final demand effects, and compositional changes — yielding a net positive effect of automation. In contrast, the net effect on labor share of value added is negative, reflecting the broader trend of declining labor shares observed in developed countries over recent decades. However, our quantitative analysis also reveals a significant discrepancy compared to A&S' findings: the size of the net positive impact of automation on aggregate employment is notably diminished. This disparity suggests that recent technological advancements, such as advanced artificial intelligence and robotics introduced in the last decade, may differ fundamentally in their labor market effects from older technologies. Consequently, these newer technologies may exert a less favorable influence on labor outcomes, underscoring the need for nuanced understanding and strategic adaptation to technological change in contemporary economies.

JEL classification: J21, J24

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1. INTRODUCTION

Automation can be defined as an expansion of the set of tasks where capital can substitute for labor (Acemoglu and Restrepo (2018a)). The last two decades have witnessed major technological

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advances, particularly in artificial intelligence (AI) and Robotics, that have the potential to reshape future lifestyles and workplaces by automating various human activities. A recent US survey (Smith and Anderson (2017)) indicates that, despite some optimism, there is widespread public unease about the societal impacts of these innovations, particularly their potential to displace entire job categories. Despite such growing public sentiment, economic literature is far from providing a consensus as to whether automation, particularly new technologies like AI and robotics, will ultimately displace labor.

Acemoglu and Restrepo (2018b) highlight that the trend of declining labor share of value added in developed economies has often been cited in Economics as evidence to claim that advancements in technologies like robotics and AI have contributed to, at the very least, a relative decline in workers' compensation. However, they stress the inadequacy of existing frameworks in fully accounting for both the direct impacts of automation and the potential countervailing effects. This deficiency underscores the need for a comprehensive framework that can capture the complexities of technological change in the labor market.

This paper extends the research conducted by David Autor and Anna Salomons (2018) (henceforth, A&S), refining and applying their theoretical framework comprising the direct and indirect effects of industry-level automation. It utilizes the latest sample of the EUKLEMS & INTANprod cross-country and cross-industry data (1995–2020) to estimate the impact of automation on labor market outcomes. Labor displacement due to automation can either take the form of employment displacement or erosion of labor's share of value added in the economy. Similar to Autor and Salomons (2018), employment is measured as both the number of workers and hours worked, while automation is measured as other-country, industry-level total factor productivity (TFP) growth.

The theoretical basis of this paper is constructed upon a framework that outlines four channels through which industry-level automation influences aggregate labor market outcomes. The first of these channels is the direct effect of automation on employment and labor shares within the industries where the automation occurs. However, productivity growth due to automation will not just be confined in the industry where it originates but will also affect employment and labor shares elsewhere in the economy. The remaining three channels measure the indirect and potentially countervailing effects of automation across the broader economy. The interplay of these four channels determines the net impact of automation, and whether it ultimately proves labor-displacing (Autor and Salomons (2018)).

Diverging from alternative approaches in this domain, this paper, akin to Autor and Salomons (2018), employs TFP growth as the primary measure of technological advancement, as opposed to more focused metrics like robotics (Graetz and Michaels (2018)) or routine task replacement. While this "omnibus" or "all-encompassing" measure might fall short in reflecting particular types of technological progress, the main advantage of using TFP growth to measure automation is that it eliminates the heterogeneity in innovation across sectors and time periods. Moreover, all margins of technological progress ultimately lead to an increase in TFP by increasing labor or capital productivity or reallocating tasks between capital and labor (A&S, 2018).

This paper contributes to the literature in several ways. Firstly, it extends the analysis of the impact of industry-specific TFP growth on labor market outcomes using Autor and Salomons (2018)'s theoretical framework. While their original analysis spanned from 1970 to 2007, significant advancements in robotics and AI have occurred since 2007. By examining data from 1995 to 2020, this study aims to evaluate the impact of this new wave of automation, driven by technologies such as AI and robotics, and ascertain whether the conclusions drawn by Autor and Salomons (2018) remain applicable in the current technological landscape or if this era of automation represents a departure from previous waves of technological progress. Secondly, this paper makes methodological changes to the regression specifications used by Autor and Salomons (2018). Primarily, the lag structure of the explanatory variable (TFP growth) is changed in line with the demands of the new data and based on literature examining the persistence of contemporaneous TFP shocks, which suggest longer and more variable lags between innovation and productivity growth than accounted for by A&S (Gort and Klepper (1982); Foster et al. (2018)). Moreover, several additional controls that were omitted in A&S' analysis are added to Specification 3 to measure the final demand effects of automation.

A preliminary summary of the results of the paper is as follows: Automation as embodied in TFP growth has been slightly employment-augmenting but significantly labor-share-displacing across the 25 years in the data sample (1995–2020). The results of this paper are qualitatively similar to those of Autor and Salomons (2018) who also find the net effect on employment to be positive but that on labor share to be negative. However, quantitatively, the net effects of TFP growth on aggregate employment and hours worked are much smaller in this paper than those of Autor and Salomons (2018). This discrepancy in results for aggregate employment and hours worked can be attributed to the following: (1) differences in lag structures employed in the regression specifications; (2) the inclusion of additional controls in specification 3 of this paper, which significantly reduce the positive productivity effects found in A&S' analysis; and (3) a potentially fundamental difference in the way new technologies of the last two decades affect employment compared to technologies of the past. For labor share of value added, the results of this paper are both qualitatively and quantitatively similar to those of A&S. The appendix also details a series a robustness checks for the estimates of this paper, which show the stability of the results.

2. LITERATURE REVIEW

The economic literature on the impact of automation on the future of work is vast and varied. Acemoglu and Restrepo (2019) point out that the debate on this issue in economics is characterized by a "false dichotomy": one side contends that the rise in automation will lead to the elimination of labor-intensive and cognitively demanding work, leaving an increasingly dwindling set of activities where labor can add value; while a contradictory view claims that automation will actually increase labor demand and wages like other waves of technological innovations have done in the past. Aghion et al. (2022) also highlight the existence of a dichotomy, classifying economic literature regarding the impact of automation on labor into the "old view of negative direct effects and positive indirect effects" and the "new view of positive direct effects and negative indirect effects."

The "negative direct effects and positive indirect effects" view (old view) suggests that the direct effect of automation is to displace employment, reduce labor shares, and suppress wages. However, there exist countervailing forces that increase the demand for labor and limit the wage decline induced by automation. There are varying views within this strand as to what the countervailing forces actually are.

Acemoglu and Restrepo (2019) highlight several countervailing forces like reduced costs of production; increased productivity in previously automated tasks, i.e., deepening of automation; and induced capital accumulation. However, they argue that these forces are generally incomplete and by themselves cannot balance out the direct negative effects of automation. Despite this, previous waves of technological innovation and automation have not induced a secular downward trend in labor shares. They posit that this is because of an even powerful countervailing force — the creation of new labor-intensive jobs by automation. However, Aghion et al. (2017) suggest a different counterbalancing force, pointing to the well-known "Baumol Cost Disease" effect. Baumol (1967) suggests that "economic growth is constrained not by what we do well but instead what is essential and hard to improve," which is why sectors with rapid productivity like agriculture and industry see declines in GDP shares, whereas relatively slower productivity growth sectors like services see increases. In the context of automation and labor outcomes, because labor tasks are the "weak link," i.e., they are essential but expensive, labor shares remain elevated because of the Baumol force (Aghion et al. (2017)).

The old-view analyses, which are primarily run at industry or national levels, show mixed results regarding the impact of automation but generally lean more towards the view emphasizing the negative impact of automation on labor outcomes. Within the broad framework of the old-view analyses, varying measures of automation have been used to conduct empirical analysis. Early papers (Krueger (1993); Autor et al. (1998); Bresnahan et al. (2002)) use computers or IT as proxies for automation. A newer measure of automation involves using automation-related patents. Research based on this method provides mixed evidence — Mann and Püttmann (2017) find negative effects of automation on employment, while Webb (2019) finds positive effects. Autor and Salomons (2018) use industry-level movements in TFP as a measure of automation and find net positive effects for employment and net negative effects for labor share of value added. Recently, with the provision of data on the deployment of robots at the country and industry level by the International Federation of Robotics (IFR), several papers have used exposure to robots as a measure of automation (Autor and Dorn (2013); Acemoglu and Restrepo (2020); Cheng et al. (2019); Dauth et al. (2021); Graetz and Michaels (2018)). In these papers, the job-destruction effect of automation dominates.

The "positive direct effects and negative indirect effects" view (new view) suggests that automation increases employment at the firm level because the increase in productivity induced by automation allows the firms that adopt automation to offer better quality-adjusted prices compared to opponent firms, thereby expanding their market size, and increasing labor demand. However, there might be an overall (indirect) negative effect if firms adopting automation cause substantial decreases in employment for non-automating firms, leading the latter to exit the market (Aghion et al. (2022)).

The new-view analyses are based on firm-level research, which has been made plausible with the availability of firm-level microdata on technology adoption in recent years. These studies conducted using such firm-level data from a wide range of countries, including the United States (Acemoglu et al. (2022)), the United Kingdom (Webb (2019)), and France (Aghion et al. (2021); Acemoglu et al. (2020)), generally predict a positive effect of automation on employment in firms adopting the automation. Therefore, this relatively new line of research on automation at the firm level is seemingly at odds with the old strand of literature that supports a more pessimistic view of automation (Aghion et al. (2022)).

3. DATA

The main analysis of this paper draws from the 2023 release of the EU KLEMS & INTANprod database, which is an industry-level panel dataset providing information on output, productivity, employment, and capital formation for developed countries for the period 1995–2020. The analysis in this paper is limited to 12 developed countries: Austria, Belgium, Germany, Denmark, Spain, Finland, France, Italy, Netherlands, Sweden, the United Kingdom, and the United States of America. Moreover, the analysis focuses on 27 market industries out of the 42 industries available in the database. It drops non-market sectors such as public administration, defense, and the private household sector. The 27 market industries can be grouped into five broad sector groups: (1) mining, utilities, and construction; (2) manufacturing; (3) high-tech services; (4) low-tech services; and (5) health and education (See Appendix Table A1).

Specification 2 of this paper requires calculating supplier and customer weights of industries. These are calculated from the input-output coefficients given in the World input-output Database (Timmer et al. (2015)).

Each specification controls for country-level business cycle effects. Data on business cycle indicators are acquired from OECD Composite Leading Indicators: Reference Turning Points and Component Series.

3.1. **Summary Statistics**

Table 1 summarizes trends in aggregate hours worked and labor share of value added by country. It shows that growth of log hours worked has been positive without exception; that is, employment as measured by aggregate labor hours has been rising in all countries in the last three decades. However, the rate of growth of labor hours has been declining, with the most rapid growth seen in the 1990s and the lowest growth during the 2010s. The growth patterns of labor share of value added are more varied across countries and over time: on average, labor share is rising in the 1990s but falling in subsequent decades, with the sharpest decline in the 2000s.

Tables 2 and 3 summarize the trends in employment, hours, labor share, and TFP by decades and by five broad industry sector groups, respectively. They show results from baseline regressions of decade and sector group dummy variables on the main variables of interest. All regression models in this paper are weighted by time-averaged shares of the relevant weighting variable (employment, hours worked, value added), multiplied by time-varying country shares in the total annual value of the weighting variable. Employment growth (the number of workers and hours) is positive in all decades but is lowest in the 2000s. It is negative in manufacturing; strongly positive in services and health and education; and modestly positive in mining, utilities, and construction. Labor share is strongly negative in manufacturing and modestly positive or negative in others. TFP growth is strongly positive in manufacturing. The baseline regression results, therefore, paint the following broad picture: sectors where productivity growth is the highest (e.g., manufacturing) show the largest declines in labor outcomes (the number of workers, hours worked, value added shares).

Table 1: Trends in Hours Worked and Labor Shares of Value Added

Country	**100 × Δ log hours worked**			**100 × Δ log labor share**		
	1990s	**2000s**	**2010s**	**1990s**	**2000s**	**2010s**
Austria	2.124	1.043	0.115	-0.766	-0.318	0.385
Belgium	3.215	2.611	1.196	0.392	-0.167	-0.773
Germany	1.106	1.127	0.782	0.286	-0.251	0.519
Denmark	2.932	0.908	0.633	-0.806	0.351	-0.174
Spain	5.363	2.581	-0.96	1.217	-1.439	0.105
Finland	2.675	1.38	0.831	-0.852	0.108	-0.935
France	2.36	1.777	0.429	-0.639	0.014	0.102
Italy	2.168	1.436	2.003	-0.539	-0.194	-2.178
Netherlands	3.652	1.466	1.557	0.08	-0.124	0.701
Sweden	1.518	1.291	1.262	0.666	0.393	0.349
UK	2.198	1.659	1.109	0.936	1.525	0.146
USA	5.367	0.156	1.162	2.661	-1.711	0.587
Average	2.89	1.453	0.843	0.22	-0.153	-0.097

4. METHODOLOGY

Following Autor and Salomons (2018), this paper makes use of an accounting framework to estimate the aggregate impact of automation on labor outcomes. The specifications below are taken from Autor and Salomons (2018). However, methodological changes have been made to some of the specifications (details below) to both refine A&S' analysis and also to ensure it is consistent with the new data being used in this paper.

The key outcome variables measured in this paper are (1) employment as measured by "log change in labor hours worked" and "log change in number of people employed" and (2) "log change

Table 2: Trends in Key Variables (By Decade)

Decade	Emp	Hours	Lab Share	TFP
1990s	2.230***	2.172***	0.890	0.399
	(0.251)	(0.267)	(0.676)	(0.245)
2000s	0.577***	0.075	-0.229	0.140
	(0.222)	(0.240)	(0.157)	(0.228)
2010s	1.197***	1.168***	-0.018	0.385***
	(0.135)	(0.145)	(0.137)	(0.128)

Notes. Standard errors clustered by country-industry in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Trends in Key Variables (By Broad Sector)

Broad Sector	Emp	Hours	Lab Share	TFP
Health and Education	1.760***	1.571***	0.772	-0.960***
	(0.132)	(0.169)	(0.475)	(0.069)
High-Tech Services	1.743***	1.516***	0.109	0.478
	(0.251)	(0.171)	(0.131)	(0.467)
Low-Tech Services	0.769***	0.289*	0.033	0.158
	(0.196)	(0.147)	(0.147)	(0.299)
Manufacturing	-1.033***	-1.306***	-0.320***	1.188***
	(0.181)	(0.175)	(0.085)	(0.237)
Mining, utilities, and construction	0.462*	0.275	-0.117	-0.687***
	(0.252)	(0.298)	(0.179)	(0.094)

Notes. Standard errors clustered by country-industry in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

in labor shares." The main measures of automation are industry-level changes in "TFP."

4.1. Addressing Endogeneity Concerns and Timing Issues

Before moving on to the main methodological framework, it is useful to highlight how this paper overcomes endogeneity and other concerns that arise in the data.

The primary endogeneity concerns relate to the use of TFP changes as a measure of automation. TFP estimates can be confounded with business cycle effects, trends within industries, and cross-industry differences in cyclical sensitivity. Moreover, a simultaneity issue arises because labor share of value added (dependent variable) is used in the calculation of TFP growth (independent variable), inducing a mechanical correlation between the two.

$$\Delta lnTFP_j = \Delta lnV_j - \bar{v}_{L,j}\Delta lnL_j - \bar{v}_{K,j}\Delta lnK_j \qquad (1)$$

In equation (1), $\Delta \ln \mathrm{TFP}_j$ denotes the log change in TFP for industry j; $\Delta \ln V_j$ is the log change in value added; $\Delta \ln L_j$ and $\Delta \ln K_j$ are the log changes in labor and capital inputs, respectively; and $\bar{v}_{L,j}$ and $\bar{v}_{K,j}$ are the labor and capital factor shares used as weights, respectively.

To overcome the simultaneity issue, "Leave-Out Mean of Industry-Level TFP growth" in all other countries is used as a proxy for "Own-country Industry-Level TFP growth." This implies that, for a given industry and country under consideration, the TFP growth for that pair is left out of the calculation. The average or mean value is then taken from the TFP growth rates of the same industry in all the other countries in the sample. This approach assumes that movements in the technological frontier in a particular industry are common among industrialized economies.

Table 4 confirms the utility of using "Leave-Out Mean industry-level TFP growth" by showing that other-country, same-industry TFP growth is a strong predictor of own-country-industry TFP growth. The regression results below are robust to country, year, sector, and business cycle main effects.

TABLE 4: Relationship between Leave-Out Mean and Own-Country-Industry TFP growth

	dlnTFP_I *(Own-country)*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
dlnTFP_OT *(Leave-Out Mean)*	0.566***	0.558***	0.554***	0.552***	0.555***	0.526***	0.441***	0.524***
	(0.115)	(0.127)	(0.124)	(0.123)	(0.125)	(0.119)	(0.117)	(0.117)
Fixed effects								
Country	NO	YES	YES	YES	YES	YES	YES	YES
Year	NO	NO	YES	YES	YES	YES	YES	YES
Country × Time Trend	NO	NO	NO	YES	NO	NO	NO	NO
Country × Business Cycle	NO	NO	NO	NO	YES	NO	NO	NO
Country × Year	NO	NO	NO	NO	YES	YES	NO	NO
Sector group	NO	NO	NO	NO	NO	YES	NO	YES
Industry	NO	NO	NO	NO	NO	NO	YES	YES
R^2	0.114	0.121	0.128	0.138	0.165	0.170	0.204	0.143
N	6 854	6 854	6 854	6 854	6 854	6 854	6 854	6 854

NOTES. Standard errors in parentheses are clustered by country-industry. All models weighted by industry value added shares within countries, multiplied by time-varying country shares in total value added. * p<0.10; ** p<0.05; *** p<0.01.

A second issue arises due to timing. Contemporaneous productivity innovations are unlikely to introduce steady-state effects immediately. In the original paper by A&S, a lag structure for log change in TFP that comprises contemporaneous and five distributed lags is employed. They justify their lag structure by using projection models that involve regressing a series of first differences of increasing length of the outcome variables on TFP growth (Òscar Jordà (2005)). They find that the effects of TFP growth on the outcome variables plateau after 3 years and, therefore, argue that not more than four or five lags of TFP growth are needed to capture the impulse response of a contemporaneous TFP shock. However, from the perspective of previous economic literature (Gort and Klepper (1982); Foster et al. (2018)) as well as comments on the original paper by Autor and Salomons (2018), a 5-year lag specification is likely insufficient to capture the dynamic effects of TFP growth. In fact, in the sample used by this paper, the Oscar Jorda projection models predict that the effects of contemporaneous TFP shocks last much longer than 3 years and only plateau after a period of 7–8 years. Therefore, the regression specifications in this paper employ a lag structure of contemporaneous and seven distributed lags to ensure completeness and also use as many observations in the data as possible (See Appendix A.4. for projection model results and further explanation).

Lastly, several fixed effects are employed in the regression specifications to control for country effects, time trends, business cycle effects, and sector group effects. Additionally, since this paper estimates "first-difference" models, industry-country effects are implicitly eliminated.

4.2. **Methodological Framework: Direct and Indirect Effects of Industry-Level Innovations**

The aggregate impact of automation on labor market outcomes is the net total of four smaller effects.

4.2.1. *Direct industry-level effects.* The first main specification estimates the within-industry "direct" effects of TFP growth on own-industry outcomes.

$$\Delta lnY_{i,c,t} = \beta_0 + \sum_{k=0}^{7} \beta_1^k \Delta lnTFP_{i,c\neq c(i),t-k} + \alpha_c + \delta_t + \alpha_c \times t + \alpha_c \times (t = peak) + \alpha_c \times (t = trough) + \epsilon_{i,c,t} \tag{2}$$

Here, i indexes industry, c indexes country, and t indexes year. $\Delta lnY_{i,c,t}$ is the outcome of interest and $\Delta lnTFP_{i,c\neq c(i),t-k}$ is the leave-out mean of TFP growth. This is a first-difference specification estimated at the industry-country-time level, and so implicitly eliminates industry-country effects. α_c represents country trends; δ_t represents time trends; $\alpha_c \times t$ represents country-time interaction terms, which allow country trends to accelerate or decelerate over the sample interval; $\alpha_c \times (t = peak)$ and $\alpha_c \times (t = trough)$ represent country-specific cyclical peak and trough indicators interacted with country indicators, respectively, to take into account country-specific business cycles. Results for this specification are reported in Table 5.

TABLE 5: Results from Specification 1 — Direct Within-Industry Effects

	$\Delta \ln Y_{i,c,t}$ (Employment & Hours)					
	Employment			Hours		
	(1)	(2)	(3)	(1)	(2)	(3)
$\sum \Delta \ln\text{TFP}_{i,c,t-k}$	–1.271***	–0.707***	–0.691***	–1.127***	–0.482***	–0.482***
	(0.241)	(0.201)	(0.193)	(0.255)	(0.191)	(0.192)
Fixed Effects						
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Sector group	No	Yes	Yes	No	Yes	Yes
Country×Time Trend	Yes	Yes	Yes	Yes	Yes	No
Country×Business Cycle	Yes	Yes	Yes	Yes	Yes	No
Country×Year	No	No	Yes	No	No	Yes
R^2	0.366	0.414	0.518	0.447	0.484	0.560
N	4866	4866	4866	4869	4869	4869

	$\Delta \ln Y_{i,c,t}$ (Labor Share)		
	(1)	(2)	(3)
$\sum \Delta \ln \text{TFP}_{i,c,t-k}$	–0.870***	–1.013***	–0.998***
	(0.214)	(0.247)	(0.253)
Fixed Effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Sector group	No	Yes	Yes
Country×Time Trend	Yes	Yes	No
Country×Business Cycle	Yes	Yes	No
Country×Year	No	No	Yes
R^2	0.070	0.071	0.112
N	4869	4869	4869

NOTES. * p<0.10; ** p<0.05; *** p<0.01. Standard errors in parentheses.

Table 5 shows the results for the effect of lagged TFP growth (leave-out mean) on three within-industry outcome variables: log number of workers (Employment), log hours of labor input (Hours), and log labor share of value added (labor share). Point estimates in each column are the sum of the six β_1^k coefficients.

Industries experiencing relative gains in productivity exhibit relative declines in employment. The coefficient in column 1 of employment can be interpreted as follows: an increase in 1 SD of TFP growth predicts a fall in own-industry employment by ≈ 1.3 log points. Inclusion of sector-group fixed effects reduces the estimate from -1.3 to -0.70. This indicates that TFP innovations may spill over across industries within a sector. These spillovers are modelled in equation 2. Estimates are analogous for labor hours worked. However, inclusion of sector-group fixed effects decreases both the significance and absolute value of the estimates. Similar to employment and hours worked, a negative relationship between TFP growth and labor shares can also be seen: A rise in TFP of 1 SD predicts a fall in own-industry labor shares by about -0.87 percentage points over a 7-year horizon.

This paper tests the robustness of these estimates using a variety of checks: (1) weighting all countries equally instead of by country size; (2) excluding contemporaneous TFP terms in specification 1 and only including lags of TFP; (3) eliminating the group of self-employed workers from the sample; and (4) imputing zeros for negative reported values of the TFP measure. The results of the robustness checks are reported in the appendix (Table A.3). The results show that the estimations in Table 5 are largely stable even after including the above robustness checks.

Therefore, the results from Table 5 indicate that industries experiencing rising productivity show negative labor outcomes within the industry where the automation occurs. However, it would be erroneous to conclude using just the results in Table 5 that productivity growth leads to labor displacement on the aggregate. Relative employment declines in industries with rising productivity do not imply that aggregate employment falls as productivity rises. The first specification estimated within-industry effects and did not incorporate potentially countervailing effects operating through other channels.

4.2.2. *Indirect Effect of Consumer and Supplier-linked sectors.* The productivity growth resulting from automation is likely to extend beyond the sector where the automation initially occurs, impacting both customer and supplier industries associated with the originating firm. For instance, industries with more efficient suppliers may experience an uptick in purchases, while those with more efficient customers may encounter fluctuations in output demands. These input-output linkages are considered by adding two new terms to the regression specification seen above.

$$\begin{aligned} \Delta lnY_{i,c,t} = \beta_0 + \sum_{k=0}^{7} \beta_1^k \Delta lnTFP_{i,c\neq c(i),t-k} + \alpha_c + \delta_t + \alpha_c \times t + \alpha_c \times (t = peak) \\ + \alpha_c \times (t = trough) + \sum_{k=0}^{7} \beta_1^k \Delta ln\widetilde{\mathrm{TFP}}^{SUP}_{i,c\neq c(i),t-k} + \sum_{k=0}^{7} \beta_1^k \Delta ln\widetilde{\mathrm{TFP}}^{CONS}_{i,c\neq c(i),t-k} + \epsilon_{i,c,t} \end{aligned} \tag{3}$$

The two additional TFP terms measure the weighted sum of TFP growth in all other domestic industries $j \neq i$ that are customer/suppliers of industry i.

The customer and supplier weights are calculated using the 2016 version of the World Input-Output Database (Timmer et al. (2015)). The supplier weights represent the proportion of value added from each domestic supplier industry j in relation to the value added of industry i. Similarly, the customer weights denote the proportions of value added from each industry i utilized in the final products of domestic industry j. Just as with the within-industry TFP growth terms, for the supplier and customer industries, industry-level, leave-out means of TFP growth for all other countries in the sample are used.

Results from Equation 2, which includes terms indicating TFP growth in customer and supplier industries, are given in Table 6. It is in this specification that this paper's results differ significantly from those of Autor and Salomons (2018). In their paper, productivity growth emanating from supplier industries predicts steep increases in employment, labor hours and wage bill, although not in labor share of value added. They point out that the positive effect on labor outcomes of supplier industry productivity growth reveals a first channel by which the negative within-industry effects of productivity on labor outcomes are countervailed.

Table 6: Results from Specification 2 — Customer & Supplier Linkages

	Industry Effects: Employment & Hours & Wage Bill		
	(1) Emp	(2) Hours	(3) Wage Bill
Own-Industry TFP growth	–0.722**	–0.500***	–0.271
	(0.215)	(0.203)	(0.233)
Supplier-Industry TFP growth	0.293	0.320	0.319
	(0.431)	(0.476)	(0.368)
Customer-Industry TFP growth	–0.024	–0.049	–0.022
	(0.271)	(0.307)	(0.326)
Fixed Effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Sector group	Yes	Yes	Yes
Country×Time Trend	Yes	Yes	Yes
Country×Business Cycle	Yes	Yes	Yes
Country×Year	Yes	Yes	Yes

The estimates from this paper's data sample show that supplier- and customer-industry TFP growth does not have a significant effect on employment or hours worked. However, the effect on labor share of value added of customer industry TFP growth is negative and statistically significant. This indicates that when there is a positive technology shock in customer industries, while there are no upstream effects in terms of employment for supplier industries, the labor share of value added of supplier industries decreases.

The differences in these results relative to Autor and Salomons (2018) could potentially indicate

Industry Effects: Nom. Value Added & Real Value Added & Labor Share			
	(4) Nom. VA	(5) Real VA	(6) Labour Share
Own-Industry TFP growth	0.730***	2.101***	–0.991***
	(0.228)	(0.459)	(0.207)
Supplier-Industry TFP growth	0.841	0.644	–0.769
	(0.544)	(0.446)	(0.494)
Customer-Industry TFP growth	1.197***	–0.779	–1.418***
	(0.242)	(0.514)	(0.195)
Fixed Effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Sector group	Yes	Yes	Yes
Country×Time Trend	Yes	Yes	Yes
Country×Business Cycle	Yes	Yes	Yes
Country×Year	Yes	Yes	Yes

Notes. * p<0.10; ** p<0.05; *** p<0.01. Standard errors in parentheses.

that newer technologies of the last two decades have different effects on labor than the technologies of the past.

4.2.3. *Final Demand Effects Through the Effect of Productivity.* Productivity in any one industry augments aggregate income and raises final demand, implying that productivity growth in any one sector can lead to increased labor demand across all other sectors (this is because labor demand is a derived demand). The regression specification below estimates the relationship between country-specific aggregate economic growth and industry-specific inputs.

$$\Delta lnY_{i,c,t} = \lambda_0 + \sum_{k=0}^{7} \lambda_1^k \Delta lnValueAdded_{j\neq i,c,t-k} + \alpha_s + \epsilon_{i,c,t} \tag{4}$$

$\Delta lnValueAdded_{j\neq i,c,t-k}$ represents the growth of own-country real or nominal value added, where own-industry output is excluded from the measure to prevent mechanical correlation with industry outcomes.

This specification is estimated in two different ways in this paper. Firstly, the regression given above is estimated in line with A&S (2018), where identification arises from sector-group fixed effects (α_s), and the indicator variables for country, year, and business cycles from specifications 1 and 2 are dropped. Additionally, this paper also estimates equation (5) including country, year, and business cycle fixed effects consistent with specifications 1 and 2.

$$\begin{aligned}\Delta lnY_{i,c,t} = \lambda_0 + \sum_{k=0}^{7} \lambda_1^k \Delta lnValueAdded_{j\neq i,c,t-k} + \alpha_s + \alpha_c \times t \\ +\alpha_c \times (t = peak) + \alpha_c \times (t = trough) + \epsilon_{i,c,t}\end{aligned} \tag{5}$$

Regression Table 7 indicates a potential second countervailing effect to the negative within-industry effects of productivity on labor outcomes.

When a similar specification to A&S (2018) is estimated, using only sector-group fixed effects to estimate the final demand effects of industry-level TFP growth, the results of this paper are similar to theirs. The results show that each log point increase in the country-level real value added predicts a ≈ 0.3 log point and ≈ 0.5 log point increase in same-country, other-industry employment and hours worked, respectively. This could potentially indicate that TFP growth emanating from

Table 7: Results from Specification 3 — Final Demand Effects (Using Limited Controls)

	(1) Employment	(2) Hours Worked	(3) Real Value Added
Aggregate Real Value Added	0.261***	0.518***	0.930***
	(0.092)	(0.097)	(0.147)
Sector-Group Fixed Effects	Yes	Yes	Yes

	(4) Wage Bill	(5) Nominal Value Added	(6) Labor Share
Aggregate Nominal Value Added	0.852***	1.013***	–0.147
	(0.068)	(0.112)	(0.109)
Sector-Group Fixed Effects	Yes	Yes	Yes

Notes. * p<0.10; ** p<0.05; *** p<0.01. Standard errors in parentheses.

any one sector raises final demand in the economy, implying that each industry's productivity growth contributes to aggregate labor demand across all sectors.

Table 8: Results from Specification 3 — Final Demand Effects (Using Full Controls)

	(1) Employment	(2) Hours Worked	(3) Real Value Added
Aggregate Real Value Added	–0.470	0.125	0.109
	(0.300)	(0.352)	(0.362)
Fixed Effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Sector group	Yes	Yes	Yes
Country×Time Trend	Yes	Yes	Yes
Country×Business Cycle	Yes	Yes	Yes
Country×Year	Yes	Yes	Yes

	(4) Wage Bill	(5) Nominal Value Added	(6) Labor Share
Aggregate Nominal Value Added	0.946***	0.430	0.413
	(0.352)	(0.349)	(0.320)
Fixed Effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Sector group	Yes	Yes	Yes
Country×Time Trend	Yes	Yes	Yes
Country×Business Cycle	Yes	Yes	Yes
Country×Year	Yes	Yes	Yes

Notes. * p<0.10; ** p<0.05; *** p<0.01. Standard errors in parentheses.

However, as shown in Table 8 below, these estimates are NOT robust to the inclusion of a full set of country, year, business cycle, and sector-group fixed effects. The inclusion of these fixed effects, which were omitted by Autor and Salomons (2018) in their paper, results in the estimates for employment, hours worked, and labor shares to be insignificant. This is in contrast with the significant and positive final demand effects on employment found in table 7.

The results from table 8 indicate that the final demand effects through the effect of productivity do not necessarily act as a countervailing force to the negative within-industry effects of TFP growth, as implied by Autor and Salomons (2018).

4.2.4. *Compositional Between-Sector Effects.* Uneven productivity growth across industries can shift the aggregate labor share through changes in relative sector sizes.

To quantify the importance of within-industry vs. between-industry shifts in labor shares, a simple shift-share decomposition can be estimated:

$$\Delta \bar{L}_{c,t} = \sum_i \bar{\omega}_{i,c,t} \Delta l_{i,c,t} + \sum_i \Delta \omega_{i,c,t} \bar{l}_{i,c,t} \tag{6}$$

The term $\Delta \bar{L}_{c,t}$ on the left indicates the change in aggregate log labor share in country c over time interval τ. The first term on the right is the contribution of within-industry changes in labor share and the second term is the contribution of between-industry shifts in labor share to aggregate changes in labor share. Here, $l_{i,c,t}$ is the log labor shares in each industry i; $\omega_{i,c,t}$ is the weight corresponding to industry i's share of value added in country c at time τ; $L_{c,t}$ therefore is the weighted sum of log labor shares of industry i: $L_{c,t} = \sum_i \omega_{i,c,t} l_{i,c,t}$.

Estimating the second term in the decomposition will give us the contribution of between-industry shifts in aggregate labor shares. If technological progress leads to an increase in the relative size (weight $\omega_{i,c,t}$) of industries with low average labor shares ($\bar{l}_{i,c,t}$), i.e., capital-intensive industries like manufacturing and mining, then this will indirectly have a negative effect on the aggregate labor share. However, if technological progress increases the relative importance of labor-intensive industries, like health and education, then this will indirectly raise the aggregate labor share.

Column 4 of Table 6 shows that an increase in own-industry TFP growth predicts an increase in industry-level nominal value added with an elasticity of 0.730. Therefore, sectors experiencing technological growth are expanding in the economy as a share of nominal value added. Since the relative sizes of industries experiencing technological growth are increasing, if these industries are mainly capital-intensive, then the aggregate labor share will fall. Conversely, if these industries are mainly labor-intensive, then the aggregate labor share will rise.

Table 9 shows that "Health and Education" is the sector group with the highest average labor share (most labor-intensive), while "Manufacturing" and "Mining, Utilities, and Construction" are the sector groups with the lowest average labor shares (most capital-intensive).

TABLE 9: Average Log Labor Shares by Industry Sector

Broad Industry Sector	Average Labor Share
Health and Education	86.46774
High-Tech Services	63.11317
Low-Tech Services	61.74819
Manufacturing	61.63176
Mining, utilities, and construction	50.25314

The summary statistics from Table 10 (snippet below) show that labor-intensive industries Health and Education have the lowest (negative) TFP growth. Manufacturing, a capital-intensive industry, has the highest TFP growth. Although mining and construction, which are also capital-intensive industries, do not show such positive TFP growth, overall, technological progress seems to be more concentrated in capital-intensive industries than in labor-intensive industries.

TABLE 10: Snippet from Table 3 (Summary Statistics)

Broad Industry Sector	100× Mean Annual Log Change TFP
Health and Education	-0.960***
	(0.069)
High-Tech Services	0.478
	(0.467)
Low-Tech Services	0.158
	(0.299)
Manufacturing	1.188***
	(0.237)
Mining, utilities, and construction	-0.687***
	(0.094)

The contribution of the between-sector shifts in labor shares to aggregate changes in labor shares is shown in the figures below with the final aggregate results.

4.3. **Aggregate Effects**

4.3.1. *Estimating Aggregate Effects.* Using estimates from all the individual specifications, this paper now quantifies the implied contribution of TFP growth on the evolution of **aggregate** employment and labor shares through all four channels outlined above.

For all outcome variables (employment, hours worked, and labor share of value added), the contributions of the first three effects (direct; supplier and customer; final demand) are estimated. The fourth compositional effect can only be estimated for labor share of value added.

The contribution of direct, within-industry effects on aggregate labor outcomes ($\Delta \ln Y_{c,t}^{\text{OWN}}$):

$$\Delta \ln Y_{c,t}^{\text{OWN}} \equiv \frac{\partial \ln Y_{c,t}}{\partial \ln \text{TFP}_{i,c\neq c(i),t}^{\text{OWN}}} = \sum_{k=0}^{7} \beta_1^k \times \sum_{i=1}^{I} \omega_{i,c} \times \Delta \ln \text{TFP}_{i,c\neq c(i),t}^{\text{OWN}} . \tag{7}$$

Here, $\ln Y_{c,t}$ is the log of the outcome variable (employment, hours, and labor shares) in country c at time t; $\sum_{k=0}^{7} \beta_1^k$ is the sum of the seven contemporaneous and lagged coefficients in Specification 1; $\omega_{i,c}$ is the average outcome-variable share in industry i in country c; and $\Delta \ln TFP_{i,c\neq c(i),t}^{\text{OWN}}$ is the own-industry TFP growth. Therefore, the direct-effect contribution can be calculated as the sum of the β_1^k's in Specification 1 multiplied by the corresponding weighted $\Delta \ln TFP_{i,c\neq c(i),t}^{\text{OWN}}$ term.

The contribution of supplier- and customer-industry effects ($\Delta \ln Y_{c,t}^{L}$) can be calculated in an analogous way:

$$\Delta \ln Y_{c,t}^{L} \equiv \frac{\partial \ln Y_{c,t}}{\partial \ln \widetilde{\text{TFP}}_{j\neq i,\, c,\, t}^{L}} = \sum_{k=0}^{7} \beta_1^k \times \sum_{i=1}^{I} \omega_{i,c} \times \Delta \ln \widetilde{\text{TFP}}_{j\neq i,\, c,\, t}^{L} , \tag{8}$$

$$L \in \{\text{SUP, CUST}\}.$$

The contribution of the final demand effect on aggregate outcomes ($\Delta \ln Y_{c,t}^{\text{FD}}$) will be the product of four terms:

1. The effect of TFP growth in industry i on the real value added in i ($\sum_{k=0}^{7} \beta_{1,\text{VA}}^k$ → estimate from Specification 2; Table 6, column 6).

2. The effect of real value added growth in i on total real value added in the economy ($\phi_{i,c} \rightarrow$ can be calculated as the average value-added share of industry i in country c).

3. The effect of growth in real value added on employment, hours, and labor shares in each industry ($\sum_{k=0}^{7} \lambda_1^k \rightarrow$ estimate from Specification 3; Table 8).

4. The size of industry i relative to overall employment, hours, and labor shares in the economy ($\omega_{i,c}$).

$$\Delta \ln Y_{c,t}^{\text{FD}} \equiv \frac{\partial \ln Y_{c,t}}{\partial \ln VA_{c,t}} \times \frac{\partial \ln VA_{c,t}}{\partial \ln \text{TFP}_{i,c \neq c(i),t}} = \sum_{k=0}^{7} \lambda_1^k \times \sum_{k=0}^{7} \beta_{1,\text{VA}}^k \times \sum_{i=1}^{I} \omega_{i,c} \times \phi_{i,c}\,. \qquad (9)$$

Focusing only on the labor-share of value added, the contribution of compositional (between-industry) shifts is

$$\Delta \ln Y_{c,t}^{\text{COMP}} = \sum_{i}^{I} \left(\Delta \widehat{\omega}_{i,c}\, \bar{\ell}_{i,c} \right), \qquad (10)$$

where $\Delta \widehat{\omega}_{i,c}$ is the predicted change in the value added share of industry i in country c (measures how the relative importance of an industry changes); $\bar{\ell}_{i,c}$ is the average log labor share in industry i and country c.

4.3.2. *Aggregate Results.* The bars in the figures 1 and 2 show how each of the direct and three indirect effects of TFP growth affect employment and hours worked, on average, over the full 25-year period (1995–2020), respectively. The final fifth bar estimates the net effect on aggregate employment, summing the direct and indirect components, over the outcome period.

FIGURE 1: Direct and Indirect Effects of TFP growth on Employment

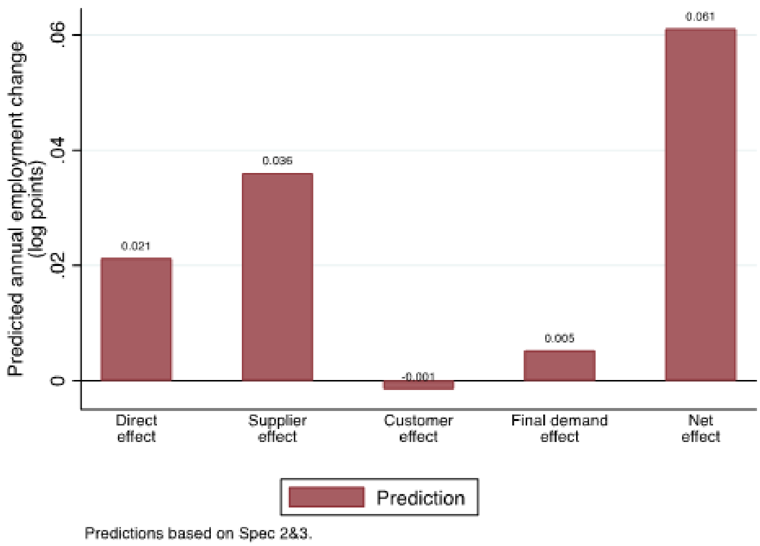


FIGURE 2: Direct and Indirect Effects of TFP growth on Hours Worked

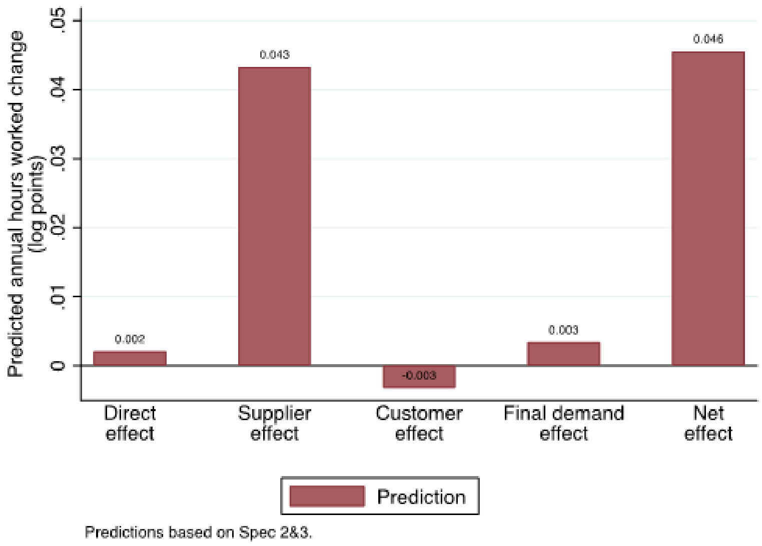
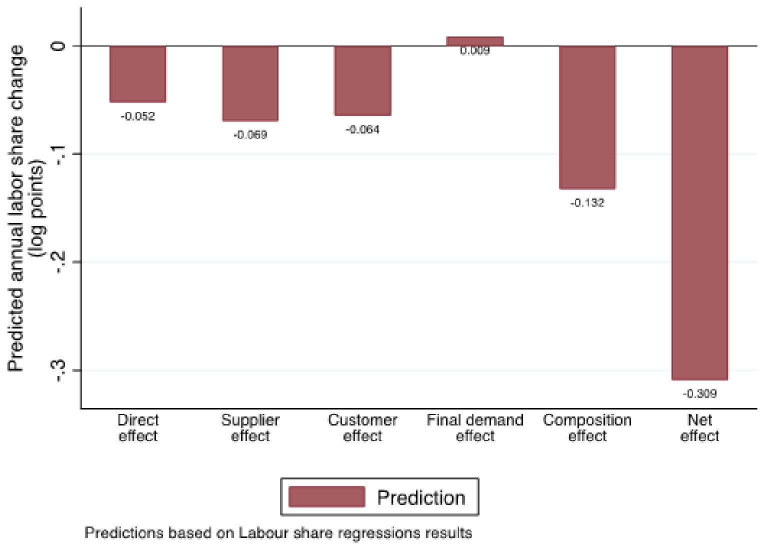


FIGURE 3: Direct and Indirect Effects of TFP growth on Labor Share of Value Added



A similar diagram is produced for labor share of value added (Figure 3). However, the fourth channel of between-sector compositional effects is also added.

The main conclusion from the diagrams is as follows: Automation as embodied in TFP growth has been slightly employment-augmenting but significantly labor-share displacing. For employment and hours worked, the positive indirect supplier, customer, and final demand effects seemingly offset the negative within-industry effect of productivity growth seen in Table 5. However, for labor share of value added, the positive offsetting indirect effects do not exist. In fact, the additional channels of interindustry linkages and final demand effects contribute negatively to aggregate labor share.

Therefore, these results imply that while technological progress, on the aggregate, has not led to workers being displaced from their jobs, the contribution of labor to the output produced in the economy has declined over the course of the 25 years in the sample.

5. LIMITATIONS

There are certain limitations of this paper that future work should aim to address. Firstly, while TFP growth is an omnibus measure that encompasses all types of technological progress, it might not adequately reflect automation, which is a particular type of technological progress. Therefore, to isolate components of technological growth that are more closely related to automation, future work should look at more direct measures of automation, including ICT-specific and AI-specific technological progress. Secondly, the leave-out mean TFP approach relies on the assumption that the technological frontier at the industry level is similar across countries. However, there is evidence to show that productivity growth at the industry-level varies across countries (ICT revolution in the 1990s was more concentrated in the US than other developed countries). Lastly, this paper shows that the direct within-industry TFP effect on employment is negative. However, firm-level studies find that there is strong positive correlation between TFP and firm-level employment growth. This discrepancy is because industry-level fluctuations in productivity reflect not only the within-firm innovations but also the between-firm innovations. These can only be considered if the industry-level data used in this paper are further refined with firm-level microdata.

6. CONCLUSION

Following the theoretical framework given by Autor and Salomons (2018), this paper uses cross-country, cross-industry data over a period of 25 years (1995–2020) to explore the relationship between industry-level changes in TFP and labor market outcomes through four channels: (1) the direct effects of changes in TFP on labor outcomes within the same industry; (2) the indirect effect of TFP changes in supplier and customer industries on own-industry labor outcomes; (3) the productivity effect of industry-level technological changes on aggregate labor demand; and (4) the compositional effect of TFP changes on shifts in labor shares between industries. This paper, therefore, contributes to not only the literature on the effects of new technologies on labor market outcomes but also the literature on macro–micro linkages that analyze how small shocks in one part of the economy are amplified and propagated throughout the economy through various direct and indirect channels (Acemoglu et al., 2016). This paper finds that for both employment and labor share of value added, there is a negative direct effect of automation on labor outcomes in the industry where the innovation occurs. For employment, this negative direct effect is offset by countervailing forces elsewhere in the economy, while for labor share of value added, it is not. These findings are in line with trends seen across developed countries of positive employment growth but declining contribution of labor in the economy.

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A. Appendix: Further Visualisation of Social Network Analysis

A.1. List of Industries

Industry Code (nace_r2_code)	Broad Sector Grouping	Industry Name (nace_r2_name)
B	Mining, Utilities, and Construction	Mining and Quarrying
C10–C12	Manufacturing	Manufacture of food products; beverages and tobacco products
C13–C15	Manufacturing	Manufacture of textiles, wearing apparel, leather and related products
C16–C18	Manufacturing	Manufacture of wood, paper, printing, and reproduction
C19	Manufacturing	Manufacture of coke and refined petroleum products
C20	Manufacturing	Manufacture of chemicals and chemical products
C21	Manufacturing	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22–C23	Manufacturing	Manufacture of rubber and plastic products and other non-metallic mineral products
C24–C25	Manufacturing	Manufacture of basic metals and fabricated metal products, except machinery and equipment
C26–C27	Manufacturing	Computer, electronic, optical products; electrical equipment
C28	Manufacturing	Manufacture of machinery and equipment
C29–C30	Manufacturing	Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment
C31–C33	Manufacturing	Manufacture of furniture; jewelry, musical instruments, toys; repair and installation of machinery and equipment
D–E	Mining, Utilities, and Construction	Electricity, gas, steam; water supply, sewerage, waste management
F	Mining, Utilities, and Construction	Construction
G45	Low-Tech Services	Wholesale and retail trade and repair of motor vehicles and motorcycles
G46	Low-Tech Services	Wholesale trade, except of motor vehicles and motorcycles
G47	Low-Tech Services	Retail trade, except of motor vehicles and motorcycles
H	Low-Tech Services	Transportation and storage
I	Low-Tech Services	Accommodation and food service activities
J	High-Tech Services	Information and communication
K	High-Tech Services	Financial and insurance activities
L	High-Tech Services	Real estate activities
M–N	High-Tech Services	Professional, scientific, and technical activities; administrative and support service activities
P	Health and Education	Education
Q	Health and Education	Human health and social work activities
R–S	Low-Tech Services	Arts, entertainment, recreation; other services and service activities, etc.

A.2. **Variable List — EUKLEMS data**

Variable	Variable label
industry	Industry Code
country	Country Code
industry_name	Industry Name
country_name	Country Name
year	Year
sectorgroup	Broad Industry Grouping
ind_hier	Industry identifier variable
country_hier	Country identifier variable
cross	Group (industry × country)
COMP	Compensation of employees, current prices, millions of national currency
EMP	Number of persons employed, th.
EMPE	Number of employees, th.
GO_CP	Gross output, current prices, millions of national currency
GO_PI	Gross output, price indexes (2015)
GO_Q	Gross output, chained-link volumes (2015), millions of national currency
H_EMP	Total hours worked by persons engaged
H_EMPE	Total hours worked by employees
II_CP	Intermediate inputs, current prices, millions of national currency
II_PI	Intermediate inputs, price indexes (2015)
II_Q	Intermediate inputs, chained-link volumes (2015), millions of national currency
VA_CP	GROSS VALUE ADDED, current prices, millions of national currency
VA_PI	GROSS VALUE ADDED, price indexes (2015)
VA_Q	GROSS VALUE ADDED, chained-link volumes (2015), millions of national currency
CAP	Capital compensation, millions of national currency
LAB	Labor compensation, millions of national currency
VATFP_I	TFP index, 2015=100 – contributions to value added growth
bcycle	Business cycle indicators
lnEMP	Natural log of EMP
lnH_EMP	Natural log of H_EMP
lnVATFP_I	Natural log of VATFP_I
lnLAB	Natural log of LAB
lnVA_CP	Natural log of VA_CP
lnVA_Q	Natural log of VA_Q
hwwage	Mean hourly wage
lnhwage	Log of mean hourly wage
laborshare	Wage Bill as a share of value added
lnlaborshare	Log of Labor Share
ln_VA_PI	Natural Log of VA_PI
weight_emp_i	Industry employment share within countries, averaged over time
weight_h_i	Industry hours worked share within countries, averaged over time

weight_VA_i	Industry VALUE ADDED share within countries, averaged over time
weight_emp_c	Share of country's EMP in total EMP by year
weight_h_c	Share of country's hours worked in total hours worked by year
weight_VA_c	Share of country's VA in total VA by year
weight_emp_i_c	weight_emp_i × Share of country's EMP in total EMP by year
weight_h_i_c	weight_h_i × Share of country's H EMP by year
weight_VA_i_c	weight_VA_i × Share of country's VA in total VA by year
D1_lnhwage	100 × annual change in log of mean hourly wage
D1_lnLAB	100 × annual change in log total wage bill
D1_lnEMP	100 × annual change in log employment
D1_ln H_EMP	100 × annual change in log hours worked
D1_ln VATFP_I	100 × annual change in log value added based TFP by country
D1_ln_VA_CP	100 × annual change in log nominal VA
D1_ln_VA_Q	100 × annual change in log VA (volume)
D1_ln_VA_PI	100 × annual change in log VA (price indices)
D1_laborshare	Annual percentage point change in labor share
D1_lnlaborshare	100 × annual log change in labor share
D1_ln VATFP_OT	Country leave-out TFP growth
VA_CP_TOT	(sum) VA_CP
VA_PI_TOT	(sum) VA_PI
VA_PYP_TOT	(sum) VA_PYP
VA_Q_TOT	(sum) VA_Q
LOVA_CP_TOT	Value added (current prices) leaving out own-industry
lnLOVA_CP_TOT	log LOVA_CP_TOT
D1_lnVACP_LO	100 × annual log change in LOVA_CP_TOT
LOVA_Q_TOT	Value added (volume) leaving out own-industry
lnLOVA_Q_TOT	log LOVA_Q_TOT
D1_lnVAQ_LO	100 × annual log change in LOVA_Q_TOT
LOVA_PI_TOT	Value added (price indices) leaving out own-industry
lnLOVA_PI_TOT	log LOVA_PI_TOT
D1_lnVAPI_LO	100 × annual log change in LOVA_PI_TOT
ct	Group (country year)
ic	Group (industry country)
it	Group (industry year)

A.3. **Robustness Tests for Table 4 (Specification 1)**

	Employment	**Hours Worked**	**LaborShare**
Test 1: All countries given equal weight			
$\Sigma\Delta \ln \mathrm{TFP}_{i,c,t-k}$	-0.752^{**}	-0.378^{**}	-0.803^{***}
	(0.149)	(0.164)	(0.200)
No. of Observations	4,866	4,869	4,869
Test 2: Excluding Contemporaneous TFP Effects			
$\Sigma\Delta \ln \mathrm{TFP}_{i,c,t-k}$	-0.901^{***}	-0.859^{***}	-0.789^{**}
	(0.178)	(0.183)	(0.333)
No. of Observations	4,866	4,869	4,869
Test 3: Setting Negative TFP growth to zero			
$\Sigma\Delta \ln \mathrm{TFP}_{i,c,t-k}$	-0.982^{***}	-0.651^{***}	-0.658
	(0.216)	(0.239)	(0.408)
No. of Observations	4,866	4,869	4,869
Test 4: Excluding Self-Employed from Employed			
$\Sigma\Delta \ln \mathrm{TFP}_{i,c,t-k}$	-0.594^{***}	-0.522^{**}	-1.075^{***}
	(0.229)	(0.205)	(0.247)
No. of Observations	4,866	4,869	4,862
Fixed Effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Sector group	Yes	Yes	Yes
Country×Time Trend	No	No	No
Country×Business Cycle	No	No	No
Country×Year	Yes	Yes	Yes

A.4. **Test for Determining Lag Structure**

Ideal lag structure for regressions can be tested using Òscar Jordà (2005) local projection models.

$$\ln Y_{i,c,t+K} - \ln Y_{i,c,t-1} = \beta_0 + \beta_1\, \Delta\mathrm{TFP}_{i,c\neq c(i),\,t-1} + \sum_{k=0}^{K} \beta_2^k\, \Delta \ln \mathrm{TFP}_{i,c\neq c(i),\,k} + \beta_3\, \Delta \ln \mathrm{TFP}_{i,c\neq c(i),\,t-2} + \beta_4\, \Delta \ln Y_{i,c,t-2} + \alpha_{c,t} + \gamma_s + \varepsilon_{i,c,t} \quad (11)$$

Since the steady-state effects of contemporaneous TFP shocks will not manifest immediately, a lag structure is used to estimate the relationship between TFP shocks and labor outcomes.

$\ln Y_{i,c,t+K}$ denotes the outcome variable in industry i, country c, and year t, and K is the time horizon for the local projection. $\ln Y_{i,c,t+K} - \ln Y_{i,c,t-1}$ represents the change in the outcome variable from the base year (t–1) to year t+K.

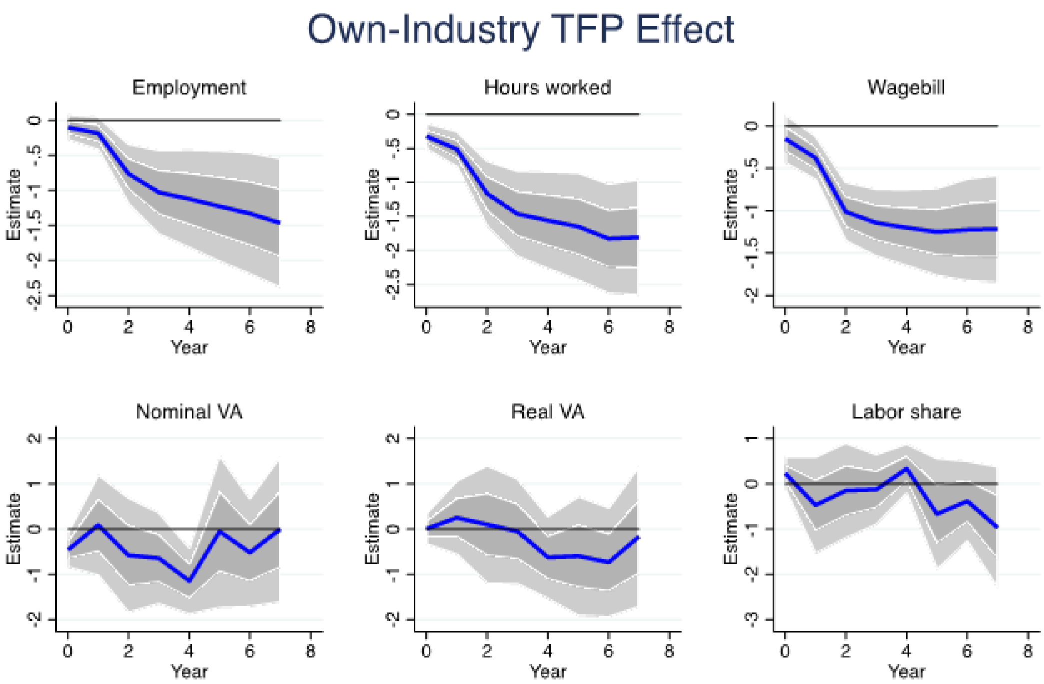
Impulse variable is $\Delta\mathrm{TFP}_{i,c\neq c(i),\,t-1}$: log change in leave-out mean TFP in base year.

Lagged history of TFP growth and the outcome variable are used as controls:

$$\Delta \ln \mathrm{TFP}_{i,c\neq c(i),\,t-2}, \quad \Delta \ln Y_{i,c,\,t-2}.$$

The models also control for country–year and sector-group fixed effects: $\alpha_{c,t}$, γ_s.

The figure below reports local projection estimates and confidence intervals for the relationship between a TFP shock and industry-level changes in the outcome variables. For almost all outcome variables, there are small or negligible contemporaneous effects. Outcome variables of interest only undergo changes in ensuing years after the TFP shock. In almost all cases, the effects of the TFP shock do *not* plateau until 7–8 years after the shock. To ensure both completeness and utilization of as many observations as possible in the dataset, seven lags are included in the main specifications along with the contemporaneous effect.



Coefficients are for observed TFP shock in t=-1, rescaled to have a unit standard deviation. Includes country-by-year and sectorgroup fixed effects, one lag of TFP and outcome variable growth, and controls for TFP shocks over over the projection horizon. Bands are 70% and 95% CIs.