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Is automation labor-displacing? Productivity growth, employment, and the labor share

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Abstract

Is automation a labor-displacing force? This possibility is both an age-old concern and at the heart of a new theoretical literature considering how labor immiseration may result from a wave of 'brilliant machines,' which is in part motivated by declining labor shares in many developed countries. Comprehensive evidence on this labor-displacing channel is at present limited. Using the recent model of Acemoglu and Restrepo (2018b) as an analytical frame, we first outline the various channels through which automation impacts labor´s share of output. We then turn to empirically estimating the employment and labor share impacts of productivity growth—an omnibus measure of technological change—using data on 28 industries for 18 OECD countries since 1970. Our main findings are that although automation—whether measured by Total Factor Productivity growth or instrumented by foreign patent flows or robot adoption—has *not* been employment-displacing, it *has* reduced labor's share in value-added. We disentangle the channels through which these impacts occur, including: own-industry effects, cross-industry input-output linkages, and final demand effects accruing through the contribution of each industry's productivity growth to aggregate incomes. Our estimates indicate that the labor share-displacing effects of productivity growth, which were essentially absent in the 1970s, have become more pronounced over time, and are most substantial in the 2000s. This finding is consistent with automation having become in recent decades less labor-augmenting and more labor-displacing.

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Introduction

One of the central stylized facts of modern macroeconomics, immortalized by Kaldor (1961), is that during a century of unprecedented technological advancement in transportation, production, and communication, labor's share of national income remained roughly constant (Jones and Romer, 2010). This empirical regularity, which Keynes (1939) deemed "a bit of a miracle," has provided economists—though not the lay public—with grounds for optimism that, despite seemingly limitless possibilities for labor-saving technological progress, automation need not make labor irrelevant as a factor of production. Indeed, mainstream macroeconomic literature often takes as given that labor's share of national income *is* constant and asks what economic dynamics enforce this constancy.[2]

But several recent developments have eroded economists' longstanding confidence in this constancy. One is a widely-shared view that recent and incipient breakthroughs in artificial intelligence and dexterous, adaptive robotics are profoundly shifting the terms of human vs. machine comparative advantage. Observing these advances, numerous scholars and popular writers anticipate the wholesale elimination of a vast set of currently labor-intensive and cognitively demanding tasks, leaving an ever-diminishing set of activities in which labor adds significant value (Brynjolfsson and McAfee, 2014; Ford, 2017; Frey and Osborne, 2017).

A widely noted empirical regularity that lends credence to this narrative is that labor's share of national income has in recent decade fallen in many nations, a trend that may have become more pronounced in the 2000s (e.g., Elsby, Hobijn and Sahin, 2013; Karabarbounis and Neiman, 2013; Piketty 2014; Autor et al. 2017b; Dao et al. 2017). Reviewing an array of within- and cross-country evidence, Karabarbounis and Neiman (2014) argue that labor's falling share of value-added is caused by a steep drop in the quality-adjusted equipment prices of Information and Communication Technologies (ICT) relative to labor. Though Karabarbounis and Neiman's work is controversial in that it implies an aggregate capital-labor substitution in excess of

[2] Ngai and Pissarides (2007) and Acemoglu and Guerrieri (2012) formulate models in which ongoing unbalanced productivity growth across sectors (as per Baumol 1967) can nevertheless yield a balanced growth path for labor and capital shares.

unity—which is a non-standard assumption in this literature—their work has lent empirical weight to the hypothesis that computerization may erode labor demand.[3]

Indeed, while a fall in the labor share is ruled out by design in most canonical macroeconomic models (e.g., Ngai and Pissarides 2007), recent literature revisits this assumption, offering models where labor displacement is one potential outcome. For example, Sachs and Kotlikoff (2012) and Berg et al. (2017) write down an overlapping-generation models in which rapid labor-saving technological advances generate short-run gains for skilled workers and capital owners, but in the longer run, immiserate those who are not able to invest in physical or human capital. Acemoglu and Restrepo (forthcoming and 2018b) consider models in which two countervailing economic forces determine the evolution of labor's share of income: the march of technological progress, which gradually replaces 'old' tasks, reducing labor's share of output and possibly diminishing real wages; and endogenous technological progress that generates novel labor-demanding tasks, potentially reinstating labor's share. The interplay of these forces can—but need not necessarily—yield a balanced growth path wherein the reduction in labor scarcity due to task replacement induces endogenous creation of new labor-using job tasks, thus restoring labor's share.[4]

The current paper assesses evidence for labor displacement, which in our terminology means productivity-enhancing technological advances that reduce labor's share of aggregate output. As our formal model below clarifies, labor displacement need not imply a decline in

[3] Although such a relative capital price decline will have no effect on factor shares if production technologies are Cobb-Douglas, there will be a decline in the labor share if the capital-labor elasticity of substitution is greater than one (a proposition for which Karabarbounis and Neiman find some evidence). Dao et al. (2017) present cross-country evidence from both developed and developing countries that machine-labor substitution, stemming from Routine-Replacing Technical Change (RRTC), contributes to a reduction in labor's share through falling middle-skilled labor demand. Analyzing data for both Europe and the U.S., Autor et al. (2017b) conclude that the falling labor share is more likely accounted for by the rise of 'winner take most' competition rather than direct capital-labor or trade-labor substitution—though this change in the nature of competition may itself be a technologically induced phenomenon.

[4] Susskind (2017) develops a model in which labor is ultimately immiserated by the asymptotic encroachment of automation into the full spectrum of work tasks. A key distinction between Acemoglu and Restrepo (forthcoming) and Susskind (2017) is that, in the latter model, falling labor scarcity does not spur the endogenous creation of new labor-using tasks or labor-complementing technologies, thus guaranteeing labor immiseration. The conceptual frameworks of both papers build on Zeira (1998) and Autor, Levy, and Murnane (2003, ALM), which feature models in which advancing automation reduces labor's share by substituting machines (or computers) for workers in a subset of activities (which ALM designate as 'tasks').

employment, hours, or wages. Rather, it simply requires that the wagebill—that is, the product of hours of work and wages per hour—rises *less rapidly* than does value-added. As highlighted in Acemoglu and Restrepo (forthcoming and 2018b), a natural mechanism through which this could occur is via task-replacing technological change, meaning technological advances that shift production tasks directly from capital to labor, thereby reducing labor's share of output. This direct negative *direct* effect of automation on labor's share may be partly or fully offset by a several countervailing forces—also spurred by automation—including rising productivity, capital deepening, and the introduction of new labor-using tasks. Nevertheless, the notion that automation directly reduces labor's share of output does not feature in canonical macroeconomic models that exhibit a balanced growth path. As will become apparent, our results are difficult to square with the simplest variants of such models.

Our work contributes to a growing literature assessing whether rapid automation has served to dampen aggregate labor demand or overall wage growth. Focusing on the first half of the twentieth century, Alexopoulos and Cohen (2016) find that positive technology shocks raised productivity and lowered unemployment in the United State between 1909 and 1949. Using contemporary European data, Gregory, Salomons, and Zierahn (2016) test whether Routine-Replacing Technical Change (RRTC) has reduced employment overall across Europe and find that while RRTC has reduced middle-skill employment, this employment reduction is more than offset by compensatory product demand and local demand spillovers.[5] In work closely related to the current paper, Dao et al. (2017) analyze sources of the trend decline in labor share in a panel of 49 emerging and industrialized countries. Using cross-country and cross-sector variation in the prevalence of occupations potentially susceptible to automation (as per Autor and Dorn, 2013), Dao et al. find that countries and sectors initially more specialized in routine-intensive activities have seen a larger decline in labor share, consistent with the

[5] Focusing not on employment but on sectoral and aggregate outputs, Nordhaus (2015) presents evidence that industrialized economies are *not* approaching an inflexion point at which technological advances generate a sharp and sustained acceleration of economic growth.

possibility of labor displacement.[6] Concentrating on industrial robotics, arguably the leading edge of workplace automation, Graetz and Michaels (2015) conclude that industry-level adoption of industrial robots has raised labor productivity, increased value-added, augmented worker wages, had no measurable effect on overall labor hours, and modestly shifted employment in favor of high-skill workers within EU countries. Conversely, using the same underlying industry-level robotics data but applying a cross-city design within the U.S., Acemoglu and Restrepo (2017) present evidence that U.S. local labor markets that were relatively exposed to industrial robotics experienced differential falls in employment and wage levels between 1990 and 2007.

Akin to Graetz and Michaels (2015) and Dao et al. (2017), the current paper applies harmonized cross-country and cross-industry data to explore the relationship between technological change and labor market outcomes. Our work advances this literature in four dimensions. First, rather than focusing exclusively on specific measures of technological adoption or susceptibility (e.g., robotics, routine task replacement), we focus initially on an *omnibus* measure of technological progress: total factor productivity growth or TFP (Solow, 1956). Using TFP as our baseline measures potentially overcomes the challenge for consistent measurement posed by the vast heterogeneity of innovation across sectors and periods.

TFP also has significant limitations as a measure of technological progress, however: since it is ultimately a regression residual, its relationship to any specific technological advance is unspecified; moreover, estimates of TFP may be confounded with business cycle effects, industry trends, and cross-industry differences in cyclical sensitivity (Basu and Fernald, 2001).[7] A second contribution of the current paper is to address both concerns. Complementing the estimates using reported TFP growth, we instrument or proxy for industry-level productivity growth with specific measures of technology and innovation, including industry-level patenting, ICT investment, and robot density. To purge the potential cyclicality of TFP, our

[6] Using an analogous approach, Michaels, Natraj, and Van Reenen (2014) find that ICT adoption is predictive of within-sector occupational polarization in a country-industry panel sourced from EUKLEMS covering 11 countries observed over 25 years.

[7] Moses Abramovitz (1956) famously declared the TFP residual, "a measure of our ignorance."

main specifications include business cycle by industry by country fixed effects, which non-parametrically absorb differential sensitivity of industry measures of productivity to business cycle variation. As a second step, we perform a set of robustness checks that use exclusively low-frequency TFP variation, thus leveraging secular shifts in TFP while purging cyclical variation.

A longstanding conceptual issue pervading this literature, and one which this paper seeks to overcome, is the tension between using microeconomic variation for identification while attempting to speak to macroeconomic outcomes. This concern applies here because we study the relationship between productivity growth, innovation, and labor displacement using cross-country-industry, over-time variation. As theory makes clear, however, there is no direct mapping between the evolution of productivity and labor demand at the industry level and the evolution of aggregate labor demand. For example, Ngai and Pissarides (2007) show that uneven rates of productivity growth across industries—which may spur substantial changes in employment across sectors as per Baumol (1967)—need not imply any deviation from an aggregate balanced growth path under some specifications of preferences.[8] Thus, at face value, the industry-level relationships that we estimate are not *necessarily* informative about aggregate outcomes of interest.

Recognizing this concern, a third contribution of this paper is to incorporate two key micro-macro linkages that, in combination with the industry-level estimates, allow us to make broader statements about aggregate effects. The first link applies harmonized data enumerating cross-industry input-output linkages to trace the effects of productivity growth in each industry to outcomes occurring in customer industries and in supplier industries—that is, industries for which the originating industry is upstream and downstream in the production chain,

[8] Specifically, the intertemporal elasticity of substitution must be unity, the elasticity of substitution across consumption goods must be non-unity, and the rate of output growth in the intermediates good sector (manufacturing) must be constant. It bears note that Ngai-Pissarides specify Cobb-Douglas production functions for each sector, meaning that labor's share is unchanging within each sector. Our far more stylized conceptual model relaxes this constraint, while our analysis suggests that this relaxation is required.

respectively.[9] The second link we explore is between aggregate economic growth and sectoral labor demand. Recognizing that productivity growth in each industry augments aggregate income and hence indirectly raises final demand, we estimate the elasticity of sectoral demands emanating from aggregate income growth and then apply our TFP estimates to infer the indirect contribution of each industry's productivity growth to final demand. Our net estimates of the impact of productivity growth and innovation on outcomes of interest therefore sum over (1) direct industry-level effects; (2) indirect upstream and downstream effects in linked sectors; and (3) final demand effects accruing through the effect of productivity growth on aggregate value-added.

A final contribution of the paper is that, by leveraging more than four decades of harmonized industry by country data, we can assess not only whether productivity growth and innovation appear to be labor-displacing, but whether this relationship has shifted over successive decades. In point of fact, we find distinctly different patterns between the first decade in our sample, the 1970s, and the three decades that follow.

The paper is structured as followed. We first lay out a simple 'task' model based on Acemoglu and Restrepo (2018a) that formalizes the notion of labor displacement, clarifies how it may be distinguished from a conventional neoclassical setting featuring balanced growth, and discusses the mapping from this stylized conceptual framework to the empirical exercise that follows.

After summarizing the data and measurement framework in Section 2, Section 3 of the paper presents our main estimates for the effect of productivity growth (measured initially by TFP) on labor input, value-added, and labor's share of value-added, accounting for both direct own-industry effects, and for indirect effects operating through input-output linkages and aggregate demand. Consistent with first principles, we find that TFP shocks raise own-industry

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[9] Specifically, we pair the EU KLEMS with tables from the World Input-Output Databse (Timmer, 2009 and 2015) to calculate Leontief inverse weighting matrix that traces the full effect of shocks in each given sector to those in customer and supplier sectors, accounting not only for first-order effects but the full set of dependencies emanating from the fact that, for example, customer industries also buy input from additional industries that are suppliers to or customers of the industry experiencing the initial shock. Our analysis follows many recent works exploiting these linkages to study the propagation of trade and technology shocks (Acemoglu et al. 2016; Pierce and Schott, 2016; Acemoglu, Akcigit and Kerr, 2017).

output, increase value-added, and lower output prices. While hours of labor input fall in sectors undergoing relatively rapid productivity growth, we find that the *indirect* effects of own-sector TFP growth robustly offset the reduction in labor hours in advancing sectors. Specifically, hours-reducing productivity growth in supplier industries spurs countervailing hours expansions in customer industries; and the cumulative contribution of each sector's productive growth to aggregate value-added, combined with a strongly positive aggregate elasticity of hours with respect to value-added, further raises the estimated net effect of industry-level productivity gains on aggregate labor hours. [10]

This pattern of falling labor input in advancing industries with countervailing gains in labor input in (relatively) non-advancing industries is consistent with models of structural change in which labor is displaced from 'progressive' to 'stagnant' sectors (Baumol, 1967; Ngai and Pissarides, 2007).[11] But our next set of results do not support the canonical version of this story in which labor input falls in advancing industries because industry output demand is inelastic. Contrary to this reasoning, we estimate that industry output demand is on average highly elastic, which would typically imply no net negative effect of productivity growth on industry-level labor demand. We find instead that labor's share of value-added *falls* significantly in advancing industries, which we refer to as labor displacement. This labor displacement is inconsistent with models of structural change that assume an underlying Cobb-Douglas production structure in each industry.

These industry-level labor displacement findings would be less interesting, however, if industry-level productivity growth spurred offsetting gains in labor share elsewhere in the economy, i.e., through input-output linkages and aggregate demand effects, as occurs with hours of labor input. We find that these countervailing effects are present in the data, but they are far less than fully offsetting: labor-displacing productivity growth in upstream supplier

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[10] As outlined in Acemoglu, Akcigit, and Kerr (2017), in a canonical Cobb-Douglas economy, productivity innovations occurring in a given sector should raise output in its customer sectors but should have no measurable effect on output in its supplier sectors due to offsetting quantity and price effects. Perhaps surprisingly, our analysis supports this prediction.

[11] As Ngai and Pissarides (2007) clarify, this prediction requires that the outputs of these sectors are gross complements in final consumption. If they are instead gross substitutes, labor flows towards progressive sectors.

industries spurs offsetting gains in labor share in customer industries, but this countervailing effect is only half as large as the estimated own-industry effect. Meanwhile, we detect no positive relationship between growth in *aggregate* value-added and growth in labor share, meaning that although industry-level productivity growth does augment aggregate growth, this does not affect labor's share of value-added.

Putting these pieces together, we estimate in Section 4 that productivity growth—measured by TFP or proxied by various direct measures of technological advance—has served to reduce labor's share of value-added in aggregate. Notably, this negative relationship was not always present, even within our four-decade analytic window. Our estimates suggest that productivity growth and innovation had virtually no net labor share-displacing effect during the 1970s. This relationship turned negative (labor-displacing) in the 1980s and 1990s, and it becomes more negative still in the 2000s.

To address concerns about the potential endogeneity of industry-level TFP, Section 5 employs two direct measures of industry-level technological advances that serve as instrumental variables for TFP: patent flows and the penetration of industrial robots. Both sets of variables prove to be significant predictors of industry-level TFP growth. And using each source of variation, we find that automation has become increasingly labor-displacing in recent decades, both at the industry level and in aggregate. Not surprisingly, the estimates for industrial robots are somewhat weaker given that the penetration of industrial robotics is relatively recent and is concentrated in a subset of industries.

In the conclusion, we briefly consider the interpretation of our findings, focusing in particular on the relationship between the industry-level and aggregate outcomes, which are observed in our data, and the underlying firm-level dynamics that may contribute to these outcomes.

1. Labor market consequences of automation: A task framework

To formalize the notion of labor-displacing technological change that frames our thinking, we sketch a simple task-based framework developed in Acemoglu and Restrepo (2018b), which in turn builds on Zeira (1998), Autor, Levy, Murnane (2003) and Acemoglu and Autor (2011).

We assume that aggregate output is produced by combining the services of a unit measure of tasks $x \in [N-1, N]$ according to the following Cobb-Douglas (unit elasticity) aggregator:

$$Y = \int_{N-1}^{N} \ln y(x) dx \,, \tag{1}$$

where Y denotes aggregate output and $y(x)$ is the output of task x.

All tasks can be performed by labor, $\ell(x)$. If a task has been technologically automated, it can also be performed by machines $m(x)$. At a point in time, tasks $x \in [N-1, I]$ are technologically automated, while the remainder are not. We further assume that labor and machines are perfect substitutes in technologically automated tasks, although their relative productivity/costs at these tasks may differ. Services of task x are equal to:

$$y(x) = \begin{cases} \alpha_L \gamma_L(x) \ell(x) + \alpha_M \gamma_M(x) m(x) & \text{if } x \in [N-1, I] \\ \alpha_L(x) \gamma_L \ell(x) & \text{if } x \in [I, N] \end{cases} \tag{2}$$

Here, α_L and α_M are efficiency terms that affect the productivity of labor and capital, respectively, at each task to which they are assigned. Meanwhile, $\gamma_L(x)$ and $\gamma_M(x)$ are task-specific efficiency terms. The task-specific efficiency of labor in task x is $\gamma_L(x)$ while, analogously, $\gamma_M(x)$ is the task-specific efficiency of machines in task x (where $x \leq I$). A key assumption is that $\gamma_L(x)/\gamma_M(x)$ is increasing in x, meaning labor has comparative advantage in higher-indexed tasks.

The threshold I denotes the frontier of automation possibilities. This threshold can rise over time due to advancements in automation, artificial intelligence, industrial robotics, etc. For expositional simplicity, we assume that both the supply of labor, L, and the supply of machines, M, are fixed and inelastic, though these assumptions have no bearing on our empirical analysis.

This simple model admits four distinct forms of technological change with a rich set of empirical implications: (1) conventional factor-augmenting technical changes, corresponding to a rise in either α_L or α_M; (2) extensive margin (labor-displacing) technical changes, corresponding to a rise I; (3) intensive margin capital- or labor-augmenting technical changes, corresponding to a rise in $\gamma_L(x)$ or $\gamma_M(x)$ for some subset of tasks in the interval $[N-1, N]$; and (4) task-creating technical change, corresponding to a rise in N. After solving for the model's equilibrium, we consider the implications of each type of technological change for labor demand.

1.1. Labor market equilibrium

In equilibrium, firms choose the cost-minimizing way of producing each task and labor and capital markets to clear. Denote the equilibrium wage rate by W and the equilibrium capital rental rate by R. Following Acemoglu and Restrepo (2018b), we impose the assumption that

$$\frac{\alpha_L \gamma_L(N)}{\alpha_M \gamma_M(N-1)} > \frac{W}{R} > \frac{\alpha_L \gamma_L(I)}{\alpha_M \gamma_M(I)} \tag{A1}$$

The first of these inequalities implies that the introduction of new tasks (a rise in N) will raise aggregate output.[12] The second inequality implies that the all tasks in the interval $[N-1, I]$ will be performed by machines.[13] Assumption A1 is not innocuous in that it implies that the wage ratio is neither so high that new task creation lowers output nor so low so that some tasks that are technologically automated are nevertheless performed by labor. In reality, the empirical analysis in our paper is silent on new task creation, so the first condition has no bearing. The second condition is only made for expositional convenience, and it is relaxed in Acemoglu and Autor (2011).

As formally demonstrated in the Appendix (Section 8), output (GDP) in the equilibrium in this model can be expressed as

$$Y = B\left(\frac{\alpha_M M}{I-N+1}\right)^{I-N+1}\left(\frac{\alpha_L L}{N-I}\right)^{N-I} \tag{3}$$

where

$$B = \exp\left(\int_{N-1}^{I} \ln y_M(x)dx + \int_{I}^{N} \ln y_M(x)dx\right). \tag{4}$$

Notice that eqn. (3) is a conventional Cobb-Douglas production function, where capital's share of output is given by the exponent $(I-N+1)$ and labor's share of output is given by the

[12] Formally, this inequality says that the ratio of labor productivity in a newly-introduced task to capital productivity in a newly-eliminated task is greater than the wage/rental ratio, so output rises.

[13] Thus, I is a 'hard' technical constraint on automation rather than a no-arbitrage condition between capital and labor.

complement $(N - I)$. The expression for the multiplier B on the Cobb-Douglas aggregator in (3) is a weighed sum of the relevant labor and capital efficiency terms (see eqn. 4). Conventionally, B corresponds to Total Factor Productivity (TFP), i.e., the Solow residual. TFP can shift in this model because one or both of the efficiency terms (y_M, y_L) rises *or* because tasks are reallocated from labor to capital (a rise in I) or from capital to labor (a rise in N). Thus, distinct from the canonical Solow model, TFP growth in this setting is not Hicks-neutral if it stems from movements in either I or N.

The demand for labor can be written as

$$W = (N - I)\frac{Y}{L} \tag{5}$$

This is again a familiar Cobb-Douglas expression, with the marginal product of labor equal to the average product of labor equal multiplied by the exponent on labor in the production function. We can rearrange this expression to obtain labor's share of output as

$$S_L = \frac{WL}{Y} = N - I \tag{6}$$

We next consider how several distinct varieties of technological change affect the equilibrium of this model.

1.2. Factor augmenting technological change

In canonical production models, technological change is factor-augmenting. Factor-augmenting change is also present in the current model. A rise in either α_L or α_M—signifying labor and capital-augmenting technical change, respectively—increases wages and output, with no effect on the labor share:

$$\frac{d\ln W}{d\ln \alpha_L} = \frac{d\ln(Y/L)}{d\ln \alpha_L} = (N - I)d\ln \alpha_L > 0,$$

and similarly,

$$\frac{d\ln W}{d\ln \alpha_M} = \frac{d\ln(Y/L)}{d\ln \alpha_M} = (I - N + 1)d\ln \alpha_M > 0.$$

with $d\ln Y/d\ln\alpha_L = d\ln Y/d\ln\alpha_M = 1$ and $dS_L/d\alpha_L = dS_L/d\alpha_M = 0$. Thus, although the model admits unconventional technological channels, it fully encompasses the conventional ones.

1.3. Extensive margin (labor-displacing) technical change

Consider a technological advance that extends the range of tasks that are technologically automated—that is, it increases I. This advance has two countervailing effects on wages, seen in the expression below:

$$\frac{d\ln W}{dI} = \frac{d\ln(N-I)}{dI} + \frac{d\ln(Y/L)}{dI} \tag{7}$$

The first term to the right of the equal sign reflects the labor-displacing effect of extensive margin technological change. Holding output constant, extensive margin technological change reduces labor's share of output and hence wages. Since capital is more cost-effective than labor in the threshold task (Assumption A1), however, extensive margin technological change also raises output.

These countervailing effects may be seen by expanding eqn. (7):

$$\frac{d\ln W}{dI} = \left[-\frac{1}{N-I}\right] + \left[\ln\left(\frac{W}{\alpha_L\gamma_L(I)}\right) - \ln\left(\frac{R}{\alpha_M\gamma_M(I)}\right)\right] \tag{8}$$

The first bracketed term in eqn. (8) is the *displacement* effect. It is negative since extensive margin technical change reallocates tasks from labor to capital (specifically, $dS_L/dI = -1$, where S_L is labor share of GDP). The second term, corresponding to rising productivity, is unambiguously positive by Assumption A1: since capital is more cost-effective than labor in newly automated tasks[14], automation raises output, a share of which is paid to labor.

This productivity effect may in turn operate through two channels, one direct and one indirect. The first (direct) effect is that automation may increase labor demand in non-automated tasks in the industry where automation is taking place. We refer to this channel as the 'Uber' effect, i.e., a technological improvement that both raises labor productivity and employment in the affected sector. Additionally or alternatively, productivity growth in a technologically advancing industry may raise labor demand in other industries. This indirect effect may occur because rising productivity raises consumer incomes and boosts final demand—what we call the 'Walmart' effect—or because automation lowers input costs to downstream customer industries, leading to output and employment growth in these

[14] Were this not the case, newly technologically automated tasks would nevertheless be performed by labor rather than machines.

downstream sectors—what we call the 'Costco' effect. Formally, these indirect effects (Walmart, Costco) exist outside of our simple model since the model contains only one sector. These distinct channels are, however, empirically distinguishable, and we will explore them below.

A notable implication of eqn. (8) is that although extensive margin technological change necessarily raises GDP, it need not raise wages due to its countervailing effects on productivity and on labor's share of output. As Acemoglu and Restrepo (2018b) emphasize, the net wage effect is more likely to be positive when capital is highly productive at the tasks that are newly automated (e.g., telephones replacing telegraphs—dramatically raising productivity while reducing labor requirements). Conversely, the wage effects may be negative when labor-replacing technologies have minimal productivity advantages over the workers they displace, e.g., self-checkout scanners at grocery stores replacing checkout clerks, or computerized phone menus replacing human customer service assistants. In the extreme case where capital is negligibly more productive at the threshold task than labor ($\ln(W/\alpha_L\gamma_L(I)) \approx \ln(R/\alpha_M\gamma_M(I))$, technological change reallocates income from labor to capital with essentially no effect on productivity, meaning that wages fall.

1.4. Intensive margin technical change, capital deepening, and elastic capital supply

While technological change along the extensive margin has an ambiguous effect on wages, technological change that boosts productivity in *already-automated* tasks necessarily raises labor demand. For example, if capital efficiency is initially identical in all technologically automated tasks ($\gamma_M(x) = \gamma_M$), and if γ_M rises with no change in I, then

$$d\ln W = d\ln Y/L = (I - N + 1)\, d\ln\gamma_M > 0.$$

That is, wages rise.

Similarly, a fall in the capital rental rate R—reflecting capital deepening—increases wages (seen in eqn. 8). In the limit where capital is perfectly elastically supplied (R is fixed), the productivity gains from technological change accrue exclusively to labor.[15]

[15] The positive wage effects of each of these three channels—intensive margin technical change, capital deepening, and elastic capital supply—reflect q-complementarity. Because capital and labor are q-complements in production, a rise in the quantity or quality of either raises the marginal product of the other.

1.5. Creation of new tasks

A final channel (unconventional) channel by which technological change may affect output and wages in this model is through the creation of new tasks in which labor has comparative advantage—that is, a rise in N. These new tasks might include novel labor-using activities (e.g., computer programming, laparoscopic surgery) or new variations of existing labor-using tasks (e.g., welding instead of riveting).

The effect of a rise in N on output and wages can be written as:

$$\begin{aligned}\frac{d\ln W}{dN} &= \frac{d\ln Y/L}{dN} + \frac{1}{N-I} \\ &= \left[\ln\left(\frac{R}{\alpha_M \gamma_M (N-1)}\right) - \ln\left(\frac{W}{\alpha_L \gamma_L (N)}\right)\right] + \left[\frac{1}{N-I}\right].\end{aligned} \tag{9}$$

In this expression, the first bracketed term reflects the rise in labor productivity stemming from the creation of new tasks, which is necessarily positive under Assumption A1. The second bracketed term reflects the *gain* in labor's share of income as tasks are reallocated from machines to workers.[16]

Combining equations (7) and (9), we can write the total effect of task-replacing technical change and new task creation on wages as

$$\begin{aligned}d\ln W =& \left[\ln\left(\frac{R}{\alpha_M \gamma_M (N-1)}\right) - \ln\left(\frac{W}{\alpha_L \gamma_L (N)}\right)\right] dN \\ &+ \left[\ln\left(\frac{W}{\alpha_L \gamma_L (I)}\right) - \ln\left(\frac{R}{\alpha_M \gamma_M (I)}\right)\right] dI + \left[\frac{1}{N-I}\right](dN - dI).\end{aligned} \tag{10}$$

This expression underscores that for labor's share to remain constant and wages to rise in tandem with productivity, task displacement and task creation must proceed at the same pace. In that case, $dS_L = dN - dI = 0$, and eqn. (10) reduces to

$$d\ln W = \left[\ln\left(\frac{\alpha_L \gamma_L (N)}{\alpha_M \gamma_M (N-1)}\right) - \ln\left(\frac{\alpha_L \gamma_L (I)}{\alpha_M \gamma_M (I)}\right)\right] dI > 0, \tag{11}$$

which is unambiguously positive.

[16] This latter term may appear an artifact of the assumption that there is a unit measure of tasks, so the creation of new labor-using tasks implies the elimination of an equal measure of technologically-automated tasks. However, even if old tasks were *not* eliminated, the creation of new labor-using tasks would raise labor's share of output. In that case, the derivative dS_L/dN would be equal to 1 rather than $1/(N-I)$, which exceeds 1.

1.6. Empirical implications

Although many of the moving parts of this model are not directly observable, some of the model's key mechanisms can be inferred from the data. The key to our empirical approach is to focus on Total Factor Productivity, represented by B in the model. TFP is central to our analysis because all margins of technical change considered above induce a shift in TFP, either by reallocating tasks from labor to capital or from capital to labor, or by increasing the efficiency of capital or labor in production (see eqn. 4).[17] Simultaneously, the fact that each of these technological channels alters TFP means that observing a change in TFP is not by itself sufficient to reveal *which* channel is operative. We can, however, use information on output, employment, earnings, and labor's share to infer these channels. Specifically, we will study how changes in industry-level TFP affect output (value-added) quantities and prices, employment, earnings, and labor's share of value added—both in the industry experiencing the TFP shift, and in the customer and supplier industries that may be indirectly affected (through Walmart and Costco channels). To empirically adjudicate between the roles played by these competing forces, we focus on labor's share of value-added. A first-order implication of the model is that technological change that is task-displacing will reduce labor's share of value-added, even if it raises employment, earnings, and output. Thus, the heart of our empirical work is assessing whether automation is labor share-displacing.

Because our model contains only a single sector, the forces discussed above can play out exclusively in the sector where they originate. A general lesson of the literature on structural change is that firm- and industry-level changes in productivity and labor input are not *necessarily* informative about aggregate outcomes of interest. Concretely, labor's share of value-added could remain constant even while all sectors become less labor intensive if the aggregate share of value added produced by labor-intensive sectors rose simultaneously. We explore the link between industry-level and aggregate effects of productivity growth on the labor share in two ways. Recognizing that productivity growth in each industry augments aggregate income and hence indirectly raises final demand, we estimate the elasticity of sectoral demands

[17] One exception is pure capital deepening, which will not raise measured TFP in this model since it does not affect $I, N, \gamma_L(x), \gamma_M(x), \alpha_L$, or α_M. Capital deepening is an outcome that we do not explore empirically.

emanating from aggregate income growth and then apply our TFP estimates to infer the indirect contribution of each industry's productivity growth to final demand. Additionally, we use harmonized input-output tables from the World Input Output Tables to estimate how innovations to own-sector productivity affect outcomes in customer (downstream) and supplier (upstream) industries. These indirect effects turn out to be sizable, revealing an important role for both industry linkages and aggregate demand. For some outcomes—employment in particular—these indirect effects fully offset the own-sector effects that we detect. For other outcomes—most critically, labor's share of value-added—they do not.

2. Data and measurement

Our analysis draws on the EU KLEMS, an industry level panel dataset covering OECD countries since 1970 (see O'Mahony and Timmer, 2009, http://www.euklems.net/). We use the 2008 release of EU KLEMS, supplemented with data from EU KLEMS 2011 and 2007 releases to maximize data coverage. Our primary analytic sample covers the period of 1970 – 2007. We limit our analysis to 18 developed countries of the European Union, excluding Eastern Europe but including Australia, Japan, South Korea, and the United States. These countries and their years of data coverage years are listed in Table 1A. The KLEMs database contains detailed data for 32 industries in both the market and non-market economy, summarized in Table 1B. We focus on non-farm employment, and we omit the poorly measured Private household sector, and Public administration, Defense and Extraterritorial organizations, which are almost entirely non-market sectors.[18] The end year of our analysis is dictated by major revisions to the industry definitions in the KLEMS that were implemented in the 2016 release. These definitional changes inhibit us from extending our consistent 1970 – 2007 analysis through to the present, though we analyze 2007 – 2015 separately using the 2017 release of the EU KLEMS.

Table 2 summarizes trends in the labor share of value-added and its components (hours, nominal wages, and nominal value-added), as well as TFP. We quantify these trends overall, by

[18] Although KLEMS classifies healthcare and education as non-market sectors, they are a substantial and growing part of GDP across the developed world and, in many countries (e.g., the U.S.), also encompass a large private sector component. We therefore choose to retain these sectors in our analysis.

sector, and by decade by estimating regression models for the change in country-industry-year outcomes (multiplied by 100) while including a variety of fixed effects to absorb country, industry, and business cycle factors.[19] In this table, and throughout the paper, regressions models are weighted by industry value-added shares within countries averaged over the sample period, and all weights sum to one within a country-year, meaning that countries are equally weighted.[20] Consequently, our results are not for the most part driven by trends in the largest economies in our database (i.e., the U.S., Japan, Germany, France, and the U.K.).

The first column of Table 2 reports estimates of the average annual labor share change (in percentage points) across the full set of industries and time periods (panel A). Panel B reports these relationships separately by decade. Panel C reports them separately for five broad sectors encompassing the 28 industries in our analysis. As detailed in the table's rubric, these sectors are: mining, utilities, and construction; manufacturing; education and health; low-tech services (including personal services, retail, wholesale and real estate); and high-tech services (including post and telecommunications, finance, and other business services). The reported regression coefficients, which correspond to *within-industry* changes in labor share, confirm a pervasive downward trend, averaging approximately 0.17 percentage points per year within our sample. This trend is most pronounced in manufacturing and in mining, utilities, and construction. It is absent from the education and health sector, and it is modest in the low-tech services sector.

Consistent with results reported in much recent work (e.g.. Elsby, Hobijn, and Sahin 2013; Karabarbounis and Neiman 2014; Autor et al. 2017b), the decline in labor share varies across decades. Labor's share of value-added trends modestly upward in the 1970s at a rate of 0.09 percentage points per years, then falls in each decade of the 1980s, 1990s, and 2000s. In our EU KLEMS data, the decline in labor share appears to be relatively steady across these latter three decades—and most rapid in the 1990s—a pattern that is somewhat distinct from papers reporting that the overall rate of labor share decline is more rapid in the 2000s than in earlier

[19] Appendix Tables 2A through 2D provide country and industry level summary statistics on trends in employment, TFP, and labor share by country and industry.

[20] The number of observations is equal to the number of country-industry cells multiplied by the number of years. Standard errors are clustered by industry-year and reported in parentheses.

decades (cf. Autor et al. 2017b). One potential resolution of this discrepancy is that our analysis reports an unweighted average of labor shares across countries, meaning that the experience of smaller countries may drive the aggregate results. In addition, the Table 2 statistics correspond exclusively to within-industry labor-share shifts, holding fixed relative industry sizes. Between-sector shifts may amplify or attenuate their effect on the aggregate labor share.[21]

Columns 2 through 4 of Table 2 decompose the trend in labor share trend into its three components: hours worked, (nominal and real) wages, and (nominal) value added.[22] This decomposition highlights that trends in hours worked are relatively stable over time—though growth is most rapid in the 1970s—while real hourly wage growth is considerably more rapid in the 1970s than in subsequent decades. Patterns also differ sharply by sector. Hours worked are declining for manufacturing but strongly increasing for high-tech services. Manufacturing is also distinctive in having the largest decline in hours and largest rise in the hourly wage.

The final column of Table 2 reports trends in TFP, which rises at an annual rate of 0.62 log points over the full sample. TFP growth is negligible in the 1970s, however, accelerates in the 1980s, and decelerates sharply in the 2000s. Manufacturing stands out for having the most rapid rate of TFP increase. Conversely, TFP growth is approximately zero in high-tech services and negative in education and health.

These descriptive tables are of course silent about the role that productivity growth generally, or technological change specifically, plays in the evolution of hours, wages, value-added, and labor's share of value added. We next explore this question, using the conceptual model above to guide interpretation.

3. Main estimates

3.1. Own-industry (direct) effects

We begin in Tables 3A and 3B by estimating the relationship between industry-level TFP growth and changes in the labor share and its components—both at the industry level and in

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[21] Note finally that we exclude agriculture, public administration, private households, and extra-territorial organizations, though we suspect that these sectors play a minor role in aggregate trends.

[22] We report nominal values because these relevant to the labor share calculation.

aggregate. Our first empirical specification (columns 1 and 2 of each panel) considers only within-industry effects of own TFP growth on own-industry outcomes. We estimate

$$\Delta \ln Y_{ict} = \beta_0 + \beta_1 \Delta \ln TFP_{ict} + \alpha_c + \delta_t + \gamma_i + \alpha_c \times (\mathrm{t} = peak) + \alpha_c \times (\mathrm{t} = trough) + \varepsilon_{ict}, \tag{12}$$

where $\Delta \ln Y_{ict}$ is an outcome of interest (e.g., employment, earnings, value-added) and i indexes industries, c indexes countries, and t indexes years. All models are weighted by industries′ value-added shares within countries, averaged over the sample period, and standard errors are clustered at the level of country-industry pairs. Our first estimate of eqn. (12) in each panel includes country (α_c) and year (δ_t) effects, while the second adds industry (γ_i) fixed effects as well as country-specific indicator variables interacted with business cycle (peak and trough) indicators.[23] As an initial omnibus measure of technology change, our main explanatory variable in this model is value-added based industry-country-year TFP, calculated by EU KLEMS. We subsequently implement several approaches to address concerns about potential endogeneity, cyclicality, and mismeasurement of TFP.

The first panel of Table 3A presents estimates for industry-level employment, measured as the (log) number of employees. The point estimate in column 1 of -0.129 implies that a one percent increase in own-industry TFP predicts a fall in own-industry employment of 0.13 percent. If rising TFP spurred industries to use existing labor more intensively rather than expand employee headcounts, then the predicted fall in employment in panel A would overstate the decline in hours of labor input. Panel B explores this possibility and finds that the opposite is the case: the fall in total labor hours is typically 30 to 40 percent larger than the fall in employment, implying that corresponding employment adjustments occur on both the extensive (employee) and intensive (hours per employee) margin.

Column 2 probe the robustness of the initial estimates by adding industry fixed effects (γ_i), which account for industry specific trends[24], as well as country business-cycle indicator variables, which absorb aggregate cyclicality effects. These additional controls have little effect

[23] Peak and trough years for each country are obtained from the OECD.

[24] Recall that the dependent variable is specified as a first difference, which intrinsically differences out industry-specific *levels* of the outcome variables. Inclusion of industry dummies therefore removes industry-specific trends.

on the coefficients of interest, modestly attenuating the relationship between TFP and employment and hours. (All point estimates remain highly significant.) These initial estimates are consistent with Autor and Salomons (2017), who find that own-industry productivity growth—whether measured by output per worker, value-added per work, of value-added based TFP—is robustly associated with falling own-industry employment.

Panel C turns the focus from hours to hourly earnings, and here we find countervailing effects: a rise in industry-level TFP predicts a sharp increase in industry-level hourly earnings. In the first column, we obtain a precisely estimated wage-TFP elasticity of 0.244. Since TFP is typically pro-cyclical, it's possible that this association confounds direct effects of own-industry TFP on earnings with cyclical effects on wages. Column 2 addresses this concern by including business cycle peak and trough indicator variables exhaustively interacted with country dummies. These controls have almost no effect on the estimated wage-TFP elasticity, likely because the combination of year and country dummies already absorb much of the cyclical variation.

Panel D estimates the relationship between industry TFP and industry wagebill. Since the wagebill is equal to the product of hours and hourly earnings, the estimated wagebill-TFP elasticity is simply the sum of the hours-TFP and wage-TFP elasticities. This elasticity is estimated at approximately 0.09 to 0.13 across all columns: a one percent rise in TFP predicts a rise in the industry-level wagebill that is one-tenth as large. That is, industry productivity growth predicts a growth in payments to labor, consistent with recent findings in Stansbury and Summers (2017).

The wage and wagebill outcomes studied in Table 3A are reported in nominal terms since they will serve as inputs into our industry-level labor-share calculations below (where labor-share is defined as the ratio of nominal industry wagebill to nominal industry value-added). The use of nominal units raises the concern that the Table 3A estimates may overstate the association between TFP and industry-level *real* wage growth, i.e., if inflation accompanies nominal wage growth. In point of fact, this is unlikely to be an issue since country-level price and wage level effects will largely be absorbed by year and country dummies—meaning that our point estimates are primarily identified by cross-industry, within-country-year variation in wage growth. To confirm that any differences between nominal and real wage levels do not skew our estimates, we have estimated companion models that are saturated with a full set of country-by-year, industry-by-year, and country-by-industry effects.[25] As anticipated, inclusion of these dummy variables, which absorb all country-year variation in wage or price levels (as well as much additional variation), has essentially no effect on the wage and wagebill estimates in Table 3A.

3.2. Accounting for inter-industry and final demand effects

We next incorporate two channels by which own-industry productivity growth might contribute to aggregate changes in labor input: final demand effects and interindustry input-output linkages. We add these channels to eqn. (12) as follows:

$$\begin{aligned}\Delta \ln Y_{ict} = \beta_0 + \beta_1 \Delta \ln TFP_{ict} + \beta_2 \Delta \sum_i \ln VA_{ict} + \sum_{k=0}^{3} \beta_3^k \times \Delta \ln \widetilde{TFP}_{ct,j\neq i}^{UP} \\ + \sum_{k=0}^{3} \beta_4^k \times \Delta \ln \widetilde{TFP}_{ct,j\neq i}^{DOWN} + \alpha_c + \delta_t + \gamma_i + \alpha_c \times (\mathrm{t} = peak) + \alpha_c \\ \times (\mathrm{t} = trough) + \varepsilon_{ict}\end{aligned} \quad (13)$$

The first term added to the estimating equation is the sum of industry-level value by country and year. This term proxies for aggregate national incomes, thus allowing aggregate growth to affect industry level outcomes. Equation (13) also contains the terms, $\widetilde{TFP}_{ct,j\neq i}^{UP}$ and $\widetilde{TFP}_{ct,j\neq i}^{DOWN}$, which reflect weighted sum of TFP growth in all other domestic industries $j \neq i$ which are either up- or downstream of industry i. In particular,

$$\Delta \ln \widetilde{TFP}_{ct,j\neq i}^{L} = \sum_{j=1}^{J} weight_{c,j\neq i}^{L} \times \Delta \ln TFP_{ct,j\neq i}^{L}, \forall\, L \in UP, DOWN \quad (14)$$

The up- and downstream weights are obtained from input-output analysis on World Input-Output Data (WIOD) over 1995-2007, averaged over time. The upstream weights are a domestic supplier industry j's final products as a share of the value added of industry i, capturing the importance of industries j in the production of industry i's output. Similarly, the downstream

[25] Recall that our outcome measures vary at the country-industry-year level, so this full set of second-order interactions does not swamp the identifying variation.

weights are shares of value added of industry i that are used in domestic industry j's final products, capturing the importance of industries j as end-consumers of industry $i's$ output. These weights therefore account not only for shocks to an industry's immediate domestic suppliers or buyers but for the full set of input-output relationships among all connected domestic industries. Formally, these weight matrices correspond to Leontief inverses of the corresponding input-output tables. We include three annual lags in up- and downstream TFP growth to allow for dynamics in these sectoral linkage effects.[26]

The third and fourth column of the four panels of Table 3A present estimates of equation (13), which account for aggregate growth effects and inter-industry linkages. In column (3), we estimate large effects of aggregate growth on industry-level employment ($\hat{\beta}_2^E = 0.30$), hours ($\hat{\beta}_2^H = 0.30$), hourly wages ($\hat{\beta}_2^W = 0.63$), and wagebills ($\hat{\beta}_2^W = 0.93$). Though these economically sizable relationships are expected, they are nonetheless important because they underscore that by raising aggregate value-added, industry-level productivity growth generally augments labor demand economy-wide, even if it potentially reduces own-sector employment.

The interindustry terms, added in column (4) of each panel, indicate that productivity growth in upstream (supplier) sectors predicts steep increases in employment, hours, and total (nominal) wagebill (though not hourly wages) in customers sectors. Conversely, productivity growth in downstream (customer) sectors has negligible effects on outcomes of interest in supplier sectors. These patterns are consistent with the simple Cobb-Douglas input-output framework in Acemoglu, Akcigit, and Kerr (2017), where innovations in a given sector generate downstream impacts on its customer sectors, who benefit from price declines, but have no net effect on its upstream supplier sectors because the price and quantity effects of any induced demand shift are offsetting. These inter-industry relationships reinforce the point that an

[26] We do not find empirical support for any lagged effect of own-industry TFP growth.

exclusive focus on own-industry effects of productivity growth on labor inputs would lead to misleading conclusions for labor aggregates.[27]

Based on the current set of findings, we can draw no strong conclusion for whether automation (as proxied by TFP) is labor-augmenting or labor-displacing in the sectors where it occurs. Since the net effect on wagebill is positive, it is tempting to interpret the net effect as *labor-augmenting*. But this inference would be premature. In our model, a technological change is labor-displacing if it reduces labor's share of output. Our results so far do not reveal whether this is occurring. To adjudicate among these competing interpretations, we harness information on industry price levels, value-added, and payments to labor as a share of value-added. We report estimates for these outcomes, fit with equation (13), in Table 3B. In the first panel, we find a strong positive association between growth in industry TFP and growth in nominal value-added. The estimated value-added-TFP elasticity is approximately equal to 0.45 in all columns. Thus, a one percent rise in TFP predicts a half-percent rise in nominal value-added.

If this rise is indeed a consequence of rising industry productivity, as we expect, then it should be accompanied by a fall in industry price. Panel B shows that this is indeed the case. A one percent rise in industry TFP predicts a fall of approximately 0.40 percent in the industry price level (that is, in the price deflator). If one is willing to make the strong assumption that rising TFP affects industry output *only* through its effect on the output price, then these estimates further imply an output demand elasticity of 1.2 ($\hat{\sigma} = -\frac{0.455}{0.387} = -1.2$), which appears prima facie reasonable.[28]

The final panel of Table 3B pulls together these empirical threads by estimating the relationship between own-sector TFP growth and labor's share of value-added, equal to nominal wagebill over nominal value-added. As implied by the estimates in panel D of Table

[27] Because the EU KLEMS data contain coarse skill measures, we cannot confidently assess to what degree rising wage payments are driven by changing skill composition versus rising wages for given skill levels. However, supplementary analyses performed by skill level for the three skill groups reported in EU KLEMS find that the wage-TFP elasticity is almost identical across all three groups. Thus, despite the coarse measurement, we strongly suspect that changing skill composition is unlikely to be the entire story.

[28] Alternatively, a reduced form interpretation of these relationships is given in panel C, where we estimate that a one percent rise in TFP predicts a rise in real output of 0.84 percent. Note that the estimated effect on real value-added is algebraically equivalent to the difference between the TFP effect on nominal output and its effect on the price level, all in log terms.

3A, where we find a wagebill-TFP elasticity of 0.11, and panel A of Table 3B ,where we find a value-added-TFP elasticity of 0.45, a rise in own-sector TFP predicts a significant fall in labor's share of value-added within that sector. Specifically, the point estimate in column 4 of panel D indicates that a one percent rise in TFP predicts a 0.34 percent fall in labor's share of value-added.

We emphasize that this own-industry effect does *not* correspond to the total implied impact of rising TFP on the labor share since it abstracts from both the aggregate growth and input-output channels. We quantify those channels below. For now, we note that the point estimate for the elasticity of labor-share with respect to aggregate growth is small in magnitude (coefficient of -0.08) and statistically insignificant, as is the estimated effect of TFP growth in customer (downstream) industries on own-industry labor share (coefficient of 0.07, also statistically insignificant). However, the coefficient on TFP on supplier (upstream) industries is large and precisely estimated with a slope of 0.79. At face value, this pattern of point estimates suggests that while own-sector productivity growth may predict a fall in own-industry labor-share, interindustry linkages provide a countervailing effect.

Table 4 gathers the primary estimates from Tables 3A and 3B into compact form. The models in Table 4 additionally include a set of country by industry by business-cycle indicator variables to allow the procyclicality of TFP to differ by industry within each country according to the state of the business cycle. A comparison of the Table 4 estimates with their counterparts in Tables 3A and 3B indicates that these further cyclicality controls have essentially no effect on the point estimates.

3.3. Using Low-Frequency Variation

Before assessing the economic magnitude of these relationships in Section 4, we address a natural concern with our estimates, which is that they rely on high-frequency (annual) variation for identification. Although we include a large set of fixed effects and time lags—including country-by-industry specific business cycle effects—to purge cyclical components of TFP and short-run adjustment dynamics, it is important to verify that our main results hold when using low frequency variation. This is done in Table 5 by fitting long differences of equation (13) on non-overlapping time intervals. Panel A of the table estimates the model with annualized 5-year changes, while panel B employs annualized 10-year changes. Both panels include country, industry, period, as well as country-by-industry and industry-by-period fixed effects.[29]

Results are robust to this modification in model specification. As before, industries experiencing relatively rapid TFP growth see a decline in employment and hours worked, a modest rise in wagebill, and a substantial increase in value-added. Estimated final demand relationships are of the same sign and comparable magnitude to earlier estimates. Interindustry linkages generally show somewhat smaller effects: upstream impacts on hours and wagebill are less positive and downstream impacts are more negative.

Of greatest interest, we continue to estimate a negative and highly significant relationship between TFP increase and labor-share declines at the industry level. The point estimates obtained using lower frequency are smaller than in the high-frequency models: -0.26 using 5-year changes and -0.16 using 10-year changes, as compared to -0.34 when using annual changes. Note, however, that the countervailing effects of upstream spillovers on labor share are less positive in these lower-frequency models. As a consequence, the implied net effects are similar to those obtained using annual variation. All told, these low-frequency models imply a predicted labor share decline of 3.4 to 6.3 log points due to TFP growth over the 1970-2007 period. These predictions bracket the corresponding predicted effect of 5.3 log points obtained when using annual variation.[30]

Lastly, Appendix Table 3A estimate our main specification (Tables 4) while filtering the main explanatory variables (TFP, aggregate value-added) using a three-year backward-looking moving average process so as to smooth out any remaining short-run fluctuations. Our conclusions are unaltered by this modification.

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[29] A small number of intervals is shorter than this 5- or 10-year length, as countries sometimes enter or exit the dataset mid-interval (see Table 1A). In particular, for panel A, 81% of periods are exactly 5 years in length. The minimum period length we use is 2 years, and the maximum is 7 years (to cover 2000-2007). For panel B, 60% of periods are 10 years in length, 20% are 7 years in length (to cover 2000-2007), and the minimum period length is again 2 years.

[30] Details on these calculations are given in the next session.

4. Quantitative implications

Our primary estimating equation (eqn. 13) permits industry-level productivity growth to affect outcomes of interest through three channels: own-industry effects, cross-industry input-output linkages, and final demand effects. This three-level structure means that the net effect of an increment to TFP occurring in any given sector on the *aggregate* outcome of interest is not directly readable from the table.

To quantify the operation of all three channels simultaneously, we differentiate equation (13) with respect to TFP in some industry i to obtain:

$$\frac{\partial \ln Y_{ct}}{\partial \ln TFP_{ict}} = \gamma_{ic}\hat{\beta}_1 + \hat{\beta}_2\hat{\beta}^{VA}\sum_i \gamma_{ic} + \sum_{j\neq i}\left(\gamma_{jc}\sum_{k=0}^{3}\hat{\beta}_3^k \times weight_{c,j\neq i}^{UP}\right) + \sum_{j\neq i}\left(\gamma_{jc}\sum_{k=0}^{3}\hat{\beta}_4^k \times weight_{c,j\neq i}^{DOWN}\right), \tag{15}$$

where Y_{ct} is an outcome of interest such as country-level employment in year t, and the scalar γ_{ic} equals industry $i's$ share in country $c's$ value-added. The first term in this expression is the *direct* (own-industry) effect of TFP growth in industry i on own-industry employment, weighted by industry $i's$ share in country $c's$ value added (γ_{ic}). The second term is the *final demand* effect, equal to the elasticity of employment with respect to aggregate value-added ($\hat{\beta}$) multiplied by the derivative of aggregate value added with respect to industry $i's$ value-added (also equal γ_{ic}) further scaled by the estimated elasticity of industry-value added with respect to TFP from column 6 of Table 4, which we write as $\hat{\beta}^{VA}$ in this expression. The third and fourth terms are the contributions of upstream and downstream linkages. These are equal to the relevant Leontief inverse weight of industry $i's$ TFP on upstream or downstream industries, multiplied by the estimated input-output effects in column 1 of Table 4, finally multiplied by each upstream or downstream industry's share in aggregate value-added.

Figures 1A, 1B, and 1C report the results of this calculation for overall employment, for hours of labor input, and for labor share respectively.[31] The first bar in Figures 1A corresponds to the direct-effect of TFP growth on own-industry employment. Its height of −0.068 implies

[31] Bootstrap confidence intervals are based on 100 replications.

that on average, productivity growth reduced own-industry employment by approximately 2.5 percent over the full 37-year period ($0.068/100 \times 37 = 2.5$). The second bar ("final demand") with height 0.073 indicates that the countervailing indirect effect of rising aggregate value-added on employment more than offset this direct effect. The third bar ("upstream effect") indicates an additional, large positive effect of rising productivity in upstream (supplier) industries on employment in customer industries. The fourth bar ("downstream effect") indicates a negligible employment reduction in downstream (supplier) industries. The final bar ("net effect") sums over these four components to estimate a net *positive* effect of productivity gains on aggregate employment, totally approximately six log points ($0.16/100 \times 37 = 5.92$) over the outcome period.

When we perform the same exercise for hours rather than workers in Figures 1B, we reach a comparable conclusion: the negative effects of rising productivity on own-industry employment and hours are more than offset by induced effects on aggregate demand and by employment growth in customer sectors.

The analogous exercise for labor share in Figure 1C, however, yields a different result. The direct effect of rising TFP on own-industry labor shares of $-0.23/100$ log points annually are *partly* offset by induced labor share gains in customer industries, equaling $0.12/100$ log points annually. Meanwhile, there is no offset through either final demand or impacts in supplier industries. This yields a net effect of -5.3 log points over the entire 1970-2007 period ($-0.143/100 \times 37 = -0.053$), which is similar to the observed change of $-0.169/100$ log points annually (see Table 2), or 6.3 log points cumulatively over the 37-year period.

To provide a reality check on our estimates, Figure 1D plots the net labor share predictions from our model (on the horizontal axis) against actual observed changes by industry (on the vertical axis). Each data point in this figure represents an industry, and the 45-degree line is added to gauge fit. Overall, this figure shows that the estimated relationship between rising productivity and falling labor share can explain a significant portion of the variation in actual labor share evolution by industry. The R-squared of a value-added weighted regression is 0.25, with a highly statistically coefficient of 0.431.

4.1. Exploring heterogeneity: Detailed estimates by sector

Our estimates so far restrict the impacts of productivity growth to be constant across industries, no matter in which industry this productivity growth originates. This may be too restrictive. Different sectors may use technologies which are differently labor-augmenting or replacing—say, robotic assembly in manufacturing versus proliferating treatment regimens in health services—resulting in different impacts of TFP growth on industry employment and wages. Additionally, some sectors may face more elastic demand for their outputs—for example because of lower demand saturation (cf. Bessen 2017)—or face higher product market competition, resulting in stronger responses of prices and output to TFP growth.

We explore sectoral heterogeneity in the effects of TFP growth in Table 6A by relaxing the symmetry restrictions imposed by our estimates in Table 4. Specifically, we augment equation (13) to allow outcome-productivity elasticities and final demand effects to differ across five broad sectors: (1) mining, utilities and construction; (2) manufacturing; (3) education and health services; (4) capital-intensive ('high tech') services; and (5) labor-intensive ('low tech') services (as was done earlier in Table 1B).[32] The specifications in Table 6A are otherwise identical to those in Table 4 save for these sectoral interactions.

A key take-away from this analysis is that all sectoral coefficients have the same sign across each sectors for each outcome and most are statistically significant. This means that our earlier findings are not driven by disparate patterns in a subset of industries. Rather, TFP growth predicts a fall in hours, a rise in wagebill, and a fall in labor share in all sectors in which it occurs. The estimated labor share elasticity to TFP growth is most negative (-0.37) in manufacturing and low-tech services and is least (-0.13) in education and health sectors. The second set of rows in the table report the final demand effects on outcomes, which are again allowed to vary by sector. Though most sectoral coefficients are comparable, we find that rising

[32] Specifically: Mining, utilities, and construction corresponds to industries C, E and F; Manufacturing is industries 15 through 37; Education and health services are industries M and N; High-tech services are industries 64, J, and 71 to 74; and Low-tech services are industries 50 to 52, H, 60 to 63, 70, and O. This particular high- and low-tech services division is obtained from the OECD.

aggregate income predicts a fall in labor share in the mining and utilities sector, though not in other sectors.[33]

4.2. Exploring heterogeneity: Detailed estimates by decade

Table 6B explores how these relationships evolve over time. To the extent that technologies have become more labor-displacing—as popular accounts suggest—we would expect the employment and labor share effects of TFP growth to turn more negative over time. The estimates in this table indeed support such a story: the labor share elasticity to TFP growth becomes successively more negative across the four decades in our sample, from −0.14 in the 1970s to −0.32 in the 1980s to −0.34 in the 1990s to −0.47 in 2000s.[34] Turning to the various components of the labor share, it can be seen that this is mostly coming from a monotonically declining wagebill-TFP elasticity (from 0.17 in the 1970s to 0.04 in the 2000s) coupled with a nearly constant real output response. As a result, TFP growth predicts an increasingly large drop in own-industry labor-share in successive decades.[35]

These own-industry effects ignore the influence of final demand and inter-industry linkages, however. To assess their contributions, Figures 2A and 2B report the predicted effect of TFP on labor hours and labor share, respectively, operating through each channel—own-industry, final demand, and inter-industry linkages—during each of the four decades of the sample. Figure 2A indicates that the estimated impact of rising TFP on total labor hours was positive in each decade, with the largest predicted effect in the 1980s and the smallest effects in the 1970s and 2000s. Most of this cross-decade variation in magnitudes stems from differences in the growth rate of TFP, which was slowest in the 1970s and 2000s and most rapid in the 1980s and, to a lesser extent, the 1990s.

[33] Appendix Table 3B presents corresponding estimates using filtered TFP and aggregate income measures to purge high frequency variation in TFP. These estimates are largely comparable to the estimates using higher frequency variation in Table 6A.

[34] This result also holds when considering a (more) balanced panel of countries where each country contributes at least one observation of in each of the four decades.

[35] Appendix Table 3C presents corresponding estimates using filtered TFP and aggregate income measures to purge high frequency variation in TFP. These estimates are largely comparable to the estimates using higher frequency variation in Table 6B.

Figure 2B reports a far starker pattern for the contribution of rising productivity to the evolution of labor shares. This effect is essentially zero in the 1970s and then is consistently negative in each of three following decades, with an estimated net impact of −4.51 log points between 1980 and 2007. It is natural to ask how much of this decadal variation stems from differences in the growth rate of TFP across periods versus decadal differences in the predictive relationship between TFP and the various components of labor share adjustment. Figure 2C answers this question by calculating a counterfactual in which TFP growth is counterfactually equalized across all time periods at the mean overall growth rate of TFP for 1970 – 2007. Strikingly, this figure shows that the predicted effect of a given increment to TFP is successively more negative for aggregate labor-share in each decade of the sample; thus, the change in coefficients across periods plays a first order role. This time pattern stems in turn from a decade-over-decade steepening of the relationship between TFP growth and own-industry labor share decline. The final demand effect of rising TFP on labor share is essentially zero in the 1970s and 1980s, becomes slightly negative in the 1990s, and turns strongly negative in the 2000s.[36] The fact that both own-industry and final demand effects become increasingly (and monotonically) more negative across each decade is potentially consistent with a scenario where technological progress has become secularly more labor-displacing.

To provide a sense of how successfully these models capture the relevant variation in the data, Figure 2D presents a scatter plot of predicted versus observed changes in industry-level labor shares in each decade, where each decade's data points are plotted with a distinct marker to highlight cross-decade differences. The 1970s stand out as the decade where there is little change observed in industry-level labor shares. Our model predicts comparatively little change in this decade as well. The subsequent three decades reveal far larger falls in industry labor shares and far more variation across industries in magnitudes. The correspondence between the model fits and observed changes in considerably closer in these three decades.

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[36] We do not allow the inter-industry slopes to vary by decade because these estimates become highly imprecise when we add parameters. The data do not reject the null hypothesis that this upstream and downstream effects are constant across decades.

These by-decade estimates only cover outcomes through 2007, when the coverage of our primary EUKLEMS database ceases. Fortunately, a 2017 EUKLEMS database release (Jäger and Van Ark 2017) can be used to cover the intervening years up to 2015, albeit for a smaller subset of countries (13 in total, see Appendix Table 1A for coverage). Although these data are not directly comparable to the earlier release because of changes in both the industry classification (see Appendix Table 1B) and in data construction, we use them to check the qualitative robustness of our direct and final demand effects for the post-2007 period.

Table 7 reports estimates of equation (12) for 2007 - 2015, including the same full set of fixed effects used in Table 4.[37] Result are very similar for the most recent decade in the long EUKELMS panel. Industry-level TFP growth is associated with a substantial rise in nominal value-added, a (small) decline in hours worked, and no increase in the wagebill, all of which are consistent with the pattern prevailing in 2000-2007 (see Table 6B). Also, as in earlier decades, there is a strongly positive elasticity of hours, wagebill, and value-added with final demand, as well as a zero elasticity of labor-share with respect to final demand. A rise in TFP predicts an even larger decline in own-industry labor share in the post-2007 period than earlier in the decade (-0.64 versus -0.47). Although not reported in Table 7, these patterns are unaffected by including a less stringent set of fixed effects or by excluding the Great Recession years. Although we hesitate to draw strong inferences given the many differences—including country coverage, industry classification, and measurement constructs—between the pre- and post-2007 EUKLEMS databases, the Table 7 estimates do not suggest that the increasingly negative relationship between productivity growth and own-industry labor-share seen in Table 6B, particularly in the final decade of the sample, reverses course after 2007.

5. Is automation labor-displacing? Applying direct measures of innovation and automation

We have so far used TFP growth as an omnibus measure of automation. This has the advantage of not restricting the analysis to a specific type of technology and its associated

[37] We do not estimate the interindustry linkage terms for this short time interval since this would require inclusion of three lag terms, truncating our event window by three of eight years.

measurement issues. But TFP is ultimately a residual, so it is difficult to know what it corresponds to. Moreover, one may be concerned that TFP growth is endogenous to, or simultaneously determined with, some of the outcomes we consider, even net of the fixed effects included in the specifications.

To address these concerns, we consider two direct industry-level measures of automation and technological change: patenting flows (as in Acemoglu, Akcigit, and Kerr 2017), and adoption of industrial robotics (as in Graetz and Michaels 2015, and Acemoglu and Restrepo 2017, among others). We use these automation measures as instrumental variables for industry-level TFP growth to isolate variation in productivity growth that is both directly related to technological advances and plausibly exogenous. As shown below, both measures of technological change are significant predictors of industry-level productivity growth. One may of course question the plausibility of the implicit exclusion restriction implied by these 2SLS estimates, i.e., that patent flows and robot penetration exert a causal effect on outcomes of interest *exclusively* through their impact on TFP. Whether one accepts this restriction or simply views these measures as proxies for industry-level technological progress, the rescaling of each measures in terms of units of TFP—as is implicitly done by the first stage of the 2SLS estimates—facilitates interpretation.

We construct patent citations by year for patents granted to both US and non-US inventors using US Patent and Trademark Office (USPTO) data by US SIC industry, cross-walked to the EUKLEMS industry level. These data are sourced from Autor et al. (2017a), who match patent grants to their respective corporate owners and then to industry codes based on corporate owners' industry affiliations. Appendix Table 4 reports the mean log number of patent citations by industry and by inventor nationality (U.S. versus non-U.S.). This table highlights the substantial heterogeneity in patent flows across sectors, with the highest levels of patenting occurring in chemicals as well as electrical equipment. We consider this patenting activity as an input in the innovation and automation process at the industry level.

Table 8 reports estimates of our baseline results using log patent citations as an instrumental variable for TFP growth. To reduce the possibility of simultaneity, we use patent citations for *non-US* inventors to instrument TFP growth in the US and use patent citations for

US inventors to instrument TFP growth outside the US. (In point of fact, our results are quite similar when using total patent citations for both.) All specifications control for growth in nominal value added by country-year and include country and year fixed effects, as well as country-specific business cycle effects.

The first stage, reported in the lower panel of the table, is highly significant: citations to patents originating in an industry are strong predictors of TFP growth within that industry. Notably, the second stage results are qualitatively similar to our OLS estimates: instrumented TFP growth has a statistically significant negative effect on hours worked and on labor share, consistent with our baseline findings. The point estimate for the impact of productivity growth—here instrumented by foreign country patent citation flows—equal to −0.35 is highly comparable to the corresponding OLS estimate in Table 4 (column 8), though of course the standard error of the 2SLS estimate is much larger.[38]

As a second instrumental variables strategy, we use the introduction of robotics as a concrete example of a recent innovation engendering a wave of automation. We rely on International Federation of Robotics (IFR) data on robot purchases by country-industry-year, and we follow Acemoglu and Restrepo's (2017) industry classification scheme to match these data to KLEMS, though we slightly modify their scheme to account for the higher aggregation of our TFP data across industries. These data cover 16 more aggregate industries over 1993 to 2007 for all but four countries in our sample.[39] Appendix Table 5 provides an overview of this classification as well as summary statistics on the number of robots per 1,000 workers and the average annual change therein, reflecting automation at the industry level. These summary statistics show that transport equipment is by far the most robot-intensive industry, followed by plastics and chemicals, metals, and electronics. These are also the sectors where robot penetration is rising most rapidly—logically, since robots were quite scarce until recently—though it rises in most industries.

[38] We do not consider input-output linkages in our instrumental variables estimates since we lack statistical power to identify these second-order terms in 2SLS models.

[39] Not included in IFR data are Canada, Ireland, and Luxembourg. Japan is excluded because of unreliable data, see Acemoglu and Restrepo (2017).

Table 9 reports estimation results from instrumenting TFP growth by the annual change in the number of robots per 1,000 workers, controlling for a country and year fixed effects as well as country-specific business cycle effects. As with patenting, robot penetration is a significant predictor of industry TFP. The first stage estimate suggests that the addition of one robot per 1,000 workers increases TFP by a statistically significant 0.175 log points. Second stage results are less precisely estimated, likely due to the relatively small number of observations, but are qualitatively similar to our OLS results. We estimate negative direct effects of automation—that is, TFP growth instrumented by robot adoption—on both hours worked and on the labor share. In the case of hours worked, we estimate that final demand effects serve to counterbalance the negative direct effect of automation on hours. But, as in our previous results, no such compensating effect is found for the labor share. The point estimate for the impact of automation on own-industry labor share is −0.195. While too imprecise to draw any confident statistical statement, this point estimate is certainly in the ballpark of our main estimates.

Overall, these results using direct measures of automation appear supportive of our prior findings on TFP growth more broadly.

6. Concluding remarks

Although our motivating model of labor displacement envisages a setting where tasks are reallocated from labor to capital in an aggregate production function, this high-level representation is consistent with a variety of within- and between- firm adjustments. At one extreme, every firm in an industry undergoing technological progress might substitute capital for labor in a subset of tasks. Alternatively, absent any within-firm change in task allocation, a technological advance might spur an increase in industry market share among relatively capital-intensive firms and a concomitant decline among relatively labor-intensive firms.[40] Under either scenario, labor's share in industry value-added would fall. Our analysis cannot speak to these within- versus between-firm dynamics. Nevertheless, we believe that the scope

[40] The relevance of this latter mechanism is supported by the industry-by-establishment analysis of changes in industry labor shares reported in Autor et al. (2017b).

of the evidence presented here complements more granular, but narrower firm and establishment-level studies.

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8. Model Appendix

The derivations in this Appendix are directly reproduced from Acemoglu and Restrepo (2018b) with minor changes to accommodate the modifications made to the model for our exposition.[41]

Factor demands are derived as follows. Suppose that Assumption A1 holds. Denote by $p(x)$ the price of task x. Using Assumption A1, this price is

$$p(x) = \begin{cases} \dfrac{R}{\alpha_M \gamma_M(x)} & \text{if } x \in [N-1, I] \\ \dfrac{W}{\alpha_L(x)\gamma_L} & \text{if } x \in [I, N]\,. \end{cases} \tag{16}$$

Due to the Cobb-Douglas structure of (1), the expenditure on task x is equal to $y(x)p(x)$ for all x and hence the output of task x is

$$y(x) = \frac{Y}{p(x)}. \tag{17}$$

Demands for machinery and labor, respectively, in task x are

$$m(x) = \begin{cases} \dfrac{Y}{R} & \text{if } x \in [N-1, I] \\ 0 & \text{if } x \in [I, N] \end{cases} \tag{18}$$

and

$$\ell(x) = \begin{cases} 0 & \text{if } x \in [N-1, I] \\ \dfrac{Y}{W} & \text{if } x \in [I, N] \end{cases} \tag{19}$$

Since labor and machinery are both inelastically supplied, we can sum the demands for each factor and set it equal to supply to obtain market clearing conditions:

$$M = \frac{Y}{R}(I - N + 1) \tag{20}$$

and

$$L = \frac{Y}{W}(N - I). \tag{21}$$

Equations (20) and (21) can be inverted to obtain expressions for the equilibrium rental and wage rates R and W: $R = (Y/M)(I - N + 1)$ and $W = (Y/L)(N - I)$.

To derive the expression for aggregate output, we use the price of the final good Y as the numeraire. With the final good price constant at unity, we have

[41] These modifications are limited to adding the two factor-augmenting terms α_K and α_L to the model.

$$\int_{N-1}^{N} \ln p(x) dx = 0. \tag{22}$$

Plugging in the expressions for task prices (eqn. 16) and the equilibrium rental and wage rates into eqn. (22), we obtain

$$\int_{N-1}^{I} \left[\ln R - \ln \alpha_M \gamma_M(x)\right] dx + \int_{I}^{N} \left[\ln W - \ln \alpha_L \gamma_L(x)\right] dx = 0. \tag{23}$$

Substituting for R and W in (23) using (20) and (21), we have

$$\begin{aligned} &\int_{N-1}^{I} \left[\ln Y - \ln(M/(I-N+1)) - \ln \alpha_M \gamma_M(x)\right] dx \\ &\qquad + \int_{I}^{N} \left[\ln Y - \ln(L/(N-I)) - \ln \alpha_L \gamma_L(x)\right] dx = 0. \end{aligned} \tag{24}$$

Rearranging

$$\begin{aligned} \ln Y = &\int_{N-1}^{I} \left[\ln\left(\frac{M}{I-N+1}\right) + \ln \alpha_M \gamma_M(x)\right] dx \\ &+ \int_{I}^{N} \left[\ln\left(\frac{L}{N-I}\right) + \ln \alpha_L \gamma_L(x)\right] dx \\ &= \int_{N-1}^{I} \ln \gamma_M(x)\, dx + \int_{I}^{N} \ln \gamma_L(x)\, dx \\ &+ (I-N+1) \ln\left(\frac{\alpha_M M}{I-N+1}\right) + (N-I) \ln\left(\frac{\alpha_L L}{N-I}\right) \end{aligned} \tag{25}$$

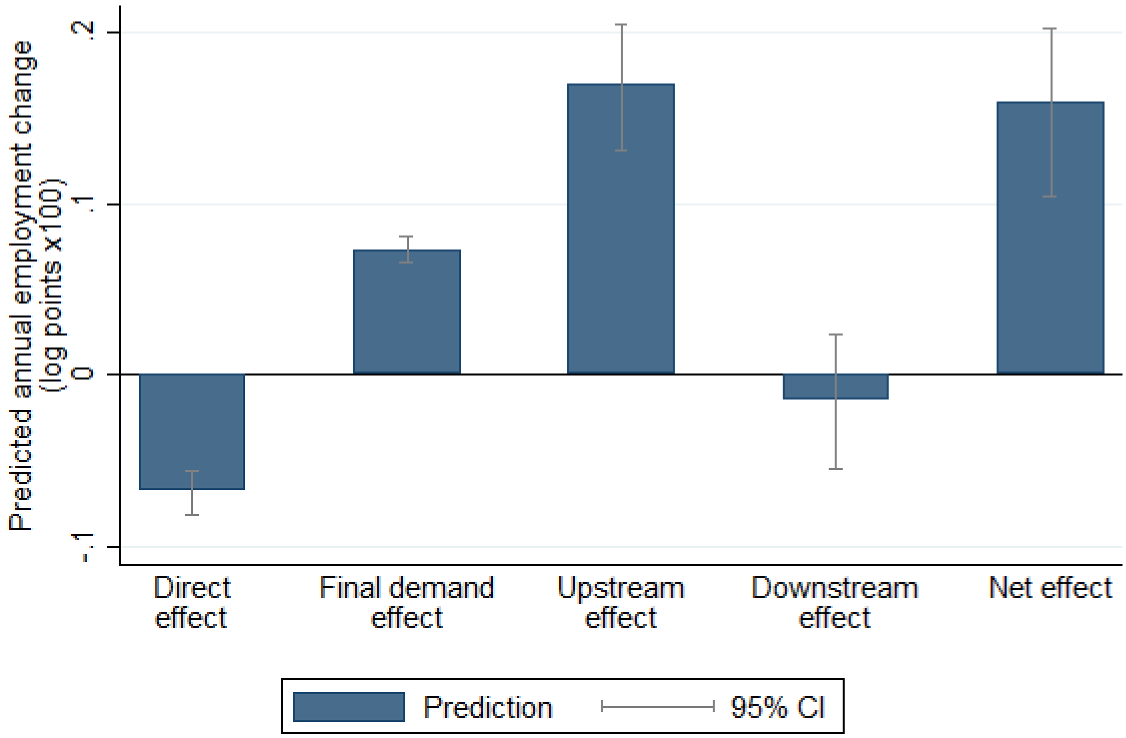
Finally, exponentiating both sides gives

$$\begin{aligned} Y = \exp&\left[\int_{N-1}^{I} \ln \gamma_M(x)\, dx + \int_{I}^{N} \ln \gamma_L(x)\, dx\right] \\ &\times \left(\frac{\alpha_M M}{I-N+1}\right)^{(I-N+1)} \left(\frac{\alpha_L L}{N-1}\right)^{(N-I)}, \end{aligned} \tag{26}$$

which is identical to eqn. (3) in the text.

9. Figures

Figure 1A: Predicted Effects of TFP Growth on Aggregate Employment, 1970 – 2007



Based on models 1 and 5 from Table 4. Predictions averaged across country-years.
Confidence interval constructed by bootstrapping predictions.

Figure 1B: Predicted Effects of TFP Growth on Aggregate Hours of Labor Input, 1970 – 2007

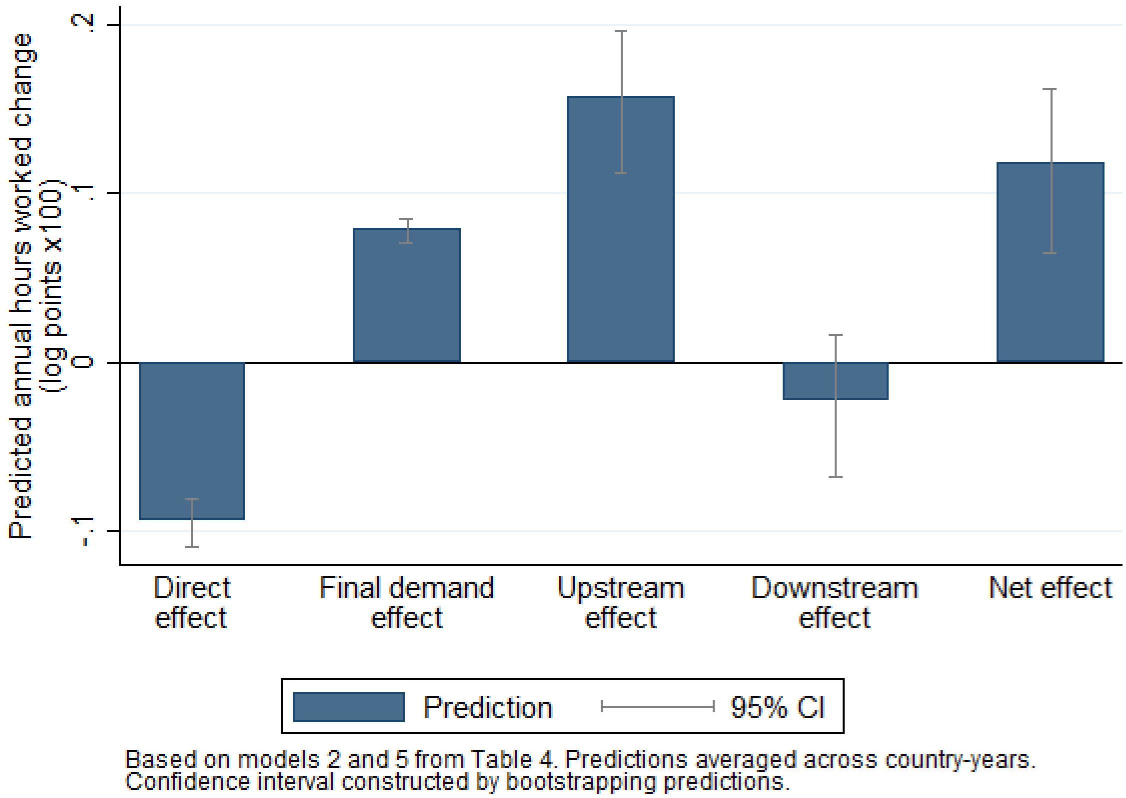
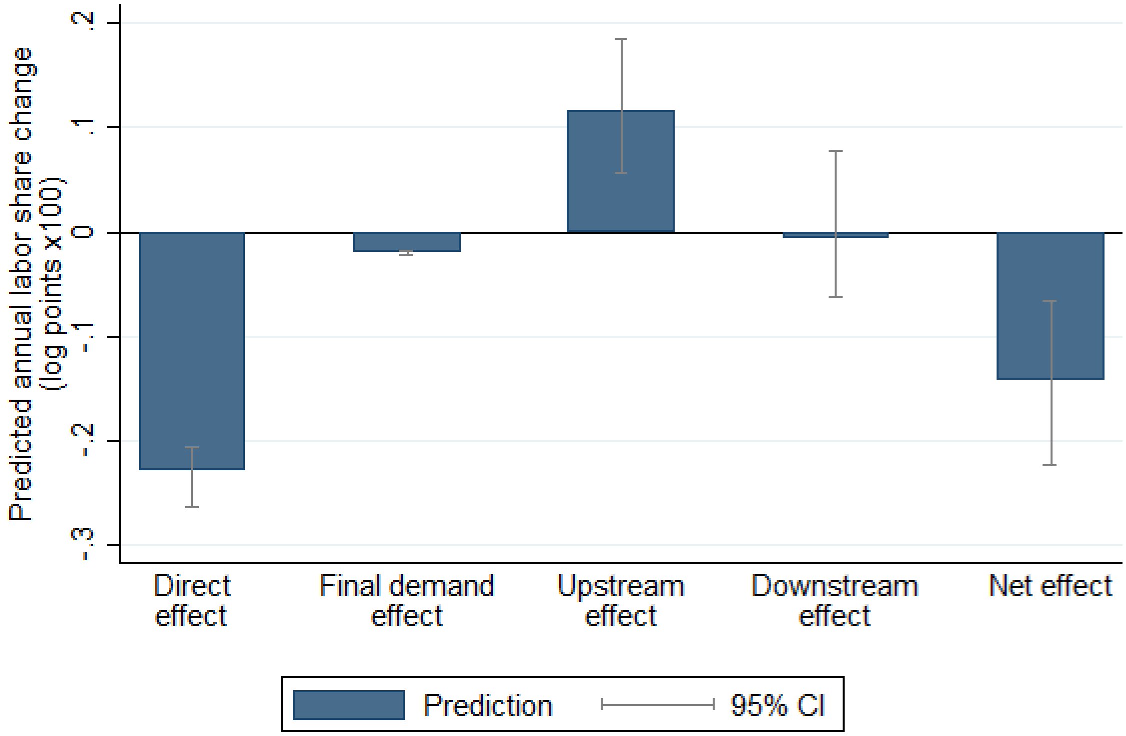
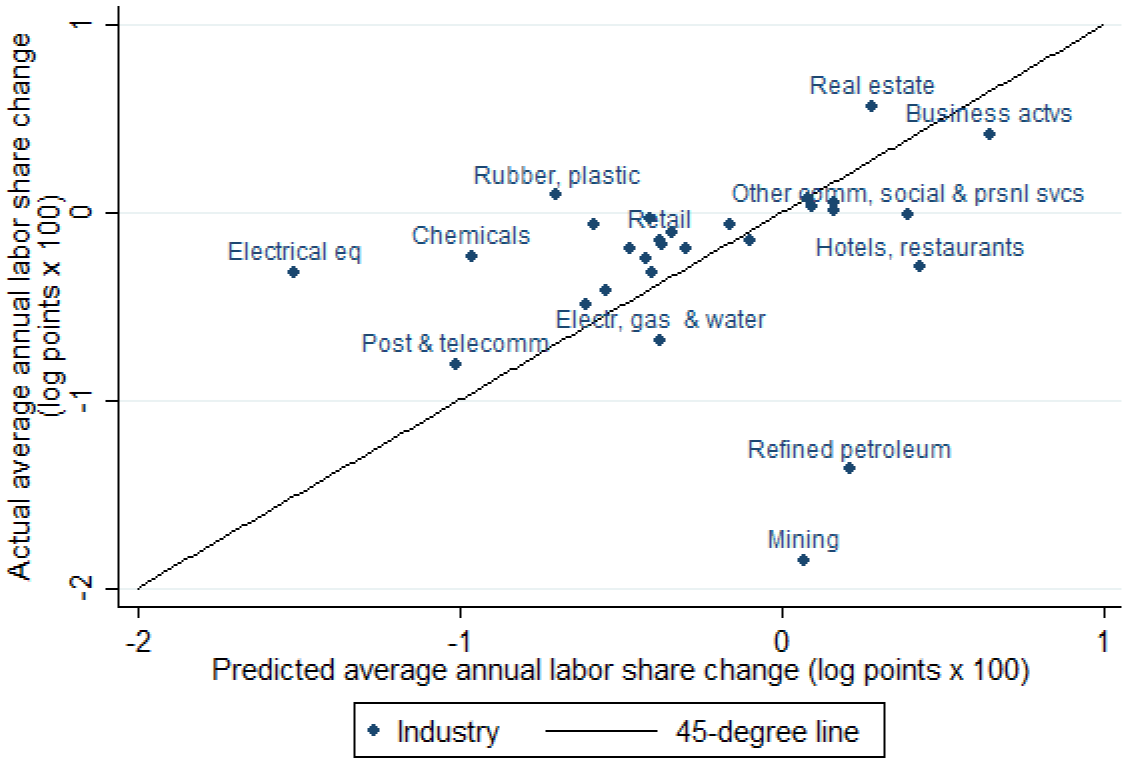


Figure 1C: Predicted Effects of TFP Growth on Aggregate Labor Share, 1970 – 2007



Based on models 8 and 5 from Table 4. Predictions averaged across country-years.
Confidence interval constructed by bootstrapping predictions.

Figure 1D: Actual versus Predicted Labor Share Change by Industry, 1970 – 2007



Prediction based on models 8 and 5 in Table 4.

Figure 2A: Predicted Effects of TFP Growth on Aggregate Hours of Labor Input by Decade, 1970 – 2007

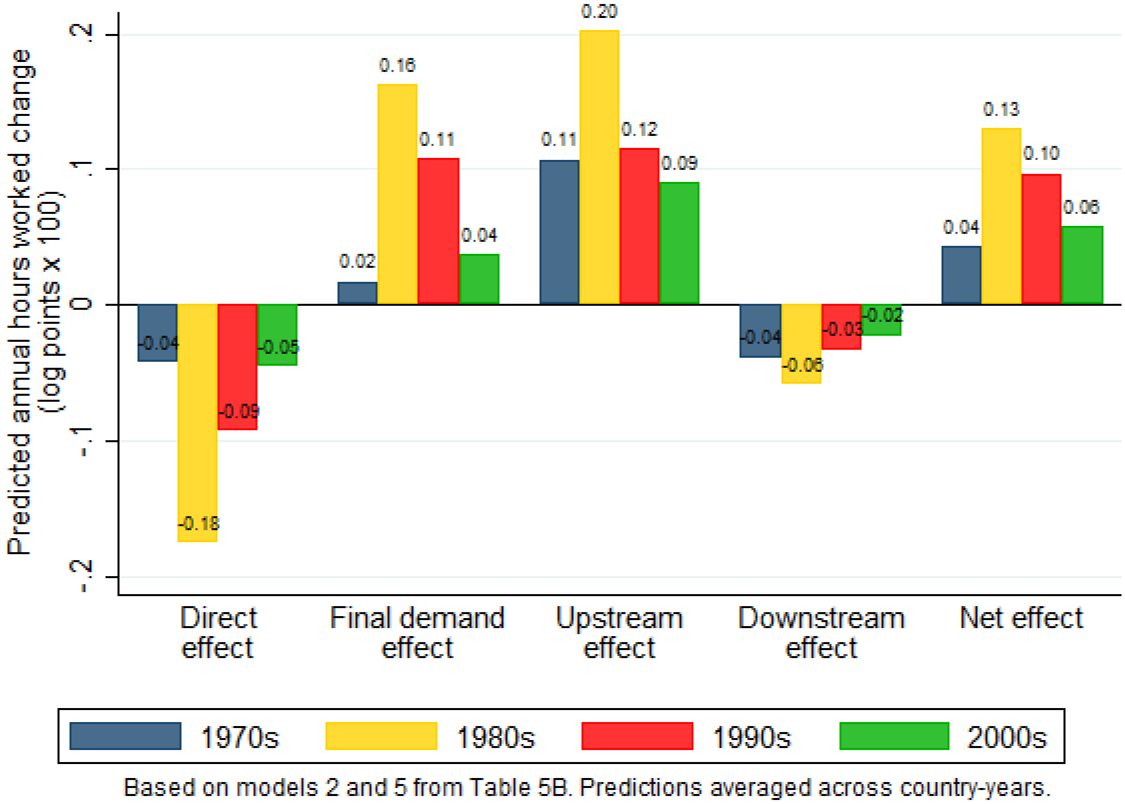
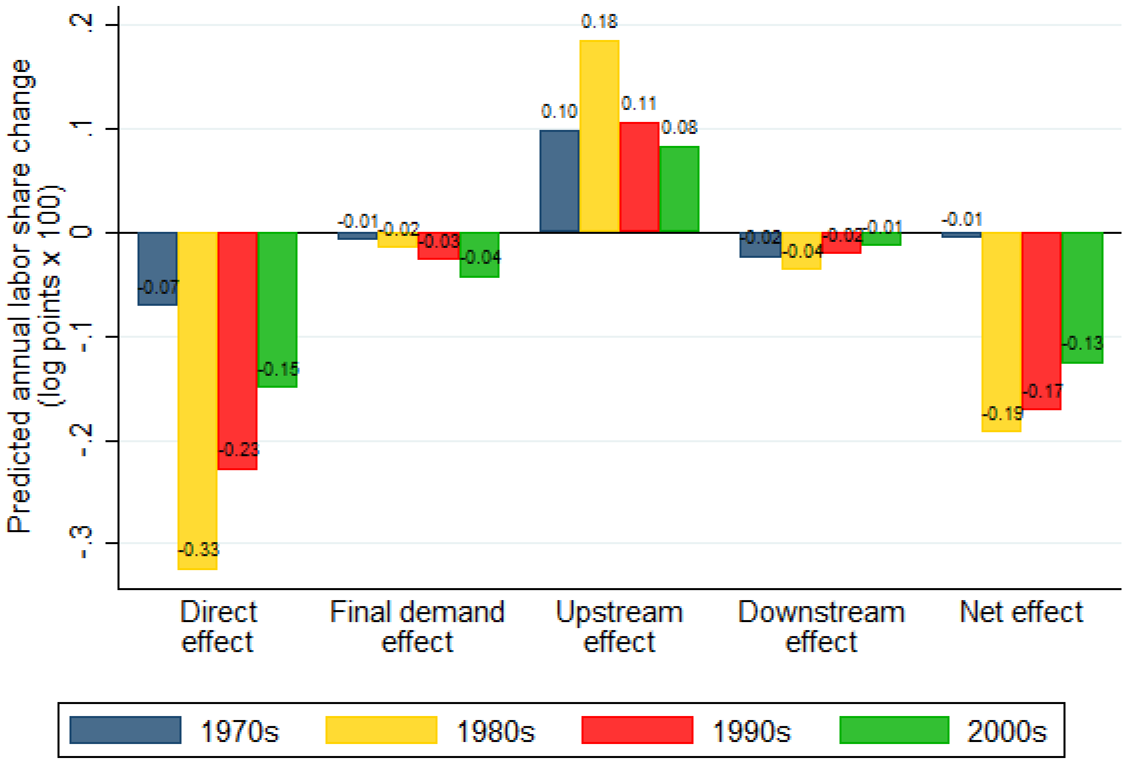
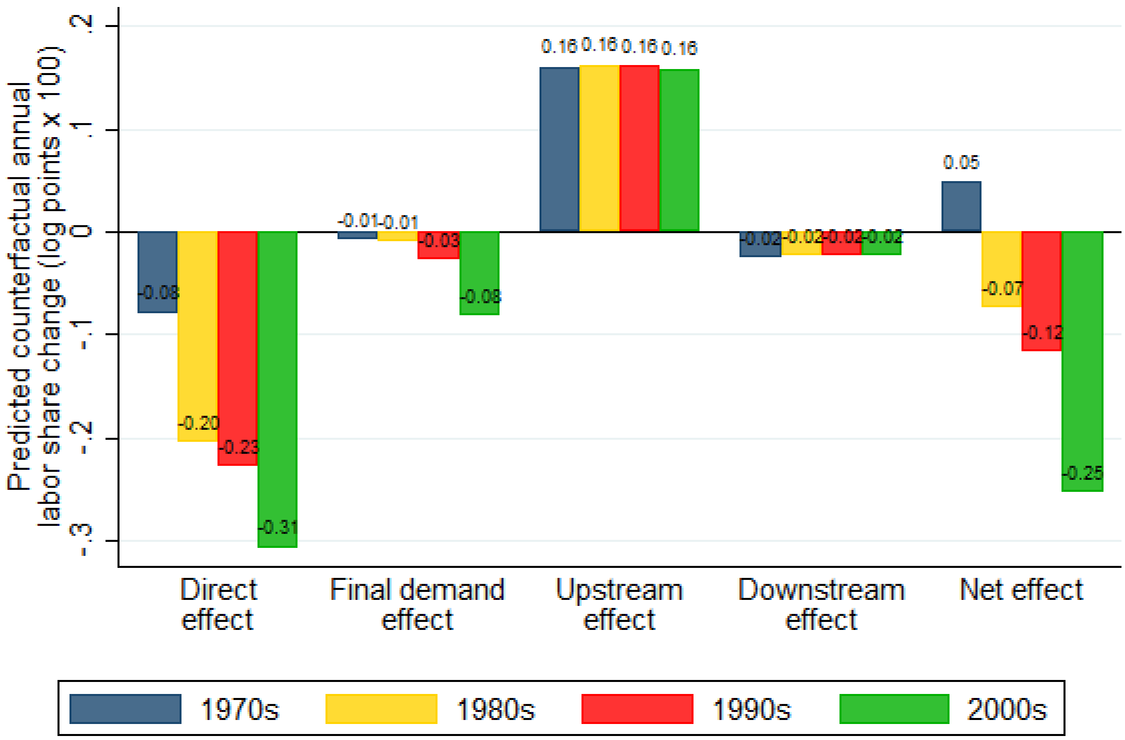


Figure 2B: Predicted Effects of TFP Growth on Aggregate Labor Share by Decade, 1970 – 2007



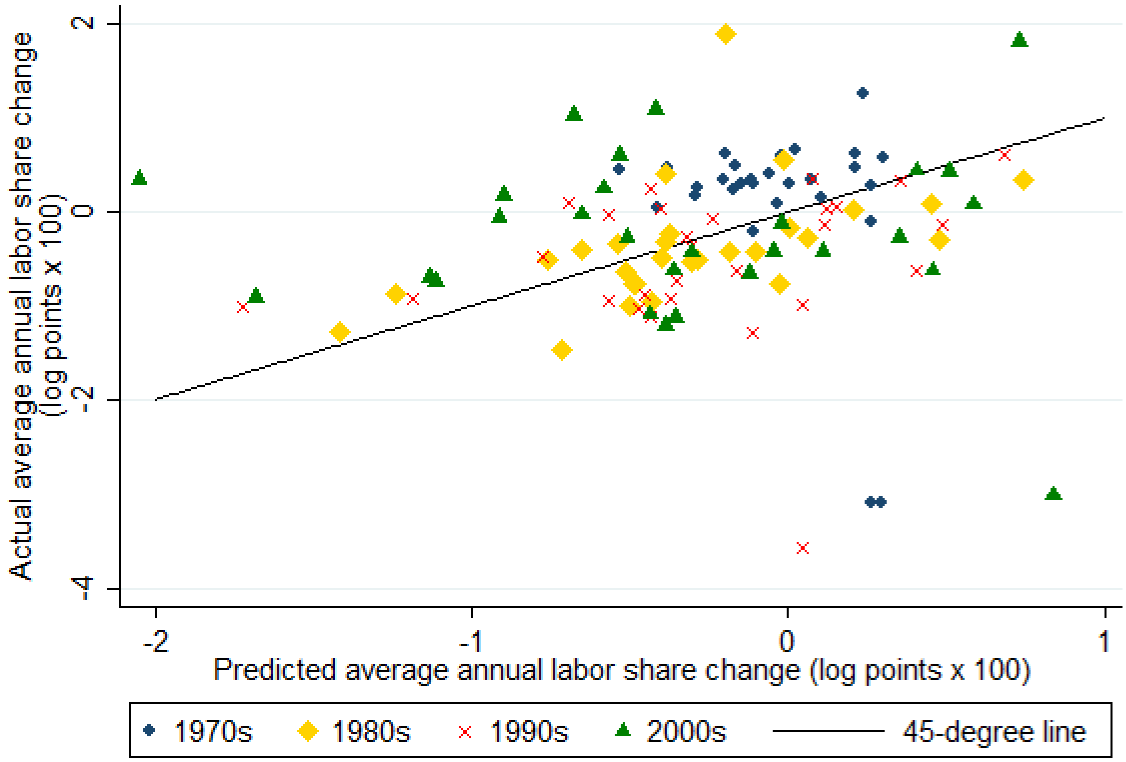
Based on models 8 and 5 from Table 5B. Predictions averaged across country-years.

Figure 2C: Counterfactual Predicted Effects of TFP Growth on Aggregate Labor Share by Decade, 1970 – 2007; TFP Growth Equalized Across Years



Based on models 8 and 5 from Table 5B. Predictions averaged across country-years.
TFP growth equalized across years, set to average annual growth in the 1990s.

Figure 2D: Actual versus Predicted Labor Share Change by Industry-Decade, 1970 – 2007



Prediction based on models 8 and 5 in Table 5B.

10. Tables

Table 1A

EUKLEMS data coverage by country

ISO code	*Country*	*Years*
AUS	Australia	1982-2007
AUT	Austria	1980-2007
BEL	Belgium	1980-2006
CAN	Canada	1970-2004
DNK	Denmark	1980-2007
ESP	Spain	1970-2007
FIN	Finland	1970-2007
FRA	France	1980-2007
GER	Germany	1970-2007
IRL	Ireland	1988-2007
ITA	Italy	1970-2007
JPN	Japan	1973-2006
KOR	South Korea	1977-2005
LUX	Luxembourg	1986-2005
NLD	Netherlands	1979-2007
PRT	Portugal	1995-2005
SWE	Sweden	1993-2007
UK	United Kingdom	1970-2007
USA	United States	1970-2005

Notes: Data coverage for TFP and employment. EUKLEMS database, 2008 release supplemented with information from 2009 and 2007 releases. Greece excluded for lack of TFP data.

Table 1B

EUKLEMS data coverage: industry

ISIC code	*Description*	*Sector grouping*
C	Mining and quarrying	1. Mining, utilities, and construction
15t16	Food, beverages, and tobacco	2. Manufacturing
17t19	Textiles, textile , leather, and footwear	2. Manufacturing
20	Wood and wood products	2. Manufacturing
21t22	Pulp, paper, paper, printing, and publishing	2. Manufacturing
23	Coke, refined petroleum and nuclear fuel	2. Manufacturing
24	Chemicals and chemical products	2. Manufacturing
25	Rubber and plastics	2. Manufacturing
26	Other non-metallic mineral	2. Manufacturing
27t28	Basic metals and fabricated metal	2. Manufacturing
29	Machinery, not elsewhere classified	2. Manufacturing
30t33	Electrical and optical equipment	2. Manufacturing
34t35	Transport equipment	2. Manufacturing
36t37	Manufacturing not elsewhere classified; recycling	2. Manufacturing
E	Electricity, gas, and water supply	1. Mining, utilities, and construction
F	Construction	1. Mining, utilities, and construction
50	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	5. Low-tech services
51	Wholesale trade and commission trade, except of motor vehicles and motorcycles	5. Low-tech services
52	Retail trade, except of motor vehicles and motorcycles; repair of household goods	5. Low-tech services
H	Hotels and restaurants	5. Low-tech services
60t63	Transport and storage	5. Low-tech services
64	Post and telecommunications	4. High-tech services
J	Financial intermediation	4. High-tech services
70	Real estate activities	5. Low-tech services
71t74	Renting of machinery & equipment and other business activities	4. High-tech services
M	Education	3. Health and education
N	Health and social work	3. Health and education
O	Other community, social and personal service activities	5. Low-tech services

Notes: ISIC revision 3 codes. We exclude agriculture (industry AtB), public administration (industry L), private households (P) and extra-territorial organizations (Q) from our analyses.

Table 2

dependent variable: 100 x log outcome by country-industry-year

	Labor share	Hours worked	Nominal hrly wage	Real hrly wage	Nominal value added	TFP
Linear timetrend	-0.169**	1.108**	7.507**	0.017**	8.784**	0.616**
	(0.059)	(0.129)	(0.159)	(0.001)	(0.200)	(0.110)
R2	0.843	0.913	0.954	0.977	0.955	0.131
Linear timetrend for:						
1970s	0.085	1.683**	14.064**	0.027**	15.662**	-0.103
	(0.140)	(0.181)	(0.258)	(0.002)	(0.324)	(0.289)
1980s	-0.318**	1.357**	7.559**	0.018**	9.234**	0.936**
	(0.109)	(0.179)	(0.237)	(0.001)	(0.259)	(0.175)
1990s	-0.559**	1.136**	3.922**	0.014**	5.617**	0.659**
	(0.114)	(0.157)	(0.144)	(0.001)	(0.210)	(0.134)
2000s	-0.286~	1.307**	3.987**	0.015**	5.580**	0.381~
	(0.170)	(0.243)	(0.225)	(0.002)	(0.309)	(0.222)
Decade fixed effects	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R2	0.843	0.913	0.965	0.977	0.961	0.134
Linear timetrend for:						
Mining & utilities & construction	-0.372*	-0.066	7.636**	0.019**	7.941**	0.309
	(0.173)	(0.334)	(0.581)	(0.003)	(0.687)	(0.214)
Manufacturing	-0.259**	-0.692**	7.973**	0.021**	7.540**	2.002**
	(0.070)	(0.149)	(0.230)	(0.001)	(0.341)	(0.189)
Education & health	0.014	2.005**	7.278**	0.017**	9.269**	-0.495**
	(0.073)	(0.170)	(0.461)	(0.002)	(0.543)	(0.139)
Low-tech services	-0.090	1.560**	7.330**	0.014**	8.980**	0.374*
	(0.134)	(0.221)	(0.258)	(0.001)	(0.315)	(0.174)
High-tech services	-0.188	3.179**	7.241**	0.017**	10.607**	-0.042
	(0.136)	(0.352)	(0.366)	(0.002)	(0.495)	(0.280)
R2	0.843	0.921	0.955	0.978	0.957	0.242
Fixed effects for all models:						
Country	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Industry	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Country * business cycle	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
N	20,191	20,191	20,191	20,023	20,191	15,538

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. All models weighted by industry value added shares within countries, averaged across all years. The number of observations is equal to the number of country-industry cells multiplied by the number of years. Standard errors are clustered by country-industry and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table 3A

The direct and indirect effects of productivity growth

dependent variable: annual change in log outcome by country-industry

	A. Employment				*B. Hours worked*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ ln TFP (cit)	-0.129**	-0.093**	-0.097**	-0.099**	-0.155**	-0.120**	-0.125**	-0.130**
	(0.016)	(0.015)	(0.015)	(0.016)	(0.019)	(0.017)	(0.017)	(0.018)
Δ ln nominal value added (ct)	-	-	0.300**	0.274**	-	-	0.300**	0.291**
			(0.032)	(0.032)			(0.032)	(0.034)
Upstream Σk Δ ln TFP (c, j≠i, t-k)	-	-	-	1.121**	-	-	-	1.082**
				(0.188)				(0.203)
Downstream Σk Δ ln TFP (c, j≠i, t-k)	-	-	-	-0.079	-	-	-	-0.136
				(0.159)				(0.156)
Fixed effects:								
Country	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Industry	*NO*	*YES*	*YES*	*YES*	*NO*	*YES*	*YES*	*YES*
Country * business cycle	*NO*	*YES*	*YES*	*YES*	*NO*	*YES*	*YES*	*YES*
R2	0.125	0.261	0.284	0.290	0.130	0.249	0.269	0.273
N	15,007	15,007	15,007	13,417	15,007	15,007	15,007	13,417
	C. Nominal hourly wage				*D. Nominal wagebill*			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Δ ln TFP (cit)	0.244**	0.247**	0.238**	0.242**	0.089**	0.127**	0.113**	0.112**
	(0.022)	(0.023)	(0.023)	(0.024)	(0.018)	(0.018)	(0.017)	(0.018)
Δ ln nominal value added (ct)	-	-	0.626**	0.597**	-	-	0.926**	0.888**
			(0.033)	(0.031)			(0.041)	(0.037)
Upstream Σk Δ ln TFP (c, j≠i, t-k)	-	-	-	-0.244	-	-	-	0.839**
				(0.260)				(0.297)
Downstream Σk Δ ln TFP (c, j≠i, t-k)	-	-	-	-0.115	-	-	-	-0.251
				(0.173)				(0.193)
Fixed effects:								
Country	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Industry	*NO*	*YES*	*YES*	*YES*	*NO*	*YES*	*YES*	*YES*
Country * business cycle	*NO*	*YES*	*YES*	*YES*	*NO*	*YES*	*YES*	*YES*
R2	0.277	0.284	0.318	0.332	0.275	0.323	0.386	0.399
N	15,007	15,007	15,007	13,417	15,007	15,007	15,007	13,417

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. All models weighted by industry value added shares within countries, averaged across all years. The number of observations is equal to the number of country-industry cells multiplied by the number of years; k=3. Standard errors are clustered by country-industry and reported in parentheses, ~ p<0.10, * p<0.05, **

Table 3B

The direct and indirect effects of productivity growth

dependent variable: annual change in log outcome by country-industry

	A. Nominal value added				*B. Value added price*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ ln TFP (cit)	0.406**	0.453**	0.437**	0.455**	-0.420**	-0.394**	-0.405**	-0.387**
	(0.028)	(0.029)	(0.028)	(0.031)	(0.031)	(0.033)	(0.032)	(0.035)
Δ ln nominal value added (ct)	-	-	0.991**	0.971**	-	-	0.707**	0.705**
			(0.059)	(0.057)			(0.054)	(0.049)
Upstream Σk Δ ln TFP (c, j≠i, t-k)	-	-	-	0.044	-	-	-	-0.898**
				(0.304)				(0.257)
Downstream Σk Δ ln TFP (c, j≠i, t-k)	-	-	-	-0.323	-	-	-	-0.209
				(0.356)				(0.303)
Fixed effects:								
Country	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Industry	*NO*	*YES*	*YES*	*YES*	*NO*	*YES*	*YES*	*YES*
Country * business cycle	*NO*	*YES*	*YES*	*YES*	*NO*	*YES*	*YES*	*YES*
R2	0.343	0.392	0.469	0.459	0.369	0.387	0.438	0.429
N	15,007	15,007	15,007	13,417	15,007	15,007	15,007	13,417
	C. Real value added				*D. Labor share*			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Δ ln TFP (cit)	0.827**	0.847**	0.843**	0.842**	-0.317**	-0.325**	-0.324**	-0.343**
	(0.016)	(0.014)	(0.014)	(0.015)	(0.024)	(0.025)	(0.025)	(0.028)
Δ ln nominal value added (ct)	-	-	0.284**	0.266**	-	-	-0.065	-0.083
			(0.025)	(0.026)			(0.055)	(0.053)
Upstream Σk Δ ln TFP (c, j≠i, t-k)	-	-	-	0.945**	-	-	-	0.794**
				(0.181)				(0.299)
Downstream Σk Δ ln TFP (c, j≠i, t-k)	-	-	-	-0.118	-	-	-	0.072
				(0.147)				(0.293)
Fixed effects:								
Country	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Industry	*NO*	*YES*	*YES*	*YES*	*NO*	*YES*	*YES*	*YES*
Country * business cycle	*NO*	*YES*	*YES*	*YES*	*NO*	*YES*	*YES*	*YES*
R2	0.677	0.733	0.744	0.738	0.075	0.087	0.088	0.106
N	15,007	15,007	15,007	13,417	15,007	15,007	15,007	13,417

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. All models weighted by industry value added shares within countries, averaged across all years. The number of observations is equal to the number of country-industry cells multiplied by the number of years; k=3. Standard errors are clustered by country-industry and reported in parentheses, ~ $p<0.10$, * $p<0.05$, **

Table 4

The direct and indirect effects of productivity growth *dependent variable: annual change in log outcome by country-industry*								
	Employmen	*Hours*	*Hrly wage*	*Wagebill*	*Nominal VA*	*VA price*	*Real VA*	*Labor share*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ ln TFP (cit)	-0.101**	-0.140**	0.259**	0.119**	0.461**	-0.377**	0.838**	-0.342**
	(0.018)	(0.020)	(0.026)	(0.021)	(0.035)	(0.041)	(0.017)	(0.032)
Δ ln nominal value added (ct)	0.272**	0.293**	0.593**	0.885**	0.963**	0.693**	0.271**	-0.078
	(0.033)	(0.035)	(0.035)	(0.040)	(0.052)	(0.044)	(0.027)	(0.049)
Upstream Σk Δ ln TFP (c, j≠i, t-k)	1.343**	1.246**	-0.407	0.839*	-0.075	-1.232**	1.153**	0.914*
	(0.234)	(0.245)	(0.316)	(0.374)	(0.336)	(0.286)	(0.189)	(0.388)
Downstream Σk Δ ln TFP (c, j≠i, t-	-0.089	-0.132	-0.044	-0.176	-0.135	0.071	-0.209	-0.041
k)	(0.203)	(0.196)	(0.205)	(0.248)	(0.238)	(0.210)	(0.140)	(0.285)
Fixed effects:								
Country, industry, year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Industry*year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Country*industry*business cycle	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R2	0.463	0.444	0.456	0.533	0.640	0.605	0.816	0.308
N	13,417	13,417	13,417	13,417	13,417	13,417	13,417	13,417

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. All models weighted by industry value added shares within countries, averaged across all years. The number of observations is equal to the number of country-industry cells multiplied by the number of years; k=3. Standard errors are clustered by country-industry and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table 5

The direct and spillover effects of productivity growth

dependent variable: log annualized long change in outcome by country-industry

	Employment	*Hours*	*Hrly wage*	*Wagebill*	*Nominal VA*	*VA price*	*Real VA*	*Labor share*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				A. 5-year differences				
Δ ln TFP (cit)	-0.106**	-0.121**	0.211**	0.090~	0.350**	-0.477**	0.828**	-0.260**
	(0.024)	(0.028)	(0.048)	(0.046)	(0.040)	(0.050)	(0.030)	(0.043)
Δ ln nominal value added (ct)	0.335**	0.342**	0.715**	1.057**	1.083**	0.716**	0.367**	-0.026
	(0.049)	(0.049)	(0.069)	(0.078)	(0.058)	(0.043)	(0.039)	(0.064)
Upstream Δ ln TFP (c, j≠i, t)	0.607**	0.957**	-1.230**	-0.272	-0.399	-1.200**	0.797**	0.127
	(0.189)	(0.216)	(0.475)	(0.443)	(0.317)	(0.294)	(0.186)	(0.407)
Downstream Δ ln TFP (c, j≠i, t)	-0.576**	-0.709**	0.230	-0.480*	-0.460~	0.158	-0.616**	-0.020
	(0.207)	(0.219)	(0.236)	(0.234)	(0.243)	(0.232)	(0.180)	(0.210)
Fixed effects:								
Country, industry, period	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Country*industry	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Industry*period	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R2	0.648	0.641	0.706	0.760	0.823	0.819	0.830	0.296
N	2,934	2,934	2,934	2,934	2,934	2,934	2,934	2,934
				B. 10-year differences				
Δ ln TFP (cit)	-0.208**	-0.213**	0.378**	0.165**	0.326**	-0.435**	0.762**	-0.160**
	(0.045)	(0.044)	(0.063)	(0.048)	(0.048)	(0.054)	(0.034)	(0.050)
Δ ln nominal value added (ct)	0.233**	0.240**	0.959**	1.199**	1.171**	0.914**	0.258**	0.028
	(0.074)	(0.072)	(0.076)	(0.088)	(0.091)	(0.083)	(0.049)	(0.075)
Upstream Δ ln TFP (c, j≠i, t)	0.913*	0.726	-0.705	0.021	-0.238	-0.736~	0.487	0.259
	(0.458)	(0.447)	(0.475)	(0.569)	(0.450)	(0.386)	(0.311)	(0.381)
Downstream Δ ln TFP (c, j≠i, t)	-0.496	-0.273	-0.442	-0.715~	-0.790*	-0.355	-0.431~	0.075
	(0.342)	(0.337)	(0.408)	(0.366)	(0.365)	(0.365)	(0.250)	(0.307)
Fixed effects:								
Country, industry, period	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Country*industry	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Industry*period	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R2	0.741	0.749	0.864	0.892	0.886	0.873	0.876	0.418
N	2,934	2,934	2,934	2,934	2,934	2,934	2,934	2,934

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. All models weighted by industry value added shares within countries, averaged across all years. The number of observations is equal to the number of country-industry cells multiplied by the number of periods. Standard errors are clustered by country-industry and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table 6A

The sector-specific direct and indirect effects of productivity growth *dependent variable: annual change in log outcome by country-industry*								
	Employment	*Hours*	*Hrly wage*	*Wagebill*	*Nominal VA*	*VA price*	*Real VA*	*Labor share*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ ln TFP (cit)								
Mining & utilities & construction	-0.182**	-0.227**	0.357**	0.129~	0.441**	-0.383**	0.823**	-0.311**
	(0.046)	(0.050)	(0.082)	(0.077)	(0.069)	(0.065)	(0.037)	(0.081)
Manufacturing	-0.050**	-0.055**	0.136**	0.080**	0.449**	-0.468**	0.918**	-0.369**
	(0.015)	(0.017)	(0.025)	(0.018)	(0.060)	(0.069)	(0.016)	(0.055)
Education & health	-0.194**	-0.411**	0.484**	0.073	0.198**	-0.294**	0.506**	-0.125*
	(0.047)	(0.066)	(0.082)	(0.063)	(0.063)	(0.056)	(0.071)	(0.053)
Low-tech services	-0.125**	-0.190**	0.399**	0.209**	0.577**	-0.228**	0.804**	-0.368**
	(0.048)	(0.050)	(0.050)	(0.054)	(0.050)	(0.044)	(0.035)	(0.056)
High-tech services	-0.136**	-0.197**	0.315**	0.118*	0.419**	-0.315**	0.734**	-0.301**
	(0.048)	(0.055)	(0.044)	(0.056)	(0.066)	(0.050)	(0.037)	(0.054)
Δ ln nominal value added (ct)								
Mining & utilities & construction	0.416**	0.438**	0.573**	1.011**	1.311**	0.899**	0.411**	-0.300**
	(0.134)	(0.131)	(0.087)	(0.142)	(0.168)	(0.104)	(0.112)	(0.112)
Manufacturing	0.269**	0.282**	0.630**	0.912**	0.990**	0.706**	0.284**	-0.077~
	(0.034)	(0.039)	(0.036)	(0.043)	(0.055)	(0.050)	(0.031)	(0.044)
Education & health	0.046	0.043	0.560**	0.603**	0.631**	0.561**	0.069~	-0.028
	(0.041)	(0.047)	(0.085)	(0.101)	(0.107)	(0.084)	(0.036)	(0.054)
Low-tech services	0.309**	0.343**	0.506**	0.849**	0.875**	0.625**	0.251**	-0.026
	(0.066)	(0.071)	(0.083)	(0.074)	(0.082)	(0.070)	(0.046)	(0.082)
High-tech services	0.249**	0.286**	0.735**	1.021**	1.084**	0.729**	0.354**	-0.063
	(0.070)	(0.062)	(0.072)	(0.083)	(0.176)	(0.182)	(0.061)	(0.200)
Upstream Σk Δ ln TFP (c, j≠i, t-k)	1.314**	1.209**	-0.386	0.822*	-0.152	-1.262**	1.107**	0.974*
	(0.229)	(0.242)	(0.321)	(0.369)	(0.323)	(0.275)	(0.182)	(0.389)
Downstream Σk Δ ln TFP (c, j≠i, t-k)	-0.078	-0.119	-0.118	-0.237	-0.183	0.031	-0.217	-0.054
	(0.201)	(0.195)	(0.201)	(0.246)	(0.231)	(0.206)	(0.141)	(0.280)
Fixed effects:								
Country, industry, year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Industry*year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Country*industry*business cycle	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R2	0.468	0.454	0.462	0.535	0.645	0.611	0.822	0.310
N	13,417	13,417	13,417	13,417	13,417	13,417	13,417	13,417

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. All models weighted by industry value added shares within countries, averaged across all years; k=3. The number of observations is equal to the number of country-industry cells multiplied by the number of years. Standard errors are clustered by country-industry and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table 6B

The decade-specific direct direct and indirect effects of productivity growth

dependent variable: annual change in log outcome by country-industry

	Employment	*Hours*	*Hrly wage*	*Wagebill*	*Nominal VA*	*VA price*	*Real VA*	*Labor share*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ ln TFP (cit)								
1970s	-0.069**	-0.082**	0.253**	0.170**	0.308**	-0.591**	0.899**	-0.138**
	(0.021)	(0.023)	(0.055)	(0.048)	(0.050)	(0.056)	(0.021)	(0.045)
1980s	-0.131**	-0.173**	0.307**	0.135**	0.455**	-0.376**	0.832**	-0.321**
	(0.027)	(0.030)	(0.039)	(0.037)	(0.051)	(0.055)	(0.023)	(0.050)
1990s	-0.089**	-0.137**	0.279**	0.142**	0.478**	-0.360**	0.838**	-0.336**
	(0.025)	(0.030)	(0.042)	(0.035)	(0.058)	(0.071)	(0.026)	(0.049)
2000s	-0.111**	-0.143**	0.181**	0.038	0.504**	-0.307**	0.813**	-0.466**
	(0.021)	(0.025)	(0.026)	(0.024)	(0.040)	(0.044)	(0.020)	(0.048)
Δ ln nominal value added (ct)								
1970s	0.086*	0.121**	0.801**	0.922**	0.974**	0.829**	0.146**	-0.053
	(0.039)	(0.040)	(0.055)	(0.042)	(0.043)	(0.038)	(0.027)	(0.041)
1980s	0.351**	0.405**	0.538**	0.943**	0.981**	0.666**	0.315**	-0.037
	(0.041)	(0.047)	(0.045)	(0.053)	(0.055)	(0.050)	(0.031)	(0.059)
1990s	0.398**	0.393**	0.447**	0.840**	0.941**	0.578**	0.363**	-0.102
	(0.069)	(0.070)	(0.059)	(0.073)	(0.101)	(0.073)	(0.063)	(0.088)
2000s	0.325**	0.242**	0.374**	0.617**	0.905**	0.584**	0.325**	-0.288**
	(0.062)	(0.059)	(0.063)	(0.074)	(0.102)	(0.101)	(0.047)	(0.101)
Upstream Σk Δ ln TFP (c, j≠i, t-k)	1.102**	1.056**	-0.057	1.000**	0.033	-0.936**	0.962**	0.967*
	(0.238)	(0.250)	(0.330)	(0.373)	(0.340)	(0.298)	(0.186)	(0.409)
Downstream Σk Δ ln TFP (c, j≠i, t-k)	-0.135	-0.228	-0.066	-0.294	-0.151	0.084	-0.237~	-0.143
	(0.196)	(0.187)	(0.209)	(0.244)	(0.236)	(0.209)	(0.137)	(0.282)
Fixed effects:								
Country, industry, year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Industry*year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Country*industry*business cycle	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R2	0.470	0.450	0.460	0.535	0.641	0.610	0.818	0.312
N	13,417	13,417	13,417	13,417	13,417	13,417	13,417	13,417

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. All models weighted by industry value added shares within countries, averaged across all years. The number of observations is equal to the number of country-industry cells multiplied by the number of years; k=3. Standard errors are clustered by country-industry and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table 7

The direct and indirect effects of productivity growth

dependent variable: annual change in log outcome by country-industry

	Employment	*Hours*	*Hrly wage*	*Wagebill*	*Nominal VA*	*VA price*	*Real VA*	*Labor share*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ ln TFP (cit)	-0.042~	-0.050*	-0.045	-0.095	0.548**	-0.346**	0.893**	-0.642**
	(0.024)	(0.025)	(0.067)	(0.071)	(0.051)	(0.060)	(0.036)	(0.090)
Δ ln nominal value added (ct)	0.475**	0.665**	0.165	0.830**	0.830**	0.363*	0.467**	-0.000
	(0.082)	(0.094)	(0.129)	(0.152)	(0.175)	(0.155)	(0.077)	(0.188)
Fixed effects:								
Country, industry, year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Industry * year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Country * industry * business cycle	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R2	0.721	0.766	0.383	0.485	0.799	0.682	0.948	0.564
N	2,360	2,360	2,360	2,360	2,360	2,360	2,360	2,360

Notes: EUKLEMS 2017 release, 2007-2015. Excludes agriculture, public administration, private households, and extra-territorial organizations. All models weighted by value added employment shares within countries, averaged across all years. The number of observations is equal to the number of country-industry cells multiplied by the number of years. Standard errors are clustered by country-industry and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table 8

The effects of productivity growth, instrumented by patenting
dependent variable: annual change in log outcome by country-industry

	Employment	*Hours*	*Hrly wage*	*Wagebill*	*Nominal VA*	*VA price*	*Real VA*	*Labor share*
	(1)	(2)	(3)	(4)	(5)	(7)	(6)	(8)
Δ ln TFP (cit)	-0.542**	-0.523**	0.165	-0.358*	-0.011	-1.111**	1.101**	-0.348**
	(0.166)	(0.172)	(0.102)	(0.179)	(0.155)	(0.124)	(0.202)	(0.116)
Δ ln nominal value added (ct)	0.344**	0.340**	0.633**	0.973**	1.036**	0.776**	0.261**	-0.063
	(0.038)	(0.039)	(0.036)	(0.046)	(0.059)	(0.056)	(0.031)	(0.055)
Fixed effects:								
Country, year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Country * business cycle	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
N	14,942	14,942	14,942	14,942	14,942	14,942	14,942	14,942
					First stage for Δ ln TFP			
ln patent citations (cit) ^	0.254**	0.254**	0.254**	0.254**	0.254**	0.254**	0.254**	0.254**
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)
First-stage F-stat	26.2	26.2	26.2	26.2	26.2	26.2	26.2	26.2
Montiel-Pflueger weak instrument F-stat	71.6	71.6	71.6	71.6	71.6	71.6	71.6	71.6

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. All models weighted by industry value added shares within countries, averaged across all years. The number of observations is equal to the number of country-industry cells multiplied by the number of years. ^Coefficients and standard errors multiplied by 100. Standard errors are clustered by country-industry and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table 9

The effects of productivity growth, instrumented by robot penetration
dependent variable: annual change in log outcome by country-industry

	Employment	*Hours*	*Hrly wage*	*Wagebill*	*Nominal VA*	*VA price*	*Real VA*	*Labor share*
	(1)	(2)	(3)	(4)	(5)	(7)	(6)	(8)
Δ ln TFP (cit)	-0.318	-0.201	0.133	-0.068	0.127	-0.610*	0.737~	-0.195
	(0.329)	(0.370)	(0.236)	(0.395)	(0.371)	(0.263)	(0.408)	(0.300)
Δ ln nominal value added (ct)	0.476**	0.351**	0.461**	0.811**	1.033**	0.657**	0.377**	-0.222
	(0.116)	(0.116)	(0.124)	(0.147)	(0.116)	(0.081)	(0.107)	(0.151)
Fixed effects:								
Country, year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Country * business cycle	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
N	3,212	3,212	3,212	3,212	3,212	3,212	3,212	3,212
				First stage for Δ ln TFP (cit)				
Δ Robots per 1,000 workers (cit)	0.175**	0.175**	0.175**	0.175**	0.175**	0.175**	0.175**	0.175**
	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)
First-stage F-stat	13.2	13.2	13.2	13.2	13.2	13.2	13.2	13.2
Montiel-Pflueger weak instrument F-stat	35.4	35.4	35.4	35.4	35.4	35.4	35.4	35.4

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. All models weighted by industry value added shares within countries, averaged across all years. The number of observations is equal to the number of country-industry cells multiplied by the number of years. Standard errors are clustered by country-industry and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

11. Appendix Tables

Appendix Table 1A

EUKLEMS 2017 data coverage by country

ISO code	*Country*	*Years*
AUT	Austria	1996-2015
BEL	Belgium	1999-2015
DNK	Denmark	1996-2015
ESP	Spain	1996-2015
FIN	Finland	1985-2015
FRA	France	1981-2015
GER	Germany	1996-2015
ITA	Italy	1996-2014
LUX	Luxembourg	2009-2015
NLD	Netherlands	2001-2015
SWE	Sweden	1994-2014
UK	United Kingdom	1998-2015
USA	United States	2000-2015

Notes: Data coverage for TFP and outcome variables. EUKLEMS database, 2017 release.

Appendix Table 1B

EUKLEMS 2017 data coverage: industry

ISIC code	*Description*
B	Mining and quarrying
10-12	Food products, beverages and tobacco
13-15	Textiles, wearing apparel, leather and related prodcuts
16-18	Wood and paper products; printing and reproduction of recorded media
19	Coke and refined petroleum products
20-21	Chemicals and chemical products
22-23	Rubber and plastics products, and other non-metallic mineral products
24-25	Basic metals and fabricated metal products, except machinery and equipment
26-27	Electrical and optical equipment
28	Machinery and equipment n.e.c.
29-30	Transport equipment
31-33	Other manufacturing; repair and installation of machinery and equipment
D-E	Electricity, gas and water supply
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M-N	Professional, scientific, technical, administrative and support service activities
P	Education
Q	Health and social work
R-S	Arts, entertainment, recreation and other service activities

Notes: ISIC revision 4 codes. We exclude Agriculture, forestry and fishing (industry A), public administration (industry O), and private households (T) and extra-territorial organizations (U) from our analyses. Industries 10-12 through 31-33 are manufacturing industries.

Appendix Table 2A

Average annual growth in employment and productivity by country

	100 x Δ log employment				*100 x Δ log Total Factor Productivity*			
	1970-1980	*1980-1990*	*1990-2000*	*2000-2007*	*1970-1980*	*1980-1990*	*1990-2000*	*2000-2007*
AUS	1.44	1.88	1.64	2.42	.	0.32	0.89	-0.43
AUT	1.37	0.55	1.02	0.99	.	1.06	0.98	0.91
BEL	0.19	0.32	0.69	1.02	.	0.89	-0.35	-0.03
CAN	2.97	2.02	1.50	2.01	0.14	-0.39	0.57	-0.03
DNK	0.62	0.69	0.64	0.82	.	0.65	0.23	-0.16
ESP	1.06	1.70	2.44	3.65	0.64	0.60	-0.48	-0.65
FIN	1.19	1.03	-0.54	1.39	0.49	0.53	1.55	1.36
FRA	1.09	0.51	0.74	0.97	.	1.31	0.59	0.39
GER	0.49	1.13	0.68	0.33	1.89	0.86	0.69	0.73
GRC	2.65	1.44	1.13	1.76	.	.	.	.
IRL	1.92	0.78	4.18	3.53	.	1.17	2.20	0.16
ITA	1.48	0.99	0.36	1.47	0.99	0.30	0.40	-0.62
JPN	1.59	1.44	0.49	-0.07	1.11	1.70	-0.13	0.28
KOR	6.30	4.79	2.12	2.06	0.29	4.54	2.64	0.96
LUX	1.56	2.03	3.51	3.46	.	1.36	0.46	0.11
NLD	0.59	1.50	2.26	1.04	-0.13	0.41	0.26	0.70
PRT	1.86	-0.63	1.17	0.40	.	.	0.22	-1.36
SWE	0.93	0.66	-0.51	0.89	.	.	0.56	0.93
UK	0.26	0.52	0.41	0.92	-0.71	0.97	0.90	0.65
USA	2.51	2.00	1.75	0.12	0.55	0.14	0.62	1.79
Average	*1.60*	*1.27*	*1.28*	*1.46*	*0.53*	*0.97*	*0.67*	*0.30*

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Employment is the total number of persons engaged. TFP is value-added based. Average is the unweighted mean across countries, where within each country industries are weighted by their country-year varying value added shares.

Appendix Table 2B

Average annual growth in employment and productivity by industry

ISIC code	*Description*	*100 x Δ log employment*	*100 x Δ log TFP*
C	Mining and quarrying	-2.28	0.37
15t16	Food , beverages, and tobacco	-0.44	0.63
17t19	Textiles, textile , leather, and footwear	-3.48	1.92
20	Wood and wood products	-0.54	2.03
21t22	Pulp, paper, paper, printing, and publishing	-0.16	0.97
23	Coke, refined petroleum and nuclear fuel	-0.74	-0.08
24	Chemicals and chemical products	-0.19	2.96
25	Rubber and plastics	0.63	2.52
26	Other non-metallic mineral	-0.95	1.60
27t28	Basic metals and fabricated metal	-0.36	1.63
29	Machinery, not elsewhere classified	-0.01	1.83
30t33	Electrical and optical equipment	0.17	4.74
34t35	Transport equipment	0.02	2.44
36t37	Manufacturing not elsewhere classified; recycling	-0.12	1.20
E	Electricity, gas, and water supply	0.17	1.30
F	Construction	0.88	0.13
50	Sale, maintenance and repair of motor vehicles; retail sale of fuel	1.37	0.22
51	Wholesale trade and commission trade, except of motor vehicles	1.36	1.17
52	Retail trade, except of motor vehicles; repair of household goods	1.36	1.19
H	Hotels and restaurants	2.17	-0.88
60t63	Transport and storage	1.13	1.13
64	Post and telecommunications	0.93	3.13
J	Financial intermediation	2.23	1.14
70	Real estate activities	3.43	-0.51
71t74	Renting of machinery & equipment and other business activities	5.01	-1.63
M	Education	2.05	-0.29
N	Health and social work	3.09	-0.28
O	Other community, social and personal service activities	2.57	-1.09

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Employment is the total number of persons engaged. TFP is value added based. Unweighted averages across all countries where data is available.

Appendix Table 2C

Average level and annual percentage point change in labor share by country

	Labor share	*Average annual labor share change*			
	1970-2007	*1970-1980*	*1980-1990*	*1990-2000*	*2000-2007*
AUS	64.8%	0.24	-0.64	-0.11	-0.36
AUT	67.2%	-0.42	-0.50	-0.34	-0.40
BEL	64.1%	0.85	-0.58	0.15	0.53
CAN	59.4%	-0.27	0.14	-0.44	-0.08
DNK	67.6%	0.42	-0.35	-0.28	0.36
ESP	62.8%	-0.09	-0.25	0.12	-0.62
FIN	68.3%	-0.34	0.18	-1.09	0.02
FRA	67.9%	-0.22	-0.73	-0.23	-0.03
GER	66.6%	0.44	-0.48	0.12	-0.74
GRC	52.4%	0.19	-0.13	-0.12	0.06
IRL	59.2%	0.01	-0.46	-0.74	0.26
ITA	68.2%	0.10	-0.10	-0.77	0.13
JPN	56.6%	1.36	-0.38	-0.04	-0.12
KOR	69.5%	-0.50	0.33	-0.40	0.24
LUX	55.7%		0.97	-0.43	-0.41
NLD	68.3%	-0.02	-0.73	0.00	-0.17
PRT	59.2%	0.46	0.54	0.14	-0.02
SWE	67.9%		-0.48	-0.51	-0.03
UK	70.5%	0.08	0.10	-0.20	-0.05
USA	63.7%	-0.13	-0.14	-0.08	-0.72
Average	*64.0%*	*0.12*	*-0.18*	*-0.26*	*-0.11*

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Average is the unweighted mean across countries.

Appendix Table 2D

Average level and annual percentage point change in labor share by industry

		Labor share	
ISIC code	*Description*	*level*	*%-point Δ*
C	Mining and quarrying	46.1%	-0.64
15t16	Food , beverages, and tobacco	61.9%	-0.11
17t19	Textiles, textile , leather, and footwear	78.3%	-0.10
20	Wood and wood products	77.3%	-0.35
21t22	Pulp, paper, paper, printing, and publishing	67.5%	-0.10
23	Coke, refined petroleum and nuclear fuel	45.5%	-0.15
24	Chemicals and chemical products	53.2%	-0.07
25	Rubber and plastics	68.3%	-0.02
26	Other non-metallic mineral	65.3%	-0.20
27t28	Basic metals and fabricated metal	69.5%	-0.13
29	Machinery, not elsewhere classified	76.2%	-0.02
30t33	Electrical and optical equipment	71.3%	-0.16
34t35	Transport equipment	79.7%	-0.43
36t37	Manufacturing not elsewhere classified; recycling	83.0%	-0.31
E	Electricity, gas, and water supply	36.2%	-0.24
F	Construction	79.2%	-0.02
50	Sale, maintenance and repair of motor vehicles; retail sale of fuel	73.2%	-0.05
51	Wholesale trade and commission trade, except of motor vehicles	65.3%	-0.09
52	Retail trade, except of motor vehicles; repair of household goods	82.5%	-0.16
H	Hotels and restaurants	84.7%	-0.32
60t63	Transport and storage	73.1%	-0.26
64	Post and telecommunications	53.1%	-0.44
J	Financial intermediation	58.5%	-0.12
70	Real estate activities	7.5%	0.02
71t74	Renting of machinery & equipment and other business activities	73.0%	0.22
M	Education	92.8%	0.06
N	Health and social work	83.0%	-0.03
O	Other community, social and personal service activities	78.9%	-0.05

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Unweighted averages across all countries where data is available.

Appendix Table 3A

The direct and indirect effects of smoothed productivity growth

dependent variable: annual change in log outcome by country-industry

	Employment	*Hours*	*Hrly wage*	*Wagebill*	*Nominal VA*	*VA price*	*Real VA*	*Labor share*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ ln TFP (cit)	-0.067*	-0.090**	0.219**	0.129**	0.418**	-0.384**	0.803**	-0.289**
	(0.030)	(0.031)	(0.037)	(0.040)	(0.040)	(0.042)	(0.034)	(0.045)
Δ ln nominal value added (ct)	0.159**	0.152**	0.754**	0.906**	0.875**	0.763**	0.112**	0.031
	(0.046)	(0.050)	(0.042)	(0.051)	(0.044)	(0.036)	(0.033)	(0.054)
Upstream Δ ln TFP (c, j≠i, t)	1.652**	1.591**	0.284	1.875**	0.875*	-0.158	1.029**	1.000*
	(0.263)	(0.273)	(0.331)	(0.416)	(0.389)	(0.330)	(0.248)	(0.404)
Downstream Δ ln TFP (c, j≠i, t)	-0.025	-0.055	-0.057	-0.111	0.190	0.038	0.148	-0.301
	(0.212)	(0.210)	(0.206)	(0.244)	(0.241)	(0.220)	(0.191)	(0.297)
Fixed effects:								
Country, industry, year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Industry * year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Country * industry * business cycle	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R2	0.438	0.409	0.428	0.504	0.542	0.545	0.485	0.264
N	13,417	13,417	13,417	13,417	13,417	13,417	13,417	13,417

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. All models weighted by industry value added shares within countries, averaged across all years. The number of observations is equal to the number of country-industry cells multiplied by the number of years. TFP and nominal value added smoothed by taking three-year backward-looking moving averages. Standard errors are clustered by country-industry and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Appendix Table 3B

The sector-specific direct and indirect effects of productivity growth
dependent variable: annual change in log outcome by country-industry

	Employment	*Hours*	*Hrly wage*	*Wagebill*	*Nominal VA*	*VA price*	*Real VA*	*Labor share*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ ln TFP (cit)								
Mining & utilities & construction	-0.221**	-0.223**	0.095	-0.129	0.297**	-0.336**	0.634**	-0.425**
	(0.080)	(0.083)	(0.073)	(0.101)	(0.103)	(0.091)	(0.061)	(0.096)
Manufacturing	-0.011	-0.006	0.145**	0.139**	0.422**	-0.490**	0.912**	-0.283**
	(0.024)	(0.026)	(0.030)	(0.030)	(0.063)	(0.076)	(0.051)	(0.054)
Education & health	-0.118~	-0.275**	0.325**	0.049	0.174~	-0.457**	0.643**	-0.125*
	(0.068)	(0.090)	(0.077)	(0.096)	(0.103)	(0.087)	(0.087)	(0.059)
Low-tech services	-0.046	-0.081	0.338**	0.257~	0.544**	-0.247**	0.790**	-0.287*
	(0.092)	(0.095)	(0.122)	(0.132)	(0.089)	(0.058)	(0.076)	(0.137)
High-tech services	-0.086~	-0.138*	0.322**	0.184*	0.424**	-0.319**	0.743**	-0.239**
	(0.049)	(0.058)	(0.074)	(0.077)	(0.069)	(0.064)	(0.062)	(0.081)
Δ ln nominal value added (ct)								
Mining & utilities & construction	0.305~	0.244	0.848**	1.092**	1.296**	0.981**	0.315*	-0.204*
	(0.168)	(0.156)	(0.108)	(0.138)	(0.151)	(0.095)	(0.126)	(0.103)
Manufacturing	-0.069~	-0.122**	0.736**	0.614**	0.550**	0.650**	-0.100~	0.065
	(0.039)	(0.040)	(0.040)	(0.047)	(0.058)	(0.054)	(0.051)	(0.048)
Education & health	0.069	0.064	0.931**	0.994**	0.962**	0.822**	0.140**	0.032
	(0.066)	(0.070)	(0.068)	(0.094)	(0.096)	(0.068)	(0.053)	(0.055)
Low-tech services	0.280**	0.297**	0.602**	0.899**	0.916**	0.785**	0.131*	-0.017
	(0.087)	(0.101)	(0.091)	(0.103)	(0.077)	(0.064)	(0.051)	(0.117)
High-tech services	0.227~	0.292*	0.919**	1.211**	0.957**	0.713**	0.245**	0.253~
	(0.126)	(0.126)	(0.106)	(0.119)	(0.086)	(0.111)	(0.090)	(0.152)
Upstream Δ ln TFP (c, j≠i, t)	1.664**	1.594**	0.300	1.893**	0.857*	-0.155	1.009**	1.037*
	(0.265)	(0.275)	(0.338)	(0.428)	(0.392)	(0.329)	(0.249)	(0.408)
Downstream Δ ln TFP (c, j≠i, t)	-0.042	-0.081	-0.062	-0.143	0.155	0.016	0.137	-0.298
	(0.212)	(0.211)	(0.205)	(0.238)	(0.240)	(0.217)	(0.197)	(0.283)
Fixed effects:								
Country, industry, year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Industry*year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Country*industry*business cycle	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R2	0.442	0.414	0.430	0.507	0.545	0.547	0.488	0.265
N	13,417	13,417	13,417	13,417	13,417	13,417	13,417	13,417

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. All models weighted by industry value added shares within countries, averaged across all years; k=3. The number of observations is equal to the number of country-industry cells multiplied by the number of years. Standard errors are clustered by country-industry and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Appendix Table 3C

The decade-specific direct and indirect effects of smoothed productivity growth
dependent variable: annual change in log outcome by country-industry

	Employment	*Hours*	*Hrly wage*	*Wagebill*	*Nominal VA*	*VA price*	*Real VA*	*Labor share*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ ln TFP (cit)								
1970s	-0.129**	-0.130**	0.336**	0.206~	0.201**	-0.525**	0.727**	0.005
	(0.048)	(0.049)	(0.128)	(0.119)	(0.068)	(0.088)	(0.100)	(0.127)
1980s	-0.040	-0.068	0.220**	0.151*	0.418**	-0.397**	0.816**	-0.266**
	(0.063)	(0.066)	(0.041)	(0.063)	(0.071)	(0.058)	(0.059)	(0.049)
1990s	-0.032	-0.073~	0.229**	0.156*	0.517**	-0.347**	0.865**	-0.361**
	(0.038)	(0.039)	(0.073)	(0.071)	(0.058)	(0.077)	(0.061)	(0.081)
2000s	-0.143**	-0.142**	0.149**	0.007	0.393**	-0.330**	0.722**	-0.385**
	(0.040)	(0.043)	(0.042)	(0.046)	(0.075)	(0.067)	(0.051)	(0.075)
Δ ln nominal value added (ct)								
1970s	-0.009	0.018	1.000**	1.017**	1.045**	1.010**	0.034	-0.027
	(0.064)	(0.064)	(0.057)	(0.051)	(0.049)	(0.049)	(0.045)	(0.057)
1980s	0.216**	0.234**	0.709**	0.943**	0.847**	0.685**	0.161**	0.097
	(0.057)	(0.067)	(0.049)	(0.065)	(0.055)	(0.047)	(0.047)	(0.061)
1990s	0.229**	0.194*	0.610**	0.804**	0.747**	0.651**	0.096	0.057
	(0.086)	(0.087)	(0.064)	(0.083)	(0.093)	(0.052)	(0.078)	(0.076)
2000s	0.247**	0.094	0.602**	0.696**	0.677**	0.507**	0.173*	0.019
	(0.072)	(0.070)	(0.075)	(0.085)	(0.091)	(0.062)	(0.074)	(0.088)
Upstream Δ ln TFP (c, j≠i, t)	1.549**	1.563**	0.478	2.040**	1.128**	0.114	1.008**	0.912*
	(0.267)	(0.277)	(0.329)	(0.402)	(0.381)	(0.330)	(0.246)	(0.399)
Downstream Δ ln TFP (c, j≠i, t)	-0.029	-0.127	-0.084	-0.211	0.169	0.017	0.150	-0.380
	(0.209)	(0.204)	(0.212)	(0.239)	(0.242)	(0.223)	(0.181)	(0.301)
Fixed effects:								
Country, industry, year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Industry*year	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Country*industry*business cycle	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R2	0.441	0.411	0.431	0.505	0.544	0.549	0.486	0.266
N	13,417	13,417	13,417	13,417	13,417	13,417	13,417	13,417

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. All models weighted by industry value added shares within countries, averaged across all years. The number of observations is equal to the number of country-industry cells multiplied by the number of years. TFP and nominal value added smoothed by taking three-year backward-looking moving averages. Standard errors are clustered by country-industry and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Appendix Table 4

Average annual log number of patent citations by industry

		mean log nr of patent citations	
ISIC code	*Description*	*by non-US inventors*	*by US inventors*
C	Mining and quarrying	5.17	3.20
15t16	Food , beverages, and tobacco	3.99	1.81
17t19	Textiles, textile , leather, and footwear	4.31	2.86
20	Wood and wood products	3.06	1.91
21t22	Pulp, paper, paper, printing, and publishing	5.80	3.33
23	Coke, refined petroleum and nuclear fuel	6.11	4.37
24	Chemicals and chemical products	7.28	5.93
25	Rubber and plastics	4.98	3.10
26	Other non-metallic mineral	4.88	2.04
27t28	Basic metals and fabricated metal	5.38	3.61
29	Machinery, not elsewhere classified	6.43	5.06
30t33	Electrical and optical equipment	7.71	6.94
34t35	Transport equipment	6.31	5.42
36t37	Manufacturing not elsewhere classified; recycling	4.90	2.94
E	Electricity, gas, and water supply	1.96	1.62
F	Construction	3.95	1.81
50	Sale, maintenance and repair of motor vehicles; retail sale of fuel	2.20	0.76
51	Wholesale trade and commission trade, except of motor vehicles	2.52	1.27
52	Retail trade, except of motor vehicles; repair of household goods	4.35	2.32
H	Hotels and restaurants	2.73	1.09
60t63	Transport and storage	3.18	1.75
64	Post and telecommunications	5.89	3.73
J	Financial intermediation	4.22	2.37
70	Real estate activities	1.05	0.36
71t74	Renting of machinery & equipment and other business activities	6.50	5.44
M	Education	-1.39	-3.07
N	Health and social work	2.32	0.90
O	Other community, social and personal service activities	4.22	2.28

Notes: Average across years 1970-2007, source: USPTO.

Appendix Table 5

Robot penetration by industry

Industry	*ISIC codes included*	Mean robots per 1,000 workers	Mean annual Δ in robots per 1,000 workers
Construction	F	0.02	0.01
Education	M	0.11	0.01
Electronics	30t33	2.79	0.39
Food	15t16	1.28	0.30
Furniture	20	2.43	0.22
Glass	26	1.40	0.18
Other manufacturing	36t37	2.25	0.05
Machinery	29	2.19	0.16
Metals	27t28	3.89	0.43
Mining	C	0.65	0.09
Other non-manufacturing	50, 51, 52, H, 60t63, 64, J, 70, 71t74, N, O	0.00	0.00
Paper	21t22	0.22	0.03
Plastics and chemicals	23, 24, 25	5.37	0.84
Textiles	17t19	0.61	0.06
Transport equipment	34t35	18.41	2.48
Utilities	E	0.02	0.00

Notes: Average across years 1993-2007, source: IFR.