Revisiting the Productivity-Elasticity of Labor Demand *

Master Thesis

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Abstract

This thesis investigates the relationship between productivity growth and labor demand at the industry level. I develop a theoretical model that highlights the crucial role of the price elasticity of demand. Using an industry-level dataset covering 14 OECD countries from 1995 to 2020, I then empirically approach this relationship by replicating and extending a key regression model from Autor and Salomons (2018), which estimates the productivity elasticity of various labor market outcomes. My findings generally align with theirs - showing a negative relationship between productivity growth and both employment and aggregate hours - but also help to identify several areas that warrant further attention. First, their results predict a large positive effect of productivity on real wages, which is challenging to reconcile with the notion of a decline in labor demand. Second, there are irregularities in the temporal dynamics of the productivity shock. Finally, I find that the results are not robust to the inclusion of industry fixed effects. These findings suggest the need for a more nuanced interpretation of their conclusions and offer further insights into the complex relationship between productivity and labor demand.

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List of Abbreviation

TFP	Total-Factor Productivity
OLS	Ordinary Least Squares
IV	Instrumental Variable
AI	Artificial Intelligence
ATM	Automated Teller Machine
OECD	Organisation for Economic Co-operation and Development

1 Introduction

As emerging technologies like Artificial Intelligence (AI) reshape the way we work, deepening our understanding of the complex relationship between technological change and labor has never been more critical. Early experimental evidence suggests that AI could significantly boost productivity growth (Brynjolfsson, Li, and Raymond 2023; Noy and Zhang 2023; Dell'Acqua et al. 2023), raising important questions about whether these advances will ultimately benefit or harm workers. Within this larger debate, the traditional role of the economist has often been a reassuring one. Notably, one of Kaldor's (1961) 'stylized facts' of economic growth was that labor's share in national income had remained relatively stable across long time periods, despite the significant technological advances characterizing the 20th century. This observation shaped much of the macroeconomic discourse that followed, reinforcing the idea that technological change, typically captured through measures of productivity growth (Solow 1957), would not render labor redundant. However, as technology evolved, so too did the narrative.[1] Following Tinbergen (1974), research began to question whether technological change might disproportionately increase the demand for high-skilled workers, leaving low-skilled workers behind - a phenomenon that became known as skill-biased technological change. This idea was further refined by the task-based literature, commencing with Autor, Levy, and Murnane (2003), which argued that computer technologies primarily substitute for routine cognitive and manual tasks, typically performed by low-skilled workers, while complementing more skill-intensive non-routine tasks. Information and communication technologies, such as computers, have also been cited as a key factor behind the breakdown of Kaldor's fact and the global decline in the labor share since the 1980s (Karabarbounis and Neiman 2014). These developments have made the relationship between technological change and labor far more complex, sparking renewed concerns about the future of work.

Amid this broader discussion, approaching the effects of technological change *at an industry-level* is an important matter in its own right, as aggregate-level research can mask substantial - and often painful - adjustment processes within particular sectors. This is because relationships observed at the aggregate level cannot be directly extrapolated to individual industries, a point emphasized by a long-standing body of literature. Baumol (1967)

1. See Autor (2022) for an overview of the evolution of economic thought on the matter.

famously argued that technological change can drive 'imbalanced' growth, with employment growing unevenly across industries, and particularly so in industries that are less prone to productivity gains. Studies by Ngai and Pissarides (2007) and Acemoglu and Guerrieri (2008) built on this by developing models in which such imbalanced productivity growth can still result in a stable labor share of national income. Autor and Salomons (2018) subsequently took these ideas to the data, showing that industry-level productivity growth can have differing effects on employment at the industry level compared to the aggregate level. reduces own-industry employment, but contributes to aggregate employment levels. As such, industry-level research is essential for revealing what aggregate-level data conceals, providing more nuanced insights that can guide targeted and effective policy interventions.

Existing industry-level studies on the impact of productivity growth on labor demand offer mixed, though generally pessimistic, findings. Bessen (2019), through historical case studies of three U.S. industries, finds that while productivity growth initially boosted employment, it eventually led to a decline in labor demand as these industries matured. He attributes this shift to changes in the price elasticity of consumer demand. In contrast, Autor and Salomons (2017, 2018) take a broader approach, using a cross-country and cross-industry panel dataset covering industrialized countries from 1970 to 2007. Both studies find a clear negative relationship between productivity and employment at the industry level, with the 2018 study also reporting a weaker, though still negative, relationship between productivity and the labor share. Similarly, Bação, Gaudêncio Lopes, and Simões (2023), focusing on Portugal, report a negative productivity-elasticity of employment. By contrast, an OECD study by Calligaris et al. (2023), who cover multiple countries but excludes major industrialized economies, finds no significant relationship between industry-level productivity and employment.

Against this background, the present study replicates, extends and critically engages with the regression framework from Autor and Salomons (2018), to provide new evidence on the relationship between productivity growth and labor demand at the industry level. I begin by developing a simple theoretical model, where this relationship is shaped by two competing forces: a negative labor-saving effect driven by technological efficiency gains and a positive scale effect, where lower prices boost consumer demand. The balance between these forces depends crucially on the price elasticity of demand, echoing insights from Bessen (2019). I then empirically approach the relationship between productivity growth and labor demand using the distributed-lag regression framework from Autor and Salomons. Specifically, I approximate the effects of productivity on labor demand through indicators such as employment, aggregate hours, the nominal wage bill, value-added, and the labor share. While I focus exclusively on replicating Autor and Salomons's industry-level model - omitting their analysis of how industry-level productivity growth affects aggregate outcomes - this narrower focus allows me to explore productivity's labor market effects in greater detail and critically engage with their approach. It enables a closer examination of different specifications, the dynamic effects of productivity shocks over time and their impact on a broader range of labor market indicators, including real wages. Additionally, by covering a more recent period and improving on Calligaris et al. (2023)'s country coverage, this study provides a more up-to-date and comprehensive analysis, reflecting current economic conditions and trends.

Despite focusing on a different time period, my replication results broadly align with those of Autor and Salomons (2018), although they are smaller in magnitude. Specifically, I find that, on average, a one-percent increase in productivity growth is associated with a reduction in employment, hours, and the nominal wage bill of about one-third of a percentage point. For the labor share, I observe a slightly negative relationship too, though these estimates appear somewhat questionable, as point estimates are very inconsistently signed point across periods. However, a deeper investigation reveals some theoretical and econometric issues with the authors' approach that warrant further consideration. First, while the results suggest that productivity growth depressed employment, it also had a large positive effect on real hourly wages, which is difficult to reconcile with the idea of declining labor demand. Second, I show that the temporal adjustment displays a worrisome pattern, showing a large and positive contemporaneous adjustment, and a constant negative effect from the second period onwards. Finally, I show that the results are not robust to the inclusion of industry-level fixed effects, indicating that much of the identifying variation is between industries, casting doubt on the validity of the estimation strategy.

The remainder of the paper is structured as follows. Section 2 reviews the relevant empirical literature. In Section 3, I present a simple theoretical model of labor demand. Section 4 describes the data, while Section 5 derives and details the estimation strategy. The empirical results and their discussion are provided in Section 6. Section 7 concludes.

2 Literature Review

Section 2 reviews four key studies that utilize cross-country and cross-industry evidence to estimate the elasticity of labor demand with respect to productivity. By examining their findings, I draw several important conclusions that will help frame the analysis in this thesis.

Autor and Salomons (2018), the study I replicate here, constitutes perhaps the most prominent study examining the elasticity of employment growth with respect to productivity growth at the industry level. Their analysis draws on the EU-KLEMS dataset, which provides harmonized industry-level data for 19 OECD countries from 1970 to 2007. In their main specification, they estimate a set of stacked log-log first-difference OLS models, regressing employment, hours, the wage bill, value-added, and the labor share on total-factor productivity (TFP). Section 5 offers a detailed derivation of this regression model. Their findings suggest that industry-level productivity growth led to a decline in labor demand within the same industry. Specifically, they estimate that a one-percent increase in industry-level TFP growth resulted on average in a 0.4 to 0.8 percentage point decline in employment growth over a five-year horizon. The estimates for aggregate hours and the nominal wage bill are similarly negative, indicating that hours per worker and nominal wages were largely unaffected by productivity growth, with adjustments occurring primarily through reductions in employment. Additionally, the authors estimate that a one-percent increase in TFP growth reduced the growth rate of the labor share by approximately 0.2 percentage points. While robustness checks largely confirm these results, the estimates become smaller and less significant when using patents and citations as proxies for technological change. Table 5 in their study provides a comprehensive overview over the key regression results.

The 2018-study is closely connected to Autor and Salomons (2017), which offered an initial exploration of the effects of industry-level productivity growth on both industry- and aggregate-level employment. While both studies rely on the EU-KLEMS dataset, the earlier work differs slightly in its methodology, incorporating an instrumental-variable (IV) estimation alongside first-differenced OLS models. These OLS estimates suggest a robust industry-level productivity-elasticity of employment growth of -0.25, indicating that, between 1970 and 2007, a ten-percent increase in labor productivity growth on average led to a 2.5 percent decline in employment growth. Interestingly, replacing labor productivity with TFP yields a smaller elasticity estimate of -0.1. IV estimates are much less robust and highly sensitive to the inclusion of industry fixed effects, but generally point in the same direction.

Calligaris et al. (2023) provide another estimate of the industry-level effects of TFP on both employment and wages. Their analysis uses industry-level data from 2000 to 2018 but is limited to Belgium, Canada, Chile, Finland, France, Hungary, Italy, Japan, Latvia, the Netherlands, Portugal, Sweden, and Croatia, excluding major industrialized nations such as the United States, Germany, and the United Kingdom. The authors employ two estimation strategies: a straightforward model of partial correlations between short-term productivity changes and long-term employment changes, and an impulse-response approach to capture the reaction of industry-level outcomes to an initial productivity shock. The partial correlations model reveals a slightly positive, though statistically and economically insignificant, relationship between productivity growth and the 5-year change in employment. The impulse-response estimates support this finding, but the relationship remains marginally positive. Estimates for average wages also show weakly positive results. Interestingly, the contemporaneous wage adjustment is statistically significant at the 5% level, with a 10% productivity increase leading to a 0.5% rise in average wages in the same period. However, after five years, the change in average wages becomes statistically insignificant and approaches zero, suggesting that wage adjustments to productivity shocks occur relatively quickly.

Table 1: Literature Overview with Main Estimates.

Paper	**Dataset**	**Employment Estimate**
Autor and Salomons 2018	19 OECD countries betw. 1970-2007	-0.8 to -0.4
Autor and Salomons 2017	19 OECD countries betw. 1970-2007	-0.1
Bação, Gaudêncio Lopes, and Simões 2023	Portugal betw. 1995-2017	-0.24
Calligaris et al. 2023	12 OECD countries & Croatia betw. 2000-18	0.01

Notes: The third column refers to the estimated elasticity of employment growth w.r.t. TFP growth.

Bação, Gaudêncio Lopes, and Simões (2023) constitutes a fourth study which investigates the industry-level relationship between productivity growth and employment. The authors employ data covering 32 industries observed between 1995 and 2017, but focus exclusively on the Portuguese economy. Employing a Bayesian multilevel model, they control for factors such as wages, the rental rate of capital, and demand. The results show consistently negative elasticities across industries, with an average estimate of -0.24 and a standard deviation of 0.05. Investigating heterogeneities between industries, the authors further find a positive estimate for "Social work activities" (0.08) and a large and negative elasticity for the construction sector.

In summary, most studies estimating the industry-level elasticity of labor market outcomes with respect to TFP find negative results. Specifically, measures such as industry-level employment and the wage bill tend to decline in response to rising productivity. At the lower bound, Autor and Salomons (2018) report that a one-percent increase in productivity growth reduced the employment growth rate by up to 0.8%. At the upper bound, Calligaris et al. (2023) find no statistically significant effect, though their analysis is limited by a relatively small sample of countries. One explanation for this variation lies in the differing time horizons covered by each study. The present study seeks to provide new evidence on this relationship, focusing on a more recent period while avoiding the country coverage limitations faced by Calligaris et al. In addition, it is important to note that most discussions in the literature focus on a narrow set of labor market outcomes. While Autor and Salomons (2018) consider employment, hours, the nominal wage bill, value-added, and the labor share, they omit a discussion of the real wage bill and real hourly wages. Calligaris et al. (2023) examine only nominal wages and employment, whereas Autor and Salomons (2017) and Bação, Gaudêncio Lopes, and Simões (2023) focus solely on employment. By incorporating a broader range of outcomes, including the evolution of real wages, the present study aims to offer a more comprehensive analysis of the labor market effects of productivity growth.

3 Theory

Having reviewed several empirical studies on the relationship between industry-level productivity growth and labor demand, this section shifts to a theoretical framework that will inform the analysis of my empirical findings. Based on a simple Cobb-Douglas production function, I illustrate the relationship between productivity and labor demand within the context of long-run static labor demand theory.[2] The model reveals that this relationship

2. Refer to Borjas (2017), Cahuc and Zylberberg (2014), or Hamermesh (1993).

depends on the interplay of two competing forces: a *labor-saving effect*, where increased productivity allows firms to produce the same output with fewer inputs, reducing labor demand, and a *scale effect*, where lower prices from higher productivity boost consumer demand, output, and labor demand. Echoing Bessen (2019), the model puts central importance on the price-elasticity of consumer demand.

To formalize this relationship, I begin by assuming that an industry's aggregate production function takes the form:

$$Y = AL^{\alpha}K^{1-\alpha} \tag{1}$$

where L represents labor input, K represents capital input, and α, the elasticity of output with respect to labor (where $0 < \alpha < 1$), which reflects labor's importance in the production process. To keep the discussion brief, I only allow for Hicks-neutral technological progress A, and refrain from introducing technological change which only augments specific factors of production. However, all of the key results presented below hold under these types of technological change too.

To illustrate the labor-saving effect of productivity growth, the following analysis holds the output produced by the representative industry constant and solves for its conditional labor demand.[3] Because employing workers and operating machines incur costs, the industry aims to minimize factor usage for a given level of output. Formally, this cost-minimization problem is expressed as:

$$\min \quad C(Y, w, r) = wL + rK \quad \text{s.t.} \quad = AL^{\alpha}K^{1-\alpha} \geq \bar{Y}$$

where w corresponds to the unit-costs of labor, r corresponds to the unit-costs of capital, and $\bar{Y}$ gives the fixed level of output. Solving this problem yields the industry's conditional labor demand $\bar{L}$:

$$\bar{L} = \left(\left(\frac{\alpha}{1-\alpha}\right)\frac{r}{w}\right)^{1-\alpha}\left(\frac{\bar{Y}}{A}\right)$$

This result aligns with economic intuition: labor demand *in*creases as capital costs rise, *de*creases as labor costs increase, and *in*creases with higher output levels. Additionally,

3. The notation and terminology closely follow the derivation of the wage-elasticity of labor demand in Cahuc and Zylberberg (2014)'s chapter on labor demand.

labor demand decreases in response to technological progress. This can also be demonstrated formally by deriving the elasticity of conditional labor demand $\bar{L}$ with respect to productivity A, which is given by $\bar{\eta}^L_A = \frac{\partial A}{\partial L}\frac{L}{A_T} = -1$. In other words, for a given level of output, a one-percent increase in Hicks-neutral productivity leads to a one-percent decrease in labor demand. This is reflective of the fact that, as industry-level productivity increases, firms require fewer workers (and other inputs) to produce a fixed quantity of output, leading to a reduction in labor demand. Although space constraints prevent a detailed demonstration, it is important to note that labor- or capital-augmenting technological change also has an unambiguous negative effect on conditional labor demand, provided the production function remains of the Cobb-Douglas type. I will briefly return to this point below.

For now I focus on the scale effect of productivity on employment, which positively impacts industry-level labor demand. Specifically, productivity improvements allow firms to reduce the price of their products, spurring consumer demand and increasing output. To formally derive these scale effects, producers are now assumed to choose their level of production to maximize profits. However, because I assume that the production function in Equation 1 represents an entire industry, one cannot assume that prices are fixed. A single firm in a competitive market might be small enough so that it cannot influence prices, but if all firms within an industry expand output, prices will adjust (Borjas 2017, 91–92). To account for this fact, I assume that consumer demand for the industry's output can be modelled as a constant-elasticity demand function, the inverse demand function of which is given as $P(Y) = (\beta Y)^{\frac{1}{\varepsilon}}$, with ε giving the price-elasticity of demand. I further assume that $\varepsilon \leq 0$, meaning that consumers demand more of the industry's output at lower prices. More specifically, for $|\varepsilon| = 1$, a one-percent increase in price leads to a decrease in product-demand of one percent. If $|\varepsilon| < 1$, a one-percent increase in price leads to a decrease in demand of less than a percent and for $|\varepsilon| > 1$, consumer demand decreases by more than one percent. The respective problem is then given as

$$\max_{L} \quad \Pi(L, K) = P(Y)Y - C(Y, w, r)$$

Solving the first-order conditions yields the industry's *unconditional* demand for labor as

$$L = \left(\beta^{\frac{1}{\varepsilon}}\alpha\left(\frac{1+\varepsilon}{\varepsilon}\right)\frac{1}{w}\right)^{\left(\frac{\varepsilon}{\varepsilon-\alpha\varepsilon-\alpha}\right)}\left(AK^{1-\alpha}\right)^{\left(\frac{1+\varepsilon}{\varepsilon-\alpha\varepsilon-\alpha}\right)}$$

Taking the partial derivative with respect to A and multiplying by $\frac{A}{L}$, I obtain the elasticity of unconditional labor demand with respect to productivity as $\eta_A^L = \frac{1+\varepsilon}{\varepsilon-\alpha-\varepsilon\alpha}$. This elasticity reveals a key insight: Whether labor demand increases or decreases with productivity depends solely on ε. Put differently, it is the price elasticity of consumer demand that determines whether the scale effect outweighs the labor-saving effect, and consequently, whether η_A^L is positive or negative. Both effects exactly offset one another when product demand is unit elastic, i.e., when $|\varepsilon| = 1$. In this case, the elasticity of labor demand with respect to productivity η_A^L is zero, meaning that changes in productivity have no impact on labor demand. However, if product demand is inelastic $|\varepsilon| < 1$, the labor-saving effect exceeds the scale effect, resulting in a negative overall elasticity of labor demand with respect to productivity: labor demand decreases as productivity grows. Conversely, when product demand is elastic $|\varepsilon| > 1$, the scale effect dominates, and labor demand increases in response to a productivity shock.[4] The economic intuition behind these results goes as follows: technological change enables firms to lower their prices, prompting consumers to increase their demand. The magnitude of this demand response depends on the price elasticity. If demand is highly elastic, consumption rises sharply, leading to a significant increase in output and labor demand. If demand is inelastic, the increase in consumption - and consequently, labor demand - is much smaller.

Bessen (2015) provides an instructive example of the interplay between the labor-saving and scale effects: In the U.S., Automated Teller Machines (ATMs) were popularized in the 1970s and significantly increased the speed and reduced the cost with which customers could dispense cash and make deposits. On the one hand, this meant that fewer banking personnel were required per branch, demonstrating the labor-saving effect. Yet, the overall number of bank tellers employed did not decline. One reason for this was that ATMs reduced the cost of operating bank branches, thereby lowering the price at which financial services could be offered. Consumers responded by increasing demand, and banks, in turn, opened more branches to capture a greater market share. Indeed, while "the number of tellers required to operate a branch office in the average urban market fell from 20 to 13 between 1988 and 2004," the number of bank branches in urban areas increased by 43 percent during the same period.

Before summarizing key points and concluding this section, I want to stress some im-

4. See Blien and Ludewig (2017) and Bessen (2019) for similar findings in macroeconomic models.

portant limitations to the analysis presented here. Firstly, as mentioned before, notice that the model discussed here does not account for any type of capital-labor substitutions, and can consequently not explain a potential decline in the within-industry labor share. The crux in here is that the Cobb-Douglas production function has an elasticity of substitution equal to 1, which means that any type of technological change, be it Hicks-neutral or factor-augmenting, will not affect the capital-ratio. Only under a more general constant-elasticity of substitution production function can factor-augmenting technological change affect the capital-labor ratio. [5] Secondly, while I have derived the elasticity of labor demand with respect to technological change, the regression model I will outline in Section 5 relates labor market *outcomes* - such as employment, aggregate hours, and wages - to productivity growth. However, these outcomes are shaped in the labor market equilibrium, i.e. by the interaction of labor demand *and* labor supply. Unfortunately, deriving the full equilibrium conditions lies beyond the scope of this thesis. For now, it must suffices to note that, under standard assumptions of an upward-sloping labor supply curve and a downward-sloping labor demand curve, increases in labor demand typically lead to higher wages and employment.[6] Thirdly, there is also the possibility that labor market rigidities may prevent labor demand shocks from translating into wage or employment growth. For instance, if a minimum wage is set significantly above the competitive market wage, an increase in labor demand may not lead to higher wages. While I cannot fully resolve these concerns, I follow Autor and Salomons (2018) by restricting my analysis to 'market' sectors in an effort to address this issue. I will return to the matter of what precisely I call a 'market'-sector in the next section.

In conclusion, I would like to emphasize two key takeaways from Section 3. First, basic neoclassical labor demand theory provides no definitive answer regarding the sign of the productivity-elasticity of labor demand. Whether labor demand increases or decreases as productivity grows depends on the interplay of two opposing forces: a labor-saving effect, which is generally negative and reflects the efficiency gains brought about by technological change, and a positive scale effect, which arises from the fact that productivity growth allows for lower prices, stimulating consumer demand. This theoretical ambiguity highlights

5. Acemoglu and Restrepo (2018a, 2018b, 2019) introduce 'task-based' production functions with non-constant elasticity of substitution, which allow for the 'automation' of tasks previously performed by workers, further complicating the issue.

6. Even when labor demand or supply is fully elastic or inelastic, one would either expect employment or wages to adjust to changes in labor demand. Blundell and MaCurdy (1999) find that the elasticity of male labor supply is around -0.1, implying near inelasticity. Similarly, natural experiments by Card (1990) and Card and Krueger (1994) suggest fully elastic and fully inelastic labor demand curves, respectively.

the need for empirical analysis. Second, the extent to which the scale effect outweighs the labor-saving effect depends largely on the price elasticity of consumer demand. If consumer demand responds strongly to price changes, productivity growth will likely be more beneficial for workers. I will revisit these findings in Section 6.

4 Data

Having introduced the labor demand theory central to this thesis, the following section provides a comprehensive overview of the EU-KLEMS dataset, which will be used for the empirical analysis in Section 6. It begins by detailing the dataset's scope and coverage, followed by a review of summary statistics and an analysis of key observable trends. The section concludes with a discussion on how productivity and technological change are approximated within the dataset.

The empirical analysis in this thesis uses the 2023 release of the EU-KLEMS & INTAN-Prod Database by Bontadini et al. (2023), an updated version of the dataset employed by Autor and Salomons (2018). Maintained by the Luiss Lab of European Economics at Luiss University in Rome, Italy, the database provides key industry-level data for studying productivity and labor markets. These data are directly sourced from the national accounts of individual countries, with coverage spanning the period from 1995 to 2020. In contrast, Autor and Salomons analyzed data from 1970 to 2007. As detailed in Table 2, I utilize 38 of the 42 industries available in the dataset. In line with Autor and Salomons, I exclude 'non-market' sectors such as public administration and defense, the private household sector, and activities of extraterritorial organizations. To maintain comparability, I also follow the authors in excluding the farm sector. The sector groupings in the third column of Table 2 are also consistent with the approach of Autor and Salomons. These groupings will become relevant when sector-group fixed effects are introduced in Section 5. It is also important to note the significant variation in the size of industries in the dataset. As illustrated in the fourth column of Table 2, the share of total hours worked by each industry, summed across all years and countries, varies widely. For example, the smallest industry, Water transport, accounts for just 0.2% of total hours worked, while Construction, the largest industry, represents 9.58%.

Table 3 provides an overview of the 16 countries in the dataset, together with selected

Table 2: Industries with Share of Total Aggregate Hours.

Industry	**Industry Code**	**Sector**	**Share**
Mining and quarrying	B	M., U. & C.	0.4%
Manufacture of food, beverages, and tobacco	C10-12	Manufacturing	2.45%
Manufacture of textiles, apparel, and leather	C13-C15	Manufacturing	1.17%
Manufacture of wood, paper, and printing	C16-C18	Manufacturing	1.72%
Manufacture of coke and petroleum products	C19	Manufacturing	0.09%
Manufacture of chemicals	C20	Manufacturing	0.83%
Manufacture of pharmaceuticals	C21	Manufacturing	0.2%
Manufacture of rubber and plastic	C22-C23	Manufacturing	1.71%
Manufacture of metals and metal products	C24-C25	Manufacturing	2.61%
Manufacture of computers and electronics	C26	Manufacturing	1.34%
Manufacture of electrical equipment	C27	Manufacturing	0.82%
Manufacture of machinery	C28	Manufacturing	1.83%
Manufacture of vehicles and transport equipment	C29-C30	Manufacturing	1.91%
Manufacture of furniture, jewelry and repair	C31-C33	Manufacturing	1.57%
Electricity, gas and steam supply	D	M., U. & C.	0.34%
Water supply and waste management	E	M., U. & C.	0.51%
Construction	F	M., U. & C.	9.58%
Trade and repair of vehicles	G45	Low-Tech Serv.	0.65%
Wholesale trade, except vehicles	G46	Low-Tech Serv.	4.84%
Retail trade, except vehicles	G47	Low-Tech Serv.	9.36%
Land transport and pipelines	H49	Low-Tech Serv.	2.83%
Water transport	H50	Low-Tech Serv.	0.12%
Air transport	H51	Low-Tech Serv.	0.25%
Warehousing and support transport activities	H52	Low-Tech Serv.	1.1%
Postal and courier activities	H53	Low-Tech Serv.	0.25%
Accommodation and food service	I	Low-Tech Serv.	7.31%
Publishing, motion pictures and broadcasting	J58-J60	High-Tech Serv.	1.51%
Telecommunications	J61	High-Tech Serv.	0.38%
Computer programming and consultancy	J62-J63	High-Tech Serv.	2.05%
Financial and insurance activities	K	High-Tech Serv.	4.41%
Real estate activities	L	Low-Tech Serv.	1.53%
Professional, scientific and technical activities	M	High-Tech Serv.	6.59%
Administrative and support services	N	Low-Tech Serv.	6.22%
Education	P	Ed. & Health	4.69%
Human health activities	Q86	Ed. & Health	7.39%
Residential care, social work	Q87-Q88	Low-Tech Serv.	3.22%
Arts, entertainment and recreation	R	Low-Tech Serv.	1.79%
Other service activities	S	Low-Tech Serv.	4.44%

Notes: "M., U. & C." refers to mining, utilities, and construction. "Low-Tech Serv." and "High-Tech Serv." stand for low- and high-tech services, respectively. "Ed & Health" refers to the education and health sector. The column "Share" refers to each industry's total hours worked as a proportion of aggregate hours across the dataset. The farm sector, public administration, defense, the private household sector, and activities of extraterritorial organizations are excluded.

Table 3: Time-Averaged Labor Market Indicators per Country.

Country	Employment	Hours	Wagebill	Value-Added	Labor Share
Austria	3.54	5.84	0.16	0.26	0.60
Belgium	3.81	4.62	0.14	0.30	0.46
Denmark	2.55	3.61	1.04	1.74	0.60
Finland	2.13	3.47	0.10	0.16	0.63
France	22.91	26.96	0.87	1.36	0.64
Germany	36.74	41.66	1.25	2.08	0.60
Ireland	1.68	2.97	*NA*	*NA*	*NA*
Italy	20.39	36.03	0.62	1.09	0.57
Japan	47.72	83.53	200.64	400.75	0.50
Luxembourg	0.23	0.34	0.02	0.03	0.53
Netherlands	7.85	11.17	0.27	0.41	0.66
Portugal	3.87	6.57	*NA*	*NA*	*NA*
Spain	15.31	26.47	0.32	0.59	0.55
Sweden	4.05	6.52	1.24	2.24	0.55
UK	27.26	35.08	0.75	1.47	0.51
US	121.67	204.52	7.07	11.82	0.60

Notes: All indicators are time-averaged across 1995-2020. Employment is displayed in millions, aggregate hours in billions. Wage bill and value-added are displayed in trillions of their respective currency and come in constant prices, calculated as chain-linked volumes using 2015 as a base year. The labor share is obtained by dividing the wage bill with the value-added, *without* applying industry-weights. I have excluded the farm-sector, as well as public administration and defense, the private household sector and activities of extraterritorial organizations

time-averaged indicators. Following Autor and Salomons, I exclude data on Eastern European states, thereby limiting data coverage to 13 EU-countries, the United Kingdom, the United States and Japan. In contrast to Autor and Salomons I do not cover Australia, Canada and South Korea. Table 3 reveals that there is also substantial heterogeneity in terms of size *at the country-level*. Across the time period considered, Luxembourg, which has the smallest labor market in the dataset, had on average 529-times fewer employed persons than the U.S., the country with the largest labor market in the dataset. However, caution is needed when comparing value-added or the wage bill across countries. Although these aggregates are presented in constant prices, they are reported in their respective national currencies, and EU-KLEMS does not convert these values to a common currency such as the US Dollar. As a result, value-added and the wage bill for countries like Japan appear much larger than those for comparable countries, such as Germany. However, this issue is resolved when taking the log changes of these variables, as will be done throughout the rest of the paper.

These substantial differences in country and industry size imply that regression results are disproportionately influenced by smaller countries and industries, when treating each cross-sectional unit as equal. While Autor and Salomons do not explicitly justify their use of weighted OLS, it appears that the primary motivation is not to address heteroskedasticity, but rather to ensure that the influence a country or industry exerts on the estimated regression coefficients is reflective of their relative size. To maintain comparability with their study, I adopt the same approach to weighting observations as described in their paper. Formally, each observation is assigned the weight

$$W_{ict} = \left(\frac{\frac{1}{T}\sum_{t=1}^{T} X_{ict}}{\sum_{j=1}^{N} \frac{1}{T}\sum_{t=1}^{T} X_{jct}} \right) \cdot \left(\frac{\sum_{i=1}^{M} X_{ict}}{\sum_{k=1}^{C}\sum_{i=1}^{M} X_{ikt}} \right) \tag{2}$$

where X_{ict} represents an arbitrary weighting variable. The first term gives the time-averaged share of the relevant weighting variable within countries, thereby capturing the average size of some industry i within a country c over time. This is meant to acknowledge the significant variation in industries' relative importance within countries. The second term reflects the relative size of some country c in a particular year t compared with the other countries in the sample. This adjusts for differences in country size and aims to prevent smaller countries from disproportionately influencing the overall results. Regarding the choice of X_{ict}, Autor and Salomons (2018) generally weight regressions involving employment as the dependent variable by employment, those with aggregate hours or the real hourly wage by aggregate hours, and regressions using the wage bill, value-added, or labor share on the left-hand side by value-added. However, due to the lack of a value-added measure converted into a common currency such as the US Dollar, I generally substitute value-added with aggregate hours for weighting purposes.

Table 4, similar to Table 3 in Autor and Salomons (2018), presents summary statistics of key variables as log-changes, weighted according to the formula in Equation 2. I report summary statistics both overall and for the period before and after 2007. As shown in the table, industry-level employment, real wages, and real value-added generally increased over the entire period under consideration, though at a diminishing rate. Specifically, employment and real wages grew by an average of 1.2% and 1.4% annually before the global financial crisis, but only by 0.2% and 0.6% respectively thereafter. A similar, though even more pronounced trend is observable for real value-added, which declined from a growth rate of 2.2% before 2007 to just 0.3% afterwards. These trends reflect the broader recession that affected many industrialized countries post-2007 (Reinhart and Rogoff 2009).

Table 4: Mean Estimates of Labor Market Indicators with Standard Errors.

	Employ -ment	Aggregate Hours	Real Wages	Labor Share	Real V.A.	TFP
100 × Mean Annual Log Change	0.692*** (0.028)	0.265*** (0.037)	0.975*** (0.054)	0.045 (0.051)	1.241*** (0.060)	0.052 (0.051)
100 × Mean Annual Log Change for:						
Pre-2007	1.211*** (0.037)	0.993*** (0.043)	1.389*** (0.087)	0.159** (0.078)	2.226*** (0.070)	0.279*** (0.069)
Post-2007	0.213*** (0.042)	-0.404*** (0.059)	0.594*** (0.064)	-0.060 (0.066)	0.310*** (0.095)	-0.163** (0.074)
N	14,421	13,505	10,297	10,302	10,361	9,908
Model weighted by:	Employ-ment	Hours	Hours	Hours	Hours	Hours

Notes: Means and standard errors are obtained by regressing the respective variable on an intercept. "N" refers to the amount of observations in the first row. "Real V.A." refers to real value-added, measured as chain-linked volumes. "TFP" refers to total-factor productivity. All models are weighted according to Equation 2. The weighting variable is in the last row. *p<0.1; **p<0.05; ***p<0.01.

However, it is concerning that these trends are not entirely consistent with those reported in Table 3 of Autor and Salomons (2018). While the average growth rate of real wages is comparable to the estimates in Table 4, the reported employment and aggregate hours growth rates in their paper are substantially lower. Specifically, Autor and Salomons (2018) report employment growth rates of 0.9% for the 1990s and 0.4% for the 2000s, while hours worked increased by 0.7% in the 1990s and 0.2% thereafter. Additionally, it is puzzling that the within-industry labor share appears to have slightly increased pre-2007, which is not in accordance with much of the existing literature (e.g., Elsby, Hobijn, and Şahin (2013); Karabarbounis and Neiman (2014)) and the estimates provided by Autor and Salomons (2018). Finally, while TFP trends generally align with Autor and Salomons's estimates up until 2007, I remain skeptical about the apparent decline in TFP following the financial crisis, as indicated in Table 4. These concerns are further compounded by the limited number of observations for which TFP estimates are available. Since TFP growth is calculated using a range of variables, all of which must be present, TFP has the fewest observations compared to other variables listed in Table 4. Specifically, only 9,908 out of a potential 15,200 observations (calculated as $16 \times 38 \times 25$) include complete data for TFP.

These somewhat dubious estimates of TFP growth warrant a brief discussion of how productivity growth is estimated by Bontadini et al. (2023). This will also be informative for the analysis presented in Section 5. Generally, their approach makes use of a growth accounting decomposition in vein of Jorgenson and Griliches (1967) and Frank M Gollop and Jorgenson (1987). In this framework, the percentage growth (i.e. the log change) in TFP in period t, country c and industry i is computed as

$$\Delta \log \mathrm{TFP}_{ict} = \Delta \log V_{ict} - \bar{v}^L_{ict} \underbrace{(\Delta \log H_{ict} + \Delta \log \mathrm{LC}_{ict})}_{\Delta \log L_{ict}} - \bar{v}^K_{ict} \Delta \log K_{ict} \tag{3}$$

where $\Delta \log$ refers to the log-change and V refers to gross value-added as chained linked volumes using 2015 as a base year. $\bar{v}^L_{ict}$ refers to the year t and $t-1$ average of the share of the wage bill in value added at current prices, whereas $\bar{v}^K_{ict}$ refers to the share of capital compensation in value added.[7] Moreover, L refers to labor services here, a term which attempts to encompass more than just aggregate hours H, which represent the quantity of labor input. It also includes a labor composition index LC, which attempts to account for the 'quality' of an industry's workforce. While a detailed discussion of how this index is calculated is beyond the scope of this thesis, it is important to notice that this labor composition index is a function of the wages paid to the workers within an industry. This is justified by the assumption that wages are reflective of workers' productivity. As a result, the labor composition index is closely related to variables like the wage bill and the labor share of industrial income.[8] Conversely, capital services K represent the value of all capital inputs within a given period, industry, and country. Since these inputs are directly measured in monetary terms, a decomposition like that used for labor services is unnecessary.

Section 4 provided an introduction to the dataset used in this thesis, offering an overview of the industries and countries included in the analysis. The considerable heterogeneity observed at both the industry and country level motivates the use of a weighting scheme in the empirical analysis, which will be discussed in the following section. There, I will also revisit the method of calculating TFP. Moreover, the regression results I present in Section 6 will build upon the summary statistics and insights outlined here.

7. Notice that this is a translog-version of the production function from Equation 1.

8. For a detailed discussion of how labor services are decomposed in the EU-KLEMS dataset, see O'Mahony and Timmer (2009, 376–8).

5 Estimation Strategy

Thus far, I have reviewed the relevant empirical literature, developed a basic model of industry-level labor demand, and discussed the dataset used for my analysis. In this section, I will proceed by deriving the distributed-lag regression equation originally estimated by Autor and Salomons (2018, 15), which I will replicate in my analysis. By gradually developing the equation, I aim to clarify the rationale behind each of its components. The section concludes by discussing some remaining concerns.

Derivation

My point of departure is the log-log regression specification in Equation 4:

$$\log L_{ict} = \gamma + \beta_0 \log \mathrm{TFP}_{ict} + \varepsilon_{ict} \tag{4}$$

where i denotes industry, c denotes country and t denotes year. Each cross-sectional observation corresponds to a unique industry-country pair for a given year. L_{ict} refers to some outcome such as employment, aggregate hours or labor's share in value-added. TFP_{ict} captures total-factor productivity and ε_{ict} is the idiosyncratic error. The notation log refers to the natural logarithm. Importantly, because of the log-log specification, β_0 captures the stochastic version of the productivity-elasticity of the outcome, provided that TFP_{ict} is independent of ε_{ict}.[9] That is, β_0 reflects the percentage-change in the conditional expectation of some labor market outcome L_{ict} given a one-percent increase in TFP_{ict}.

However, as discussed in Section 4, TFP is reported as a log *change* in the EU-KLEMS data. This necessitates estimating a first-differenced version of Equation 4:

$$\Delta \log L_{ict} = \beta_0 \Delta \log \mathrm{TFP}_{ict} + u_{ict} \tag{5}$$

Here, Δ symbolizes the $t-1$ to t change in the respective variable and $u_{ict} = \Delta\varepsilon_{ict}$. Can β_0 still be interpreted as an elasticity? Yes, but the interpretation of β_0 in Equation 5 changes slightly compared to the interpretation of β_0 in Equation 4. Using the properties of the log, the change in the log of some variable X_t can be reformulated as $\Delta \log X_t = \log\left(\frac{X_t}{X_{t-1}}\right)$. Consequently, Equation 5 can be rewritten as a log-log equation, but now relating

9. Consult Wooldridge (2010, 15–18) for a proof.

the ratio of employment between two consecutive years to the ratio of TFP between the same years. Consequently, β_0 now measures the percentage change of $L_{ict}/L_{i,c,t-1}$ in response to a one-percent increase in $\text{TFP}_{ict}/\text{TFP}_{i,c,t-1}$. In other words, β_0 reflects the elasticity of employment *growth* with respect to TFP *growth*. Although these interpretations differ in an important manner, it is also clear that they are closely related. Both elasticities measure the responsiveness of labor demand to productivity, but in different contexts - one in terms of levels and one in terms of differences. At the same time, the upside of first-differencing is that it does allows for correlation between productivity and unobserved, time-invariant determinants of labor demand. That is, estimating Equation 4 will lead to inconsistent estimates of β_0 if there are time-constant factors c_{ic} at the country-industry level which both influence L_{ict} and are correlated with TFP_{ict}. First-differencing Equation 4 eliminates any such time-invariant factors c_{ic}, thereby mitigating this potential source of bias. One such time-constant characteristic could be the natural resource endowment available to a particular industry. Industries that have access to abundant natural resources, such as minerals or oil, might experience higher productivity due to the easy availability and lower cost of these essential inputs. At the same time, these resource-rich industries may also demand less labor relative to output, as resource extraction and processing can be highly capital-intensive. Other examples include an industry's regulatory environment, its market structure, capital-intensity or skill requirements.

A further challenge concerns a potential simultaneity bias. Regression Equations 4 and 5 aim to identify how labor market outcomes such as employment, aggregate hours worked and the wage bill change in response to productivity shocks. However, as evident from Equation 3 in Section 4, TFP is itself a function of these labor market outcomes, as it measures the productivity of the factor-inputs used in production. For example, if employment increases at stable value-added, TFP decreases as more factor inputs are required to produce a fixed amount of output. Due to this simultaneity, the error term in regression equation 5 will generally be correlated with the growth rate of productivity, i.e. $\mathbb{E}\left[(\Delta \log \text{TFP}_{ict})' u_{ict}\right] \neq 0$, leading to an inconsistent OLS estimate of β_0 (Wooldridge 2010, 241–245). Moreover, because employment, hours and the wage bill all factor negatively into the construction of TFP, the asymptotic bias (or inconsistency) of OLS will generally be negative for those variables. Put differently, $\hat{\beta}_0$ will generally *underestimate* the true productivity-elasticity. In contrast, because value-added contributes positively to TFP-growth, the bias for value-added is expected to be positive.

To counteract the simultaneity issue, Autor and Salomons (2018) attempt to obtain a measure of country-industry-level productivity growth which is not a function of country-industry level employment. They do so by replacing industry-level TFP growth with the leave out-mean of industry-level TFP growth in all other countries in the sample. The latter is defined as $\Delta \log \text{TFP}_{i,c\neq c(i),t} = \frac{1}{C}\sum_{j\neq c}^{C} \Delta \log \text{TFP}_{i,j,t}$, where the leave-out mean reflects the average TFP growth of the industry across all countries except the one being considered. The underlying assumption is that this leave-out mean captures shared cross-national technological advances that are common to the industries in the sample (Autor and Salomons 2017, 57). The resulting estimation equation is

$$\Delta \log L_{ict} = \beta_0 \Delta \log \text{TFP}_{i,c\neq c(i),t} + u_{ict} \tag{6}$$

Although the leave-out mean introduced by Autor and Salomons addresses simultaneity issues, it remains unclear whether it accurately reflects industry-level productivity growth or technological change. If not, its use introduces ambiguity into the regression, making the results difficult to interpret. A more in-depth exploration of this issue, however, is beyond the scope of the present study.

Building on Equation 6, the authors also incorporate country and year fixed effects into their regression model:

$$\Delta \log L_{ict} = \beta_0 \Delta \log \text{TFP}_{i,c\neq c(i),t} + \alpha_c + \delta_t + u_{ict} \tag{7}$$

While first-differencing has already controlled for time-invariant fixed effects at the industry-country level, the inclusion of year fixed effects (δ_t) is crucial to account for time-specific shocks that influence the growth rate of labor demand across multiple countries and industries. These shocks are often correlated with productivity growth, potentially biasing the results if not properly controlled for. Year fixed effects capture common global events or trends—such as financial crises—that simultaneously affect multiple countries. For instance, the 2008 financial crisis had a widespread adverse impact, particularly on OECD countries. By including year fixed effects, I control for such global shocks, isolating the effect of productivity growth on labor demand and ensuring that my estimates are not confounded by these time-specific influences. Similarly, the country fixed effects (α_c) represent linear country-specific trends and account for persistent, country-specific factors that have a time-invariant influence on the growth rate of labor demand. These factors could include long-run economic trends, structural differences, or policies unique to each country that systematically affect the growth rate of labor demand and are correlated with productivity growth. Under some specifications Autor and Salomons also introduce a sector-specific fixed-effect, following the sector-classification in Table 2. As the country-specific fixed effects, these fixed effects capture sector-specific linear trends, and account for time-invariant differences in the growth rate of labor demand across sectors. Notice further that, unlike Autor and Salomons, I do not include a country-year interaction term as well as dummy variables indicating country-specific business cycle trends. The exclusion of interaction terms is meant to keep the discussion moderately simple, whereas country-specific business cycle trends are excluded due to a lack of data.

A final issue relates to timing: Due to the use of panel-data methods such as first-differencing and fixed-effects, consistency of $\hat{\beta}_0$ hinges on the assumption of strict exogeneity: Once I control for today's productivity as well as time-invariant industry heterogeneity, future or past labor productivity should have no partial effect on today's labor demand. Put differently, once I control for $\text{TFP}_{i,c\neq c(i),\mathbf{t}}$ and c_{ci}, $\text{TFP}_{i,c\neq c(i),\mathbf{s}}$ should have no partial effect on $L_{ic\mathbf{t}}$ for $s \neq t$ (Wooldridge 2010, 287–8). This seems to be fairly implausible. As noted by Autor and Salomons, shocks to productivity can affect labor demand with a substantial time lag, which implies that past productivity shocks can affect today's labor demand growth. Under such conditions, the strict exogeneity assumption would be violated. To tackle this problem, the authors include lags to the technology variable $\text{TFP}_{i,c\neq c(i),t}$, thereby establishing a distributed lag model:

$$\Delta \log L_{ict} = \sum_{k=0}^{5} \beta_k \Delta \log \text{TFP}_{i,c\neq c(i),t-k} + \alpha_c + \delta_t + u_{ict} \tag{8}$$

The decision to include 5 lags follows Autor and Salomons (2018), who base their choice on the estimation of a set of local projection models in the spirit of Jordà (2005). Autor and Salomons argue that these estimates[10] indicate that up to 5 lags are sufficient to fully capture the impact of an industry-level TFP shock on all labor market outcomes of interest.

10. See figure 3 in their paper.

Other Concerns

Regression Equation 8 represents the equation I am going to estimate in Section 6. Recall that Equation 8 controls for time-invariant industry-country level heterogeneities, TFP-induced simultaneity, time-specific shocks, linear country- and sector-specific trends, as well as lagged effects of productivity.

Nevertheless, potential sources of endogeneity remain, which may lead to biased estimates. First, while the leave-out mean attempts to address simultaneity issues, it is unclear whether this variable accurately reflects technological change at the industry-country level. If it does not, the nature of the relationship being estimated becomes ambiguous. Additionally, there may be concerns about the sufficiency of the lags used or whether current industry-level labor demand could influence *future* productivity. If such a reverse effect exists, Equation 8 would violate the assumption of strict exogeneity. Some reassurance comes from the theoretical model in Section 3, where technological change determines labor demand, but not vice versa. Another concern is the exclusion of industry-level fixed effects by Autor and Salomons. Although country- and sector-level fixed effects are controlled for, neglecting industry-level effects could introduce bias if there are industry-specific linear trends within a sector group that correlate with productivity growth. I will revisit this issue in Section 6. Even if these concerns are addressed, endogeneity could still arise from uncontrolled determinants of labor market outcomes that correlate with productivity growth and are time-variable, that is, not accounted for by first-differencing or fixed effects. One such omitted variable could be the growth rate of capital stock: if industries with higher capital growth experience higher productivity but lower employment growth (due to automation, for example), failing to control for capital stock could lead to an underestimation of the productivity-employment elasticity. Other potential omitted factors include labor market institutions, human capital, or exposure to globalization and trade. Autor and Salomons apparently acknowledge that their approach does not fully eliminate all potential endogeneity. As they note in Autor and Salomons (2017, 49), their method "does not provide the crisp causal identification that we would ideally offer." Instead, their objective is to present a rich, *descriptive* analysis of the relationship between productivity and employment over a broad time span and across multiple countries and industries.

Section 5 has provided a stepwise derivation of regression Equation 8. In particular, I discussed the interpretation of the parameters, the motivation for the use of panel data methods, the issue of simultaneity and timing, as well as potential further sources of endogeneity. With the theoretical foundation and methodological framework in place, I now turn to the empirical application of these concepts.

6 Results

This section replicates the findings of Autor and Salomons (2018), estimating regression Equation 8 across 16 OECD countries and 38 industries for the period 1995–2020. As an extension of Autor and Salomons's work, I also examine the temporal dynamics of productivity shocks, offering additional insights into how these effects evolve over time. In the second part, I address areas that warrant constructive critique, focusing on aspects of the results that may require further scrutiny. In particular, I explore the impact of productivity growth on variables not covered in the original study, such as real wages, and present regression results that include industry-level fixed effects.

Replication

Table 5 provides estimates for regression Equation 8 across three dependent variables, measured in log-changes: Employment (including both employees and the self-employed), aggregate hours worked and the nominal wage bill. Essentially, Table 5 can be viewed as a reproduction of the first row of Table 5 in Autor and Salomons (2018), albeit with slight modifications. Most importantly, the authors provide an estimate for the *sum* of the six period-specific estimates only, arguably because their primary interest lies in the cumulative effect of a one percent increase in productivity growth over the contemporaneous and subsequent periods. To gain a more precise insight into the dynamics by which the effect of a productivity shock unfolds, I also present period-specific point estimates. For comparability, the row beneath the point estimates shows the sum of these estimates across the six periods under consideration, just as in the original study. However, unlike Autor and Salomons, I do not report standard errors for these sums. For the point estimates I do provide cluster standard errors at the industry-country level to account for potential serial correlation (and heteroskedasticity) within the same cross-sectional unit over time, following the approach taken in the original study. Specifically, I use the "bias-reduced linearization" adjustment proposed in Bell and McCaffrey (2002) and refined by Pustejovsky and Tipton (2018).

Table 5: Regression Results for Employment, Aggregate Hours and Nominal Wage Bill, *Without* Industry-Level Fixed Effects

	Dependent variable (in log-changes):					
	Employment		Aggregate Hours		Nominal Wage Bill	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log \text{TFP}'$	0.15^{**}	0.16^{**}	0.26^{***}	0.27^{***}	0.29^{***}	0.30^{***}
	(0.07)	(0.07)	(0.08)	(0.08)	(0.09)	(0.09)
$\Delta \log \text{TFP}'_{t-1}$	-0.01	0.01	-0.05^{**}	-0.03	-0.03	-0.001
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$\Delta \log \text{TFP}'_{t-2}$	-0.08^{***}	-0.04^{**}	-0.09^{***}	-0.05^{**}	-0.13^{***}	-0.10^{***}
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
$\Delta \log \text{TFP}'_{t-3}$	-0.16^{***}	-0.12^{***}	-0.16^{***}	-0.12^{***}	-0.18^{***}	-0.14^{***}
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
$\Delta \log \text{TFP}'_{t-4}$	-0.11^{***}	-0.08^{***}	-0.11^{***}	-0.08^{***}	-0.13^{***}	-0.10^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$\Delta \log \text{TFP}'_{t-5}$	-0.13^{***}	-0.10^{***}	-0.14^{***}	-0.12^{***}	-0.12^{***}	-0.09^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
$\sum_{k=0}^{5} \Delta \log \text{TFP}'_{t-k}$	-0.33	-0.16	-0.3	-0.13	-0.29	-0.13
Model weighted by	Employment		Aggregate Hours		Aggregate Hours	
Country f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Sector group f.e.	No	Yes	No	Yes	No	Yes
Industry f.e.	No	No	No	No	No	No
N	7,779	7,779	7,782	7,782	7,775	7,775
R^2	0.27	0.31	0.36	0.39	0.47	0.49
Adjusted R^2	0.27	0.31	0.36	0.39	0.46	0.48

Notes: $\Delta \log \text{TFP}'_t$ refers to the period t other-country-same-industry mean of TFP-growth in percent, as discussed in Section 5. The employment variable encompasses both employees and the self-employed. Standard errors are reported in parantheses and clustered at the industry-country level. *p<0.1; **p<0.05; ***p<0.01

Before turning towards a discussion of the regression results, notice how the number of observations used in my estimation is only about half the size of those in Autor and Salomons (2018). This discrepancy is partly due to the fact that the authors' analysis covers 37 years and 19 countries, whereas my dataset only spans 26 years and 16 countries, as well as the limited availability of TFP estimates within those 26 years, as discussed in Section 4. Additionally, the statistical software I use automatically excludes observations with missing data for any covariates, further reducing the sample size. As a result, despite having 26 years of data, at best I am able to run 21 regressions per country-industry pair. This not only reduces statistical power but also means that some years do not factor into the calculation of specific point estimates. For example, data from 1995-1999 will not factor into the calculation of the contemporaneous shock, whereas data from 2016-2020 will not factor into the calculation of the last lag.

Putting these concerns aside for now, point estimates for employment, hours and nominal wage bill show a strikingly similar pattern. Across all variables and specifications, the point estimate for the contemporaneous effect of productivity is positive, comparably large and statistically significant, at least at the 5%-level. I estimate that a 1%-shock in the growth rate of leave-out mean productivity lifted contemporaneous employment growth on average by about 0.15%, aggregate hours growth by 0.26% and the growth rate of the nominal wage bill by 0.29%. Adding sector group fixed effects has almost no effect on that estimate. However, this positive effect immediately vanishes in the first lag, as estimates become all close to zero and mostly statistically insignificant. For the second to fifth lag, point estimates then become decisively negative. For employment, my estimates for the second to fifth lag hover around -0.08 to -0.13 for the specification without sector-group fixed effects and between -0.04 to -0.12 with sector-group fixed effects. I estimate even more negative lagged effects for both the growth rate of aggregate hours and the nominal wage bill, but again, estimates become closer to zero once I add sector-group fixed effects. Importantly, one might interpret the large contemporaneous effect I estimate as evidence for a potential simultaneity bias. However, as discussed in Section 5, because employment, aggregate hours and wages all factor negatively into the calculation of TFP, if anything, the contemporaneous effect I obtain should *underestimate* the true contemporaneous effect of a productivity shock.

Notably, when I focus solely on the sum of my estimated coefficients, as Autor and Salomons do too, I find estimates which display a similar pattern as those reported in their study. Most notably, for all dependent variables, the sign of my estimates aligns with the authors' findings: Both Autor and Salomons and I observe a negative relationship between productivity growth and employment, aggregate hours, and the nominal wage bill. Moreover, once I add sector-group fixed effects, the sum of estimates halves, which is precisely as in Autor and Salomons (2018) and implies that a significant share of the identifying variation in column 1, 3 and 5 is between-industry. I will return to this issue later. A third similarity to the authors' findings is that my estimates for the three dependent variables are all fairly similar in size, irrespective of whether I use sector-group fixed effects or not. That has two implications: Firstly, it suggests that productivity adjustments primarily occur at the extensive margin - by increasing the number of workers employed - rather than through extending working hours for those already employed. Secondly, it implies that productivity growth has a negligible effect on mean hourly nominal wages. Not in line with the authors' findings is the size of the effects I estimate: The authors obtain estimates which are about twice as large as mine.[11]

Table 6 provides estimates for the log-change in nominal value-added, real value-added (measured as chain-linked volumes) as well as labor's share in value-added and replicates the second row of Table 5 in Autor and Salomons (2018), albeit using different weights. Recall that, due to a lack of data, I use aggregate hours as a weighting variable. Interestingly, I find a large positive contemporaneous shock of 0.58% and 0.63% for nominal and real value-added, respectively. These results are robust to the inclusion of sector-group fixed effects. Nominal value-added subsequently exhibits a pattern closely resembling that of the growth rates of employment, hours, and the nominal wage bill - turning negative after one period and remaining so throughout the subsequent lags. In sum, I find a 6-period productivity-elasticity w.r.t. nominal value-added of -0.13. As before, adding sector-group fixed effects makes these estimate slightly more positive. Again, these results are more positive than the ones estimated by Autor and Salomons (2018). On the other hand, point estimates for real value-added are fairly inconsistently signed across the 5 lags and essentially oscillate around the 0%-mark, irrespective of whether I include sector-group fixed effects or not. Across all six periods I find that a one-percent shock to the growth rate of productivity is associated with an increase in mean real value-added growth of roughly half a percentage point, which

11. Notice that Autor and Salomons rescale their productivity measure to have a unit standard deviation, which implies that all of their estimates need to be divided by one leave-out mean TFP standard deviation (i.e. 2.58 log points) to be comparable.

Table 6: Regression Results for Nominal Value-Added, Real Value-Added Hours and the Laborshare, *Without* Industry-Level Fixed Effects

	Dependent variable (in log changes):					
	Nominal Value-Added		Real Value-Added		Labor Share	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log \mathrm{TFP}'$	0.58***	0.59***	0.63***	0.63***	−0.30***	−0.29***
	(0.09)	(0.09)	(0.11)	(0.11)	(0.06)	(0.06)
$\Delta \log \mathrm{TFP}'_{t-1}$	−0.23***	−0.20***	−0.13***	−0.12**	0.20***	0.20***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
$\Delta \log \mathrm{TFP}'_{t-2}$	−0.06	−0.03	0.01	0.02	−0.07	−0.07
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)
$\Delta \log \mathrm{TFP}'_{t-3}$	−0.21***	−0.18***	−0.05	−0.04	0.03	0.03
	(0.06)	(0.06)	(0.06)	(0.06)	(0.04)	(0.04)
$\Delta \log \mathrm{TFP}'_{t-4}$	−0.07*	−0.04	0.06	0.06	−0.06*	−0.06*
	(0.04)	(0.04)	(0.05)	(0.05)	(0.03)	(0.03)
$\Delta \log \mathrm{TFP}'_{t-5}$	−0.14***	−0.11**	−0.03	−0.03	0.02	0.02
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)
$\sum_{k=0}^{5} \Delta \log \mathrm{TFP}'_{t-k}$	−0.13	0.04	0.48	0.52	−0.17	−0.17
Model weighted by	Aggregate Hours		Aggregate Hours		Aggregate Hours	
Country f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Sector group f.e.	No	Yes	No	Yes	No	Yes
Industry f.e.	No	No	No	No	No	No
N	7,775	7,775	7,782	7,782	7,782	7,782
R^2	0.40	0.41	0.31	0.33	0.08	0.08
Adjusted R^2	0.40	0.41	0.31	0.32	0.07	0.08

Notes: $\Delta \log \mathrm{TFP}'_t$ refers to the period t other-country-same-industry mean of TFP-growth in percent, as discussed in section **??**. "Real Value-Added" refers to value added in constant prices, calculated as chain-linked volumes. The labor share variable refers to the share of the real wage bill in real value-added. Standard errors are reported in parantheses and clustered at the country-industry level. *p<0.1; **p<0.05; ***p<0.01

is fairly in line with the authors' estimate under the sector-group fixed effect specification. Taken together, because the log change in nominal value-added is just the sum of the log-change in real value-added and the log change in the overall price-level, notice how these results logically imply that industry-level productivity growth has a deflationary effect. This nicely aligns with what I labelled the labor-saving effect of productivity growth in Section 3: Productivity growth lowers prices, thereby stimulating consumer demand and real output. Finally, column 5 and 6 of Table 6 present estimates for the elasticity of the growth rate of the labor share w.r.t. productivity. As visible, point estimates are generally inconsistently signed and hover between -0.3 and 0.2. Still, at -0.17, the dynamic effect I estimate is very similar to the one estimated by the authors. Just as Autor and Salomons, I find a strikingly small R^2 though, which suggests that productivity growth has little explanatory power for the evolution of the labor share. Therefore, these estimates should be taken with some scepticism.

Discussion

The replication of results from Autor and Salomons (2018) generally aligns with the original findings and supports the narrative of productivity-driven declines in labor demand. Efficiency gains allowed industries to reduce labor usage, exerting downward pressure on 'conditional' labor demand. On the other hand, productivity improvements simultaneously led to price reductions, boosting consumer- and labor demand. Yet, these scale effects were insufficient to offset the labor-saving effects, resulting in an overall decrease in labor demand and, consequently, employment.

However, the results also reveal a significant positive effect of productivity growth on real hourly wages, which complicates the narrative of productivity as purely detrimental to workers. To understand this, recall that the labor share is defined as the ratio of the real wage bill to real value-added. Thus, the log-change of the real wage bill equals the sum of the log-change in real value-added and the log-change in the labor share. This implies that the dynamic productivity-elasticity of the real wage bill is approximately $-0.17 + 0.48 = 0.31$ without sector-group fixed effects, and roughly 0.35 with them. Furthermore, since the real wage bill is the product of aggregate hours and the real average hourly wage, we can calculate the elasticity of real hourly wage growth with respect to productivity growth by subtracting the elasticity of aggregate hours from that of the real wage bill. This results in a real hourly wage growth rate of $0.31 - (-0.3) = 0.61$. In other words, a one-percent shock to productivity growth increased real hourly wages by 0.61%, while it reduced employment growth by 0.33%. To prove the point, Table 8 in Appendix A provides regression results for real wages and the real wage bill. Interestingly, a similar approach applied to the results documented in Autor and Salomons (2018) produces an even larger elasticity of real hourly wages of around 0.83%. These findings suggest that, while productivity growth tightened labor markets, it also significantly increased real wages for those remaining employed, driving a substantial rise in the real wage bill. This dynamic challenges the notion that productivity growth unambiguously harms workers.

Even more concerning, this result appears implausible from the perspective of standard economic models. Under typical assumptions—such as a downward-sloping labor demand curve and an upward-sloping labor supply curve—productivity-induced shifts in labor demand would result in wages and employment moving in the same direction. Yet, here we observe wages rising substantially even as employment contracts, which suggests a different underlying mechanism. To be fair, Autor and Salomons do not explicitly claim that productivity growth unequivocally reduces labor demand across the board. While the size of the positive wage adjustment might seem challenging to explain, alternative frameworks - such as those incorporating skill-biased technological change - could help rationalize these dynamics (see, e.g., Katz and Murphy (1992)). However, by omitting a discussion of real wage effects, their analysis risks leaving the impression that productivity growth has unambiguous negative consequences for workers. In reality, the story is more complex.

Of course, a more pessimistic interpretation is that the results are implausible, raising doubts about whether the estimation strategy fully captures the true relationship between productivity growth, employment, and real wages. These doubts about the empirical approach are further compounded by the characteristics of the temporal pattern I find. Specifically, my estimates suggest that a shock to productivity growth had a large, positive contemporaneous effect on the growth rate of employment, aggregate hours, the nominal wage bill, and both nominal and real value-added. However, in subsequent periods, the point estimates turn negative, resulting in an overall negative effect of productivity growth on employment, hours, and the nominal wage bill, and a neutral effect on nominal value-added. Interestingly, a similar temporal pattern has already been documented by Autor and Salomons (2017), suggesting that this counterintuitive pattern may not be an anomaly of my results. It appears unreasonable that a productivity boost would have a positive immediate impact on, for example, employment growth, but ultimately lead to a decline in that variable. This *could* reflect a dynamic adjustment process in the labor market - such as an initial hiring surge followed by job reductions as firms increase efficiency. However, due to its static nature, the model I derive in Section 3 cannot provide insights into this dynamic process, meaning that this explanation remains speculative and requires further investigation. Again, a more bleak assessment would be that these patterns raise concerns about the validity of the estimation strategy itself: the counterintuitive and inconsistent effects across periods suggest that my estimates may not fully capture the causal effect of productivity shocks, raising concerns about whether the identification strategy sufficiently isolates exogenous variation in productivity growth. While this may not have been the authors' intent, omitting point estimates could inadvertently downplay the complexities of the relationship between productivity growth and various outcomes, as well as the challenges inherent in identifying the effects of productivity growth.

Finally, the fact that the estimates both I and Autor and Salomons obtain seem to change quite a bit once sector-group fixed effects are added raises some questions about the extent to which these results might be driven by between-industry variation rather than within-industry variation. To stress-test the results above, Table 7 repeats the six regressions but additionally includes a full set of industry-level fixed effects. As visible, while many of the point estimates have turned insignificant by now, one can broadly observe a temporal pattern comparable to the one described in Table 5 and 6: Employment, hours, the wage bill and nominal value-added still display a large positive contemporaneous response, and a slight negative adjustment in the following periods. However, this downward adjustment is now more moderate than before, which implies that the cross-period effect of productivity growth is now actually slightly *positive* for all four variables. This continues the trend already observable when I included sector-group effects: The more between-industry variation one takes out of the regression model, the more positive does the effect of productivity growth on employment, hours, the nominal wage bill and nominal value-added become. For real value-added, the real wage bill and real hourly wages on the other hand, the inclusion of industry-level fixed effects reduces the size of the estimate. I now estimate that, across six periods, a 1%-increase in the growth rate of productivity increased the growth rate of real value-added by 0.35 percent, the growth rate of the real wage bill by 0.24 percent, and growth

Table 7: Regression Results for all Indicators,
With Industry-Level Fixed Effects

	Dependent variable (in log-changes):					
	Employ-ment	Agg. Hours	Nom. WB	Nom. VA	Real VA	Labor-share
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log \text{TFP}$	0.19^{**}	0.29^{***}	0.31^{***}	0.60^{***}	0.62^{***}	-0.29^{***}
	(0.08)	(0.08)	(0.10)	(0.09)	(0.11)	(0.06)
$\Delta \log \text{TFP}'_{t-1}$	0.06^{**}	0.01	0.03	-0.18^{***}	-0.15^{***}	0.21^{***}
	(0.03)	(0.03)	(0.03)	(0.06)	(0.05)	(0.05)
$\Delta \log \text{TFP}'_{t-2}$	0.01	-0.01	-0.06^{*}	-0.003	-0.02	-0.06
	(0.03)	(0.03)	(0.04)	(0.06)	(0.05)	(0.05)
$\Delta \log \text{TFP}'_{t-3}$	-0.06^{**}	-0.07^{*}	-0.10^{**}	-0.15^{**}	-0.07	0.05
	(0.03)	(0.04)	(0.04)	(0.06)	(0.06)	(0.04)
$\Delta \log \text{TFP}'_{t-4}$	-0.03	-0.04	-0.06^{**}	-0.01	0.03	-0.05
	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)
$\Delta \log \text{TFP}'_{t-5}$	-0.05^{***}	-0.07^{***}	-0.06^{**}	-0.09^{*}	-0.06	0.03
	(0.02)	(0.02)	(0.03)	(0.05)	(0.05)	(0.05)
$\sum_{k=0}^{5} \Delta \log \text{TFP}'_{t-k}$	0.12	0.11	0.05	0.17	0.35	-0.11
Model weighted by	Employ-ment	Agg. Hours	Agg. Hours	Agg. Hours	Agg. Hours	Agg. Hours
Country f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Sector group f.e.	No	No	No	No	No	No
Industry f.e.	Yes	Yes	Yes	Yes	Yes	Yes
N	7,779	7,782	7,775	7,775	7,782	7,782
R^2	0.36	0.43	0.40	0.34	0.35	0.08
Adjusted R^2	0.35	0.42	0.40	0.34	0.35	0.08

Notes: $\Delta \log \text{TFP}'_t$ refers to the period t other-country-same-industry mean of TFP-growth in percent, as discussed in Section 5. "Nom. WB" refers to the nominal wage bill, "Nom. VA" to nominal value-added and "Real VA." to real value-added. Standard errors are reported in parantheses and clustered at the country-industry level. *p<0.1; **p<0.05; ***p<0.01

of real hourly wages by 0.13 percent. In light of the labor demand framework developed earlier, these estimates suggest that productivity increases actually slightly increased labor demand, leading to increased employment and real wages. This would imply that the scale effect slightly exceeded the labor-saving effect of productivity. However, these increases still fell short of the gains in capital remuneration, implying that the labor share nonetheless declined slightly.

The fact that the initial findings are not robust to the inclusion of industry-level fixed effects suggests that the negative relationships observed earlier are not driven by within-industry variation. In other words, within a given industry, higher productivity growth is not necessarily associated with lower employment, which explains why the estimates in Table 6 are not negative. However, when making comparisons between industries, those with higher productivity growth tend to exhibit lower employment growth. While that is an interesting finding in itself, as discussed in Section 5, it may not directly inform the causal impact of productivity growth. More specifically, these estimates might be influenced by unobserved industry-level linear trends which, if not controlled for, could bias the regression results.

However, while adding industry-level fixed effects controls for such unobserved trends, it does *not* fundamentally alter the temporal dynamics discussed earlier, which remain an unresolved issue. This regression-specification also does little to address concerns regarding the extent to which the leave-out mean is truly a reliable measure of technological change at the industry-level. Moreover, while industry-level fixed effects account for linear trends, they cannot capture other truly time-varying factors, such as changes in capital input. Therefore, the purpose here is not necessarily to suggest that the results in Table 7 are more valid than those in Tables 5 and 6. Rather, while they may offer valuable insights, the primary intention is to emphasize that certain aspects of the analysis warrant further scrutiny.

7 Conclusion

The labor market consequences of productivity growth have long fueled societal debate, and with the rise of emerging technologies such as AI, these concerns have once again taken center stage. Amidst this overarching discourse, industry-level studies can uncover painful adjustment processes that may be obscured by aggregate data. As Autor and Salomons

(2018) and others have emphasized, industry-level elasticities cannot simply be inferred from broader trends, making it essential to study sector-specific dynamics. By doing so, this research not only deepens our theoretical understanding of labor markets but also equips policymakers with more precise tools to anticipate and address industry-specific challenges, enabling more targeted and effective interventions.

In light of these considerations, the present study replicates, extends, and critically engages with the key industry-level specification in Autor and Salomons (2018). At a general level, my replication results align with those in the original study, though they are smaller in magnitude. Specifically, I find that a 1% increase in industry-level productivity growth reduced the growth rate of employment, aggregate hours, and the nominal wage bill by about 0.3%. In contrast, I do not observe a significant effect of productivity growth on nominal value-added, but I do estimate a positive effect of around 0.5% for real value-added. Regarding the labor share, I find a slightly negative effect on its growth rate, though the temporal pattern is ambiguous, and the low R-squared indicates weak explanatory power for this relationship. Building on these findings and extending their approach, I offer several avenues for constructive criticism. First, somewhat puzzlingly, the results indicate that productivity had a large and positive effect on real wages, implying that productivity growth may be less detrimental to workers than initially expected; however, this finding could also raise concerns about the reliability of the estimation strategy. Second, the temporal pattern of a productivity shock indicates a large and positive contemporaneous adjustment in employment, hours, and the wage bill, which seems implausible. Finally, the results are not robust to the inclusion of industry-level fixed effects, raising questions about how much of the observed relationship is driven by between-industry variation. More specifically, after controlling for industry-level fixed effects, the effect of productivity growth on employment, hours, and the wage bill becomes slightly positive.

While I can only remain speculative about the origins of these results, my discussion of the estimation strategy in Section 5 offers some potential insights. Specifically, I have highlighted that the use of the leave-out mean productivity indicator introduces a sense of ambiguity into the regression equation. Additionally, I noted that the model likely fails to account for all potential confounders, which could lead to biased estimates. To address these concerns, future research could explore alternative indicators of productivity growth or technological change that avoid the simultaneity issues associated with TFP while offering greater clarity. In addition, a more focused approach - such as a natural experiment - might yield more precise insights by targeting a specific industry or innovation, rather than relying on broad cross-country and cross-industry analyses. For now, I can cautiously suggest that Autor and Salomons's results may be less robust than initially assumed, and that future technological advances might pose less of a threat to workers in affected industries than previously implied.

A Appendix: Additional Results

Table 8: Regression Results for Real Wages and Real Wage Bill

	Dependent variable (in log changes):					
	Real Wage Bill			Real Hourly Wages		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log \text{TFP}'$	0.33***	0.33***	0.33***	0.07*	0.07	0.04
	(0.11)	(0.11)	(0.11)	(0.04)	(0.04)	(0.04)
$\Delta \log \text{TFP}'_{t-1}$	0.08*	0.08*	0.06	0.13***	0.11***	0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$\Delta \log \text{TFP}'_{t-2}$	−0.06	−0.05	−0.07*	0.03	0.001	−0.07
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$\Delta \log \text{TFP}'_{t-3}$	−0.02	−0.004	−0.03	0.14***	0.12***	0.04
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
$\Delta \log \text{TFP}'_{t-4}$	−0.001	0.004	−0.02	0.11***	0.09**	0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
$\Delta \log \text{TFP}'_{t-5}$	−0.01	−0.01	−0.03	0.13***	0.11**	0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$\sum_{k=0}^{5} \Delta \log \text{TFP}'_{t-k}$	0.31	0.36	0.24	0.61	0.49	0.13
Country f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Sector group f.e.	No	Yes	No	No	Yes	No
Industry f.e.	No	No	Yes	No	No	Yes
N	7,782	7,782	7,782	7,782	7,782	7,782
R^2	0.24	0.27	0.32	0.09	0.10	0.15

Notes: $\Delta \log \text{TFP}'_t$ refers to the period t other-country-same-industry mean of TFP-growth in percent, as discussed in section 5. All models are weighted using aggregate hours. Standard errors are reported in parantheses and clustered at the country-industry level. *p<0.1; **p<0.05; ***p<0.01

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Berlin, September 19, 2024