Robocalypse Now–Does Productivity Growth Threaten Employment?

By David Autor and Anna Salomons[1]

"Any worker who now performs his task by following specific instructions can, in principle, be replaced by a machine. This means that the role of humans as the most important factor of production is bound to diminish—in the same way that the role of horses in agricultural production was first diminished and then eliminated by the introduction of tractors." Wassily Leontief (1983)

Abstract

Is productivity growth inimical to employment? Canonical economic theory says no, but much recent economic theory says 'maybe'—that is, rapid advances in machine capabilities may curtail aggregate labor demand as technology increasingly encroaches on human job tasks, ultimately immiserating labor. We refer to this immiseration scenario as the "robocalypse," and explore empirically whether it is coming to pass by analyzing the relationship between productivity growth and employment using country- and industry-level data for 19 countries over 35+ years. Consistent with both the popular ('robocalypse') narrative and the canonical Baumol hypothesis, we find that industry-level employment robustly falls as industry productivity rises, implying that technically progressive sectors tend to shrink. Simultaneously, we show that country-level employment generally grows as aggregate productivity rises. Because sectoral productivity growth raises incomes, consumption, and hence aggregate employment, a plausible reconciliation of these results—confirmed by our analysis—is that the negative own-industry employment effect of rising productivity is more than offset by positive spillovers to the rest of the economy. Rapid productivity growth in primary and secondary industries has, however, generated a substantial reallocation of workers into tertiary services, which employs a disproportionate share of high-skill labor. In net, the sectoral bias of rising productivity has not diminished aggregate labor demand but has yielded skill-biased demand shifts.

[1] Autor: MIT Department of Economics, Cambridge, MA 02142 (dautor@mit.edu); Salomons: Utrecht University School of Economics, 3584 EC Utrecht, The Netherlands (a.m.salomons@uu.nl). Paper prepared for the ECB Forum on Central Banking, June 2017. The authors thank Daron Acemoglu, James Bessen,Maarten Goos, Dietmar Harhoff, Philipp Hartmann, Kang-Kook Lee, and an anonymous reviewer for valuable suggestions.

1 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 ultimately 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). We refer to this scenario—where the endless march of technology ultimately immiserates labor—as the 'robocalypse.'[3]

While labor immiseration is a theoretical impossibility in canonical macroeconomic models of the economy, several recent papers develop models in which labor immiseration is one potential outcome. Sachs and Kotlikoff (2012) and Berg et al. (2017) develop 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 (2016) consider a model where two countervailing economic forces determine the evolution of labor's share of income: the march of technological progress, which gradually replaces 'old' tasks, reduces labor's share of output, possibly diminishing real wages; and endogenous technological progress that generates novel labor-demanding tasks. 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. Susskind (2017) develops a model in which labor is ultimately immiserated by the asymptotic encroachment of automation into the full spectrum of work tasks.[4] These models do not prove that

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.

3 Short for the robotic apocalypse, of course.

4 A critical distinction between Acemoglu and Restrepo (2017) 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.

such immiseration will occur, but, contrary to canonical models, they sketch scenarios where it could.

A burgeoning empirical literature tests specifically whether technological progress has reduced aggregate labor demand or dampened overall wage growth. One robust finding in several recent papers is that labor's share of national income has fallen in many nations, perhaps commencing in the 1990s, and becoming plainly visible in the 2000s (e.g., Elsby, Hobijn and Sahin, 2013; Karabarbounis and Neiman, 2013; Piketty 2014; Dao et al. 2017). Reviewing an array of within- and cross-country evidence, Karabarbounis and Neiman (2014) argue that labor's falling share is due to a steep drop in the quality-adjusted equipment prices of Information and Communication Technologies (ICT) relative to labor. Though scholars have not reached consensus on this conclusion, Karabarbounis and Neiman's work has lent empirical weight to the conjecture that computerization is gradually rendering human labor redundant.[5]

If correct, this finding represents a substantial deviation from prior historical episodes. Alexopoulos and Cohen (2016) find that positive technology shocks raised productivity and lowered unemployment in the United State during the first half of the twentieth century. Focusing on contemporary European data, Gregory, Salomons, and Zierahn (2016) test whether Routine-Replacing Technical Change (RRTC) has reduced employment overall across Europe. They find that while RRTC has reduced middle-skill employment, this employment reduction is more than offset by compensatory product demand and local demand spillovers.[6] Looking directly at robotics, Graetz and Michaels (2015) estimate 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 17 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) conclude 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. One factor limiting the generalizability of this evidence is that robots are currently prevalent in only a small set of industrial applications, primarily in heavy industry. As robotics advances to encompass a broader set of non-industrial activities—e.g., healthcare, maintenance, cleaning, food preparation—the labor market consequences may also change.

[5] Although such a relative capital price decline should 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. (2017) 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.

[6] 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.

Recent public concern about the adverse employment effects of new workplace technologies has ample historical precedent. Over the last two centuries, scholars, political leaders, and social activists have issued periodic warnings that advancing automation threatened to make labor redundant and skills obsolete. The best-known early example is the Luddite movement of the early 19th century, in which a group of English textile artisans protested the automation of textile production by seeking to destroy some of the machines. But this worry is hardly antiquarian. In 1927, U.S. Secretary of Labor James J. Davis foresaw a "…lack of employment caused by revolutionary appliances" (*NY Times*, 1927). Concern over automation and joblessness during the 1950s and early 1960s prompted U.S. President Lyndon B. Johnson in 1964 to empanel a "Blue-Ribbon National Commission on Technology, Automation, and Economic Progress" to confront the productivity problem of that period—specifically, the problem that productivity was rising so fast it might outstrip demand for labor. The commission ultimately concluded that automation did not threaten employment, but it viewed the possibility of technological disruption as sufficiently severe that it recommended, as one newspaper (*The Herald Press*, 1966) reported, "a guaranteed minimum income for each family; using the government as the employer of last resort for the hard core jobless; two years of free education in either community or vocational colleges; a fully administered federal employment service, and individual Federal Reserve Bank sponsorship in area economic development free from the Fed's national headquarters."[7]

That these dire predictions have proved inaccurate in earlier generations does not guarantee that they will be incorrect going forward. Although scarce labor should not be left fallow in the equilibrium of a competitive economy, no economic law stipulates that the scarcity value of labor will always be sufficient to support a reasonable standard of living. Indeed, the real earnings of less-educated workers in both the Germany, United States, and United Kingdom have fallen sharply over the last two to three decades *despite* a steep reduction in the non-college share of the working age population (Autor and Wasserman, 2013; Dustmann et al. 2014; Blundell, 2016). These losses, which are typically attributed to skill-biased demand shifts (Autor, Katz, and Kearney 2008), underscore that technological change can directly reduce demand for broad skill groups even if it does not diminish labor demand in aggregate.

Abstracting from specific models, the fundamental concern raised by this literature is that labor-saving technological progress may ultimately curtail employment. This paper explores that concern by testing for evidence of employment-reducing technological progress. Harnessing data from 19 countries over 37 years, we characterize how productivity growth—an omnibus measure of technological progress—affects employment across industries and countries and, specifically, whether rising productivity ultimately diminishes employment, numerically or as a share of working-age population. We focus on overall *productivity* growth rather than specific technological innovations because (a) heterogeneity in innovations defies consistent classification and comprehensive measurement, and (b), because

7 See Autor (2015), on which this paragraph draws, for further discussion.

productivity growth arguably provides an inclusive measure of technological progress (Solow, 1956). While our primary productivity measure is raw labor productivity, measured as output per worker, we document that using either value-added per worker or Total Factor Productivity in place of output per worker yields highly comparable conclusions.

Relative to existing literature, our paper is distinct—and we think useful—in several respects. First, we apply a comprehensive albeit reduced-form approach to measuring technological progress, studying the employment consequences of rising labor productivity per se rather than the impact of specific technological innovations, adoptions, or rollouts (as in Akerman, Kostol and Mogstad, 2014; Graetz and Michaels, 2015; Acemoglu and Restrepo, 2017). While our approach does not provide the crisp causal identification that we would ideally offer, it provides a panoply of robust, cross-national, cross-industry, and over-time findings that provide a rich descriptive picture and a cohesive story of productivity growth's nuanced relationship to employment growth.

Second, we explore a comprehensive set of outcomes—employment, output, value-added, skill input—that in combination substantiate the plausibility and soundness of our main findings. Third, we investigate both the direct and indirect employment effects of productivity growth by explicitly allowing for cross-sectoral productivity spillovers. These cross-sectoral spillovers prove to be of first-order importance for our results. Finally, alongside the impact of productivity growth on overall employment, we explore distributional consequences for the demand for high-, medium-, and low-skill labor. Notably, these distributional consequences appear substantially more consequential than the total employment effects.

Our analysis proceeds in four steps. We first explore whether country-level labor productivity growth is in net employment-augmenting or employment-diminishing in aggregate. We next drill down to industry-level data to test whether, holding aggregate national productivity growth constant, industries experiencing differential productivity growth see a net increase or reduction in employment. Part three of the analysis considers the simultaneous effect of industry-level productivity growth on own-industry versus aggregate employment growth. This extension allows us to assess whether productivity growth in each major sector generates spillovers to employment in other sectors. We can further ask whether these own-industry effects and cross-sectoral spillovers have changed with time—in particular, whether their net effects have declined in the 2000s. The final empirical section of the paper assesses the implications of sectoral productivity growth for labor demand by skill group. This is relevant because, even if productivity growth has no effect on the *level* of employment, it may nevertheless have non-neutral impacts on the relative demand for high-, middle-, and low-educated workers.

Over the 35+ years of data explored here, we find that productivity growth has been employment-augmenting rather than employment-reducing; that is, it has *not* threatened employment. This is true whether we measure employment as the number of employed workers or the ratio of employed workers to working-age population.[8] This strong finding emerges despite robust evidence that industries experiencing rising labor productivity exhibit falling employment (as per Baumol, 1967). The reason that industry-level productivity growth typically raises net employment is because productivity growth in each sector—particularly in services—generates employment growth spillovers elsewhere in the economy. These spillovers are sufficiently large that they more than offset employment losses in industries making rapid productivity gains. Individually, we estimate that both the employment-reducing and employment-increasing effects of productivity growth are economically sizable: however, their net effect makes for a rather modest positive impact of productivity growth on employment. These same results hold whether our productivity measure is output per worker, value-added per worker, or sectoral level productivity. Moreover, we confirm that these results hold not just for employment but for final consumption, meaning that productivity growth leads to a significant output response that appears to offset its direct employment-reducing effect. This highlights that final demand increases and inter-industry output linkages play an important role in countervailing the task-replacing effects of technological change.

Despite the relative neutrality of productivity growth for aggregate labor demand, we estimate that this same force has been non-neutral for labor demand across skill groups. Specifically, rapid productivity growth in primary and secondary industries (manufacturing in particular) has generated a substantial reallocation of workers into tertiary service activities, both in high skill-intensive services (e.g., health, education, finance) and in low skill-intensive services (e.g., food service, cleaning, hospitality). Because these sectors have a comparatively bimodal skill distribution of employment—with a disproportionate share of employment in either high- or low-education jobs—the expansion of services relative to other sectors has tended to favor high- and low-skill workers at the expense of middle-skill workers (consistent with the reasoning in Goos, Rademakers, Salomons, and Vandeweyer, 2015). Productivity growth has therefore contributed indirectly to the well-known phenomenon of employment polarization (see Goos, Manning, and Salomons, 2009 and 2014; Michaels, Natraj and Van Reenen, 2013), though we find that the sectoral skew has been far stronger in favor of high- than low-skill labor.

A central—and yet simultaneously, pedestrian—takeaway from our analysis is that productivity growth is *not* the primary driver of rising or falling employment. We estimate that net employment changes resulting directly or indirectly from productivity growth are quite modest, amounting to only a few percentage points of net employment over more than three decades. Instead, the primary driver of employment growth is estimated to be population growth; the number of workers rises roughly in lock-step with the overall growth of citizens in a country. This observation, which is almost self-evident but not tautological, suggests that the conventional narrative in which automation is the critical factor in either eroding or augmenting employment misses the mark. Our findings instead support a more prosaic neoclassical story in which both labor supply and final demand for goods and

8 Because our focus is on 'jobs' rather than total labor payments, we do not explore wage-bills or hours as outcomes in this analysis. See Ngai and Pissarides (2008) for a model of how uneven productivity growth across sectors can rationalize the falling or non-monotone behavior evolution of aggregate market hours over the twentieth century.

services jointly determine the level of employment, and where the key driver of both forces is the population of consumer-workers.

Since our data, like all others, are drawn from the past, nothing in our findings demonstrates that the so-far benign relationship between productivity growth and employment won't soon take a more sinister turn: as the fine print of every investment prospectus notes, past performance is not an indicator of future outcomes. Moreover, our omnibus approach to measuring technological progress does not distinguish among different technological advances that may have different labor market consequences, e.g., the personal computer versus the shipping container. We also note that measured labor productivity growth may emanate from non-technological sources, such as advancing trade and offshoring possibilities. The labor market consequences of these distinct sources of productivity growth—arising from heterogeneous technological advances as well as shifts in trade, offshoring, and global production chains—clearly warrant in-depth study that extends beyond the high-level approach applied here.

Nevertheless, our broad-brush analysis underscores a key insight of much recent work on the labor market impacts of technological progress, which is that the primary societal challenge that these advances have posed so far is not falling aggregate labor demand but instead an increasingly skewed income distribution (Brynjolffson and McAfee, 2014; Autor, 2015). Concretely, although the raw count of jobs available in industrialized countries is roughly keeping pace with population growth, many of the new jobs generated by an increasingly automated economy do not offer a stable, sustainable standard of living, while simultaneously, many highly-paid occupations that are strongly complemented by advancing automation are out of reach to workers without a college education. This process by which technological progress (alongside other causes) skews the distribution of rewards increasingly towards educated elites has been abundantly visible across the industrialized world for close to four decades (Katz and Autor, 1999; Acemoglu and Autor, 2011). Our analysis suggests that the productivity-induced sectoral reallocations of labor contribute indirectly to this powerful underlying trend.

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). We use the 2008 release of EU KLEMS, supplemented with data from EU KLEMS 2011 and 2007 releases to maximize our data coverage (1970-2007). We limit our analysis to 19 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 1. The KLEMs database contains detailed data for 32 industries in both the market and non-market economy, summarized in Appendix Table 1. 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.[9] The end year of our analysis is dictated by major revisions to the industry definitions in the KELMS 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 plan to do so in future work.

Table 1
EUKLEMS data coverage by country

ISO code	Country	Years
AUS	Australia	1970-2007
AUT	Austria	1970-2007
BEL	Belgium	1970-2007
DNK	Denmark	1970-2007
ESP	Spain	1970-2007
FIN	Finland	1970-2007
FRA	France	1970-2007
GER	Germany	1970-2007
GRC	Greece	1970-2007
IRL	Ireland	1970-2007
ITA	Italy	1970-2007
JPN	Japan	1973-2006
KOR	South Korea	1970-2007
LUX	Luxembourg	1970-2007
NLD	Netherlands	1970-2007
PRT	Portugal	1970-2006
SWE	Sweden	1970-2007
UK	United Kingdom	1970-2007
USA	United States	1970-2005

Notes: EUKLEMS database, 2008 release supplemented with information from 2007 and 2009 releases.

We operationalize the measurement of employment and productivity as follows. Our primary employment measure is the number of persons engaged in work, though we have also experimented with excluding the self-employed and obtain similar results. Because measurement of value-added outside of manufacturing is typically somewhat speculative, our primary labor productivity is real gross output per worker. However, we also present a set of models using value-added per worker and value-added based total factor productivity. These alternative measures yield qualitatively similar findings, although total factor productivity growth seems to have the most strongly positive effect on employment. Table 2 summarizes employment and productivity growth by country for each of the four decades of our sample. Appendix Table 2 reports the corresponding data at the industry level, averaging across all countries and the entire sample period.

9 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.

To document the relationship between productivity growth and consumption growth we use the 2013 release of the World Input Output Database (WIOD). WIOD provides world input-output tables covering 40 countries, including the 27 countries of the European Union, as well as 13 other major economies, for the years 1995 through 2011 (see Timmer et al. 2015). To link country and industry-level employment and productivity outcomes to the WIOD, we employ the WIOD's harmonized Socio Economic Accounts Database (SEA, release July 2014). The SEA database is sourced from EU KLEMS and further processed for full compatibility with the WIOD.

Table 2
Average annualized growth in employment and productivity by country

	100 x Δ log employment				100 x Δ log labor 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	1.00	1.18	3.28	0.84
AUT	1.37	0.55	1.02	0.99	2.21	2.29	2.17	2.01
BEL	0.19	0.32	0.69	1.02	1.40	1.73	2.54	1.38
DNK	0.62	0.69	0.64	0.82	1.30	1.62	2.36	1.97
ESP	1.06	1.70	2.44	3.65	2.08	1.29	0.94	1.33
FIN	1.19	1.03	-0.54	1.39	2.50	2.31	2.59	1.99
FRA	1.09	0.51	0.74	0.97	2.06	2.04	1.73	1.36
GER	0.49	1.13	0.68	0.33	2.22	0.67	2.29	1.52
GRC	2.65	1.44	1.13	1.76	2.41	-0.06	0.72	1.64
IRL	1.92	0.78	4.18	3.53	2.32	2.89	2.16	2.27
ITA	1.48	0.99	0.36	1.47	2.42	1.80	2.15	0.07
JPN	1.59	1.44	0.49	-0.07	1.72	2.68	0.52	0.94
KOR	6.30	4.79	2.12	2.06	4.11	5.14	3.82	3.27
LUX	1.56	2.03	3.51	3.46	2.54	4.43	2.36	2.05
NLD	0.59	1.50	2.26	1.04	2.73	-0.63	1.62	0.94
PRT	1.86	-0.63	1.17	0.40	3.37	3.54	2.61	0.85
SWE	0.93	0.66	-0.51	0.89	0.97	1.29	2.74	1.92
UK	0.26	0.52	0.41	0.92	0.98	1.33	3.48	2.34
USA	2.51	2.00	1.75	0.12	0.36	0.94	1.97	2.30
Average	**1.53**	**1.23**	**1.27**	**1.43**	**2.04**	**1.92**	**2.21**	**1.63**

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Labor productivity is calculated as gross output over the total number of persons engaged. Average is the unweighted mean across countries.

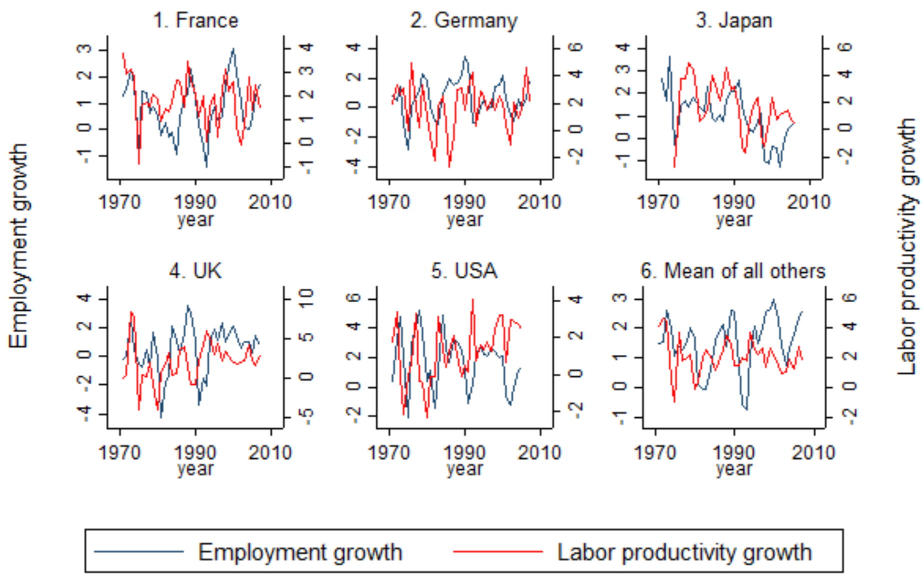
3 The big picture

Lay intuition would suggest that as countries become more productive, national incomes should rise, spurring additional consumption and concomitant employment growth. Figure 1 informally tests this intuition by plotting the evolution of productivity growth and employment growth in the five largest economies in our sample—France, Germany, Japan, the UK, and the US—as well as for the average of the remaining fourteen countries.[10] The productivity series is equal to the year-on-year log change in gross output per worker, while the employment series equals the year-on-year log change in the number of persons engaged in work, each multiplied by 100. Consistent with intuition, there is a striking time-series relationship between productivity growth and employment growth in all panels of the figure. From inspection, it appears that productivity growth typically leads employment growth by one to three years. However, the 2000s suggest a recent deviation from this pattern in which productivity and employment growth decouple: in the US and Japan, productivity rises rapidly in the 2000s while employment grows minimally; in the UK, conversely, productivity growth slows while employment grows relatively steadily. We return to the puzzle posed by this decoupling below.

Figure 1

Employment and productivity growth, 1970 –2007: Large countries

(x-axis: year; y-axis: employment growth (left-hand scale), labor productivity growth (right-hand scale))



Figures are for the total economy, excluding agriculture, public administration, private households and extraterritorial organizations. All growth rates obtained as log changes x 100. Graph 6 reports unweighted mean growth rates across the remaining 14 countries. Productivity is gross output per worker.

To statistically characterize these time-series relationships, we estimate a set of stacked first difference OLS models of the form:

$$\Delta \ln E_{ct} = \beta_0 + \beta_1 \Delta \ln LP_{ct} + \left[\sum_{k=1}^{K} \beta_{2+k} \Delta \ln LP_{ct-k} + \alpha_c \right] + \varepsilon_{ct}$$

[1]

[10] Appendix Figure 1a shows similar results separately for 6 other countries; and Appendix Figures 1b and 1c highlight that the same patterns are found when alternatively using value added per worker as the productivity measure, or when using growth in employment to the total working age population.

where $\Delta \ln E_{ct}$ is the log change in employment in country c in time interval t, and $\Delta \ln LP_{ct}$ is the contemporary economy-wide growth in labor productivity. This model pools cross-country and over-time variation to estimate the conditional correlation between productivity and employment growth. Due to the log-log specification, estimates of β_1 correspond to elasticities. We perform these estimates without applying country weights, meaning that each country is given equal weight in the regression analysis. We can also augment the basic model by adding the terms in square brackets, representing, respectively, k time lags of labor productivity growth $\Delta\ln LP_{ct-k}$, and a set of country fixed effects α_c.[11]

Table 3a

The effect of productivity growth on employment growth at the country level.
Dependent variable: Annual log change in employment by country

	(1)	(2)	(3)	(4)	(5)	(6)
	A. OLS					
Δ ln productivity (c, t)	0.016 (0.032)	-0.046 (0.030)	-0.054 (0.035)	-0.080* (0.034)	-0.043 (0.033)	-0.064~ (0.033)
Δ ln productivity (c, t-1)	-	-	0.170** (0.035)	0.154** (0.033)	0.177** (0.032)	0.163** (0.032)
Δ ln productivity (c, t-2)	-	-	0.074* (0.035)	0.055~ (0.033)	0.059~ (0.032)	0.051 (0.032)
Δ ln productivity (c, t-3)	-	-	0.090** (0.033)	0.059~ (0.031)	0.063* (0.031)	0.050 (0.031)
Δ ln total population (c, t)	-	-	-	-	1.459** (0.144)	1.013** (0.187)
Country fixed effects	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*
R2	0.000	0.203	0.071	0.244	0.201	0.278
N	696	696	639	639	639	639
Σk Δ ln productivity (c, t-k)	0.016 (0.032)	-0.046 (0.030)	0.280** (0.057)	0.190** (0.060)	0.256** (0.053)	0.199** (0.059)
	B. IV					
Δ ln productivity (c, t)	0.319** (0.101)	0.326** (0.091)	0.671** (0.238)	0.586** (0.179)	0.747** (0.236)	0.648** (0.182)
Δ ln productivity (c, t-1)	-	-	0.502** (0.179)	0.457** (0.147)	0.497** (0.178)	0.448** (0.147)
Δ ln productivity (c, t-2)	-	-	0.322~ (0.186)	0.282~ (0.153)	0.320~ (0.185)	0.275~ (0.153)
Δ ln productivity (c, t-3)	-	-	0.242 (0.168)	0.191 (0.135)	0.185 (0.169)	0.130 (0.135)
Δ ln total population (c, t)	-	-	-	-	1.471** (0.238)	1.441** (0.282)
Country fixed effects	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*
N	696	696	639	639	639	639
Sanderson-Windmeijer F-stat	88.8	102.2	23.0	39.5	23.2	38.7
Σk Δ ln productivity (c, t-k)	0.319** (0.101)	0.326** (0.091)	1.737** (0.473)	1.516** (0.329)	1.748** (0.471)	1.501** (0.329)

Notes: All models estimate stacked annual differences over 1970-2007 for the total economy, excluding agriculture, public administration, private households, and extra-territorial organizations. The number of observations is equal to the number of countries multiplied by the number of years. Standard errors in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

[11] Our country-level estimates are unweighted so that larger countries do not have greater influence on the point estimates than smaller countries. When we turn to country-industry level estimates below, we weight industries by their relative sizes within countries, though again each country is given equal weight.

Table 3a presents a first set of results. Contrary to the impression given by Figure 1, the column 1 estimate in panel A finds a statistically insignificant and inconsistently signed conditional correlation between productivity growth and employment growth. The point estimate of 0.02 in column 1 implies that a 10 percent rise in labor productivity predicts a trivial one-fifth of a percentage point rise in employment. When country dummies are added to the model in column 2, so that identification comes from over-time, within-country variation, the point estimate becomes weakly negative, implying that rising productivity predicts falling national employment.

3.1 Building on the basics

Two limitations of the bare bones OLS setup are likely to bias the regressions towards finding a null or negative relationship between productivity growth and employment. First, Figure 1 suggests that there is a non-trivial lag structure between productivity growth and employment. These lags are absent from our initial OLS estimates. Second, because employment serves as *both* the dependent variable of the estimating equation *and* the denominator of the main explanatory variable (i.e., output divided by employment), measurement error in employment will tend to induce simultaneity between the dependent and (negative of) the independent variables, thus biasing OLS estimates downward. We address both issues in subsequent estimates in Table 3a.

Columns 3 and 4 of the upper panel of Table 3a augment our simple static setup with three lags of the productivity growth measure ($\Delta \ln LP_{ct-k}$).[12] Summing across the contemporaneous and lag coefficients, and focusing on the model containing country dummies (even-numbered columns), we obtain an employment-productivity elasticity of 0.19. This estimate implies that a ten percent rise in aggregate labor productivity in a given year predicts a two percent rise in aggregate employment over the ensuing four-year interval.

While these simple distributed lag models address the timing issue highlighted by Figure 1, they do not address the simultaneity bias problem noted above—specifically, that transitory fluctuations (or measurement errors) in the employment variable may generate simultaneity that biases the point estimate downward. Panel B of Table 3a attempts to tackle this issue by re-estimating each of the OLS models using an instrumental variables specification in which labor productivity growth in each country c is instrumented by the average of the contemporaneous labor productivity growth in all *other* countries c' in the sample. Appendix Table 3 reports the first stage estimates of these instrumental variables models, which are well identified across all columns and readily clear the Sanderson-Windmeijer (2016) F-test criterion for weak identification.

The IV estimates for the employment-productivity elasticity reported in panel B are in all cases larger (more positive) than their OLS counterparts. Distinct from the OLS

[12] We considered one-, two-, and three-year lags. These lags are always positive and in most cases statistically significant. A fourth lag is never statistically significant.

models, both the lagged *contemporaneous* productivity growth measures strongly predict employment growth in IV specifications. In the first pair of columns, we obtain a contemporaneous productivity-employment elasticity of approximately 0.33. Adding three lags boost this estimate to 1.52, which is nearly an order of magnitude larger than the corresponding OLS estimate.

It is worth considering which set of estimates—OLS or IV—should be viewed as more reliable. While the IV estimates purge the simultaneity bias stemming from measurement error that potentially biases OLS estimates downward, the other-country instruments do not resolve all threats to validity and may introduce threats of their own. An optimistic view of the instrument is as follows. The common cross-country component of labor productivity growth may plausibly reflect shared cross-national technological advances. If so, the predictive relationship between other-country and own-country productivity growth should capture the technologically driven component of rising productivity, purged of both measurement error and idiosyncratic own-country shocks. This will produce a strong first stage, which is precisely what we see.

The problem that this IV strategy potentially introduces is that these shared technology shocks may not pass the exclusion restriction. Suppose that when countries experience rising productivity, they apply some of their greater purchasing power to import goods from abroad, stimulating employment growth among trading partners. In this case, our instrumental variable approach will likely exaggerate the causal effect of own-country productivity growth on own-country employment because productivity growth will affect employment both through own-productivity gains and from simultaneous growth of export demand from trading partners. This source of bias, which is a macroeconomic doppelganger of the well-known 'reflection problem' in estimating peer effects, may help to explain why instrumental variables estimates are much larger than their OLS counterparts.[13] These observations suggest caution in placing great weight on the instrumental variables estimates, and cause us to favor the OLS models going forward.

3.2 Employment, population, and employment to population

Because we have so far taken total employment as our dependent variable, the estimates above do not directly answer the question of whether productivity fluctuations affect the employment *rate*—that is, the fraction of working age adults who are employed. If for example population growth and productivity growth covary positively at the country-by-time level, we might find that rising productivity predicts rising employment and, simultaneously, a fall in the employment-to-population ratio. To explore this possibility, the final two columns of Table 3a include the log of

[13] A further limitation of the IV approach is that, by using each country as an instrument for every other country, it is asymptotically equivalent to using the time series average of cross-country productivity growth as the instrument for each country simultaneously. To see this, observe that in a finite set of countries, our instrument differs from the time series of average cross-country productivity growth only because it omits own-country productivity growth from the time-series average. As the number of countries becomes large, this distinction becomes irrelevant.

country-by-year population as an additional regressor. Unsurprisingly, these estimates confirm that population is a strongly positive and highly significant predictor of employment; the number of workers rises with population. Less expected but equally consequential, the population control has almost no detectable effect on the estimated relationship between productivity and employment. The estimated productivity-employment elasticity is equal to 0.19 in the final OLS specification that excludes population (column 4), and is equal to 0.20 in the companion specification that includes population (column 6). Thus, omission of population from our macro-level regressions does not appear to bias the coefficients of interest.

Table 3b

The effect of productivity growth on employment growth at the country level. Dependent variable: Annual log change in employment to working age population by country

	A. OLS			
Δ ln productivity (c, t)	0.010 (0.029)	-0.026 (0.030)	-0.048 (0.033)	-0.056~ (0.033)
Δ ln productivity (c, t-1)	-	-	0.167** (0.033)	0.162** (0.032)
Δ ln productivity (c, t-2)	-	-	0.056~ (0.032)	0.050 (0.032)
Δ ln productivity (c, t-3)	-	-	0.059~ (0.031)	0.047 (0.031)
Country fixed effects	*NO*	*YES*	*NO*	*YES*
R2	0.000	0.082	0.064	0.138
N	696	696	639	639
Σk Δ ln productivity (c, t-k)	0.010 (0.029)	-0.026 (0.030)	0.235** (0.053)	0.203** (0.059)
	B. IV			
Δ ln productivity (c, t)	0.396** (0.098)	0.396** (0.093)	0.912** (0.276)	0.776** (0.200)
Δ ln productivity (c, t-1)	-	-	0.572** (0.208)	0.505** (0.164)
Δ ln productivity (c, t-2)	-	-	0.401~ (0.216)	0.339* (0.170)
Δ ln productivity (c, t-3)	-	-	0.294 (0.195)	0.218 (0.150)
Country fixed effects	*NO*	*YES*	*NO*	*YES*
N	696	696	639	639
Sanderson-Windmeijer F-stat	88.8	102.2	23.0	39.5
Σk Δ ln productivity (c, t-k)	0.396** (0.098)	0.396** (0.093)	2.179** (0.549)	1.839** (0.367)

Notes: All models estimate stacked annual differences over 1970-2007 for the total economy, excluding agriculture, public administration, private households, and extra-territorial organizations. The number of observations is equal to the number of countries multiplied by the number of years. Standard errors in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

A final noteworthy finding emerging from the final OLS specification in column 6 is that the coefficient on the log population variable is almost exactly equal to unity ($\hat{\beta} = 1.01, SE = 0.19$), suggesting that employment rises equiproportionately with population. If so, productivity growth should have roughly the same impact on the employment to population *rate* as it does on aggregate employment.[14] Table 3b confirms this hypothesis. When we replace the log population measure in equation (1) with the log of the employment-to-population ratio among working-age adults, we again find nearly identical point estimates for the employment-productivity elasticity. In the final (most complete) OLS specification in column 4 of Table 3b, this elasticity is estimated at 0.20, as compared to either 0.19 in the Table 3a specification that excludes population or to 0.20 in the Table 3a specification that includes population. The instrumental variables estimates are somewhat less stable than the OLS models, but the findings for employment to population in these models are qualitatively similar nonetheless to the earlier IV estimates for employment. We place limited weight on these models for the conceptual reasons noted above.

In estimates not tabulated here, we have confirmed that our results are highly comparable when using plausible alternative measures of employment: the number of hours worked in place of the number of workers; excluding self-employed workers; or treating part-time workers differently from full-time workers. We have additionally performed analogous estimates using as our measure of productivity value-added per worker, which differs from our primary output per worker measure by abstracting from fluctuations in the prices or quantities of energy, materials, or services used in production.[15] Our results are quite similar when using value-added, confirming a positive and statistically significant employment-productivity elasticity comparable to that reported above. In aggregate, rising labor productivity is unambiguously associated with growing employment and a rising employment to population ratio.

4 Breaking it down: Industry-level evidence

The country-by-time evidence above supports the longstanding presumption that productivity growth is not inimical to employment. But this analysis falls far short of addressing the concern that specific innovations may ultimately reduce net employment. Indeed, history provides numerous examples in which sectors with rapidly rising productivity have ultimately seen large falls in employment. Agriculture is the leading example of a sector that has shed employment as productivity has risen.[16] But agriculture is not an anomaly. Using more than a century of data on employment and productivity from textile, motor vehicle, and iron and steel production, Bessen (2017) shows that employment in each of these sectors followed an “inverted U” pattern: rising dramatically over multiple decades during an initial stage of innovation, then ultimately peaking and declining in later stages of maturity. Bessen interprets this pattern through a model of heterogeneous final demand, where demand becomes less elastic as the highest value needs are satisfied. Thus,

[14] They could differ to the extent that growth of overall population and working-age population are not perfectly correlated

[15] A disadvantage of value-added as a productivity measure is that it is typically poorly measured outside of manufacturing.

[16] Johnston (2001) documents that the U.S. agricultural, forestry, fishing and hunting employment was 11.8 million in 1900 and 1910 and then declined in each subsequent decade, reaching 3.4 million in 1990 (the last data point in Johnston’s series). The U.S. Bureau of Labor Statistics estimates that employment in these sectors was 2.1 million in 2014 (Hogan and Roberts, 2105).

in the initial stage of product or productivity innovation, price declines make formerly unavailable or prohibitively expensive goods affordable for mass consumption, yielding a large positive demand response. As high priority consumption demands are satisfied (e.g., clothing, cookware, and motor transportation become cheap and abundant), further labor- and cost-saving innovations yield only a modest further increase in demand. When this stage is reached, productivity advances depress sectoral employment.[17]

While our harmonized country-industry EU KLEMS data do not offer the historical sweep available to Bessen (2017), they provide considerable cross-industry, cross-country, and over-time variation with which to analyze the relationship between productivity and employment. We drill down on this relationship at the level of industries in this augmented estimating equation, where industries are indexed by i:

$$\Delta \ln E_{ict} = \beta_0 + \beta_1 \Delta \ln LP_{ict} \; [+ \; \delta_t + \; \alpha_c + \; \gamma_i] + \varepsilon_{ict}. \tag{2}$$

This equation captures the own-industry productivity-employment elasticity using variation across countries, over time, and across sectors within countries. The bracketed terms, which we add successively, purge several sources of potentially confounding variation: year effects take out common time trends affecting productivity and employment growth in all industries and countries simultaneously; country effects take out common trends affecting all industries within a country; and industry effects take out industry-specific trends that are common across countries.[18] We weight observations by the industry employment share in total country-level employment, averaged over the sample period. Thus, each country is given equal weight as above, while within each country, the weight given to each industry is proportional to its average share of own-country employment. Standard errors are clustered at the level of country-industry to avoid the Moulton (1986) aggregation problem. Panel A of Table 4 presents OLS estimates, while panel B presents IV estimates.

Table 4 depicts a clear inverse relationship between industry-level productivity growth and industry-level employment. Across all columns of panel A, we estimate a strong, stable negative employment-productivity elasticity. The point estimate of -0.25 for the employment-productivity elasticity in column 1 implies that a 10 percent rise in labor productivity yields a 2.5 percent fall in industry employment. This estimate is essentially unaffected by inclusion of time, country, industry effects or any combination thereof (columns 2 through 4). Consonant with the Table 3 estimates, we find that country-level population growth is a strong predictor of employment

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17 Masuyama (2002) introduces a model where elasticities of demand change across a hierarchy of products as consumer incomes rise. As Bessen (2017) notes, however, Matsuyama's framework focuses attention on the *income* elasticity of demand whereas the sectoral-level evidence (i.e., from textiles, transportation, and iron and steel) suggests instead a first-order role for own-price elasticities (substitution effects) rather than income effects.

18 Industry-by-country fixed effects are already implicitly taken out by first-differencing in the stacked first-difference model.

growth (in this case at the industry level) but has no detectable impact on the estimated employment-productivity elasticity.

Table 4

The effects of productivity growth on employment growth at the industry level.
Dependent variable: annual log change in employment by country-industry.

	A. OLS				
Δ ln productivity (cit)	-0.248** (0.024)	-0.259** (0.023)	-0.275** (0.024)	-0.249** (0.024)	-0.248** (0.024)
Δ ln population (ct)	-	-	-	-	0.895** (0.191)
Country fixed effects	*NO*	*YES*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*	*YES*
R2	0.110	0.155	0.201	0.300	0.305
N	19,451	19,451	19,451	19,451	19,451
	B. IV				
Δ ln productivity (cit)	-0.302** (0.042)	-0.305** (0.039)	-0.534** (0.041)	0.050 (0.109)	0.048 (0.108)
Δ ln population (ct)	-	-	-	-	1.036** (0.181)
Country fixed effects	*NO*	*YES*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*	*YES*
Sanderson-Windmeijer F-statistic	593.1	578.5	525.4	53.3	53.4
N	19,451	19,451	19,451	19,451	19,451
	First stage for Δ ln productivity				
Mean Δ ln productivity (it) in other countries	0.690** (0.028)	0.689** (0.029)	0.611** (0.027)	0.303** (0.042)	0.303** (0.042)

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is measured at the country-industry-year level. All models weighted by industry employment shares within countries, averaged over the period. 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-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

In Appendix Table 4, we test whether these conclusions are altered when we allow for first and second-order lags of productivity growth, as was the case with the *aggregate* productivity growth estimates in Table 3. These industry-level productivity lags are in all cases small, generally insignificant, and do not affect the message of Table 4, which is that own-industry productivity growth dampens employment growth. (We omit industry-level productivity lags from subsequent tables for brevity.)

Might these estimates be biased downward by simultaneity stemming from correlated measure in the dependent and independent variables? Panel B of Table 4 explores this concern using an analogous strategy to that applied in Table 3: instrumenting own-country-industry productivity growth with contemporaneous own-industry productivity growth in other countries. Surprisingly, the IV point estimates are modestly *more negative* than the corresponding OLS estimates, suggesting that simultaneity bias is likely not a first order issue for the industry level regressions.[19]

We infer that during the time period under study, industries that experienced rapid productivity growth exhibited diminished employment growth. This result is in the spirit of the classic Baumol (1967) model, which posits that technologically advancing sectors—that is, those experiencing high productivity growth—will tend to contract relative to technologically lagging sectors.

5 Reconciling the micro elasticity with the macro elasticity

Given that aggregate productivity gains yield aggregate employment gains while sectoral productivity gains yield sectoral employment declines, we conjecture that the *indirect* positive effect of productivity growth on employment across sectors dominates the direct negative effect of own-sector productivity growth on own-sector employment. These indirect impacts may, in turn, accrue either through rising final demand (an income effect) or through interindustry demand linkages.

We explore evidence for this interpretation in Table 5 by pooling our macro (country-level) and micro (industry-level) approaches to estimate:

$$\Delta \ln E_{ict} = \beta_0 + \beta_1 \Delta\ln LP_{ict} + \sum_{k=0}^{3} \beta_{2+k} \Delta\ln\widetilde{LP}_{ct-k,j\neq i} \; [+ \delta_t + \alpha_c + \gamma_i] + \varepsilon_{ict}. \quad [3]$$

Here, $\Delta\ln LP_{ict}$ is the log change in own-industry labor productivity as per equation (2), and $\Delta\ln\widetilde{LP}_{ct,j\neq i}$ is the average log change in labor productivity in *other* industries in the same country and time period. In this estimating equation, the coefficient β_1 estimates the own-industry employment-productivity elasticity and the coefficient vector β_{2+k} estimates the indirect effect of productivity growth outside of own-industry i on industry $i's$ employment. Drawing upon our results above, we apply two simplifications to the empirical approach. First, because the Table 4 estimates suggest that simultaneity bias is not a first-order issue here, we omit the instrumental variables approach used in our country-level estimation. Second, we use both contemporaneous and k lags of aggregate productivity ($\Delta\ln\widetilde{LP}_{ct,j\neq i}$) to capture the dynamics revealed by the estimates in Table 3.

[19] That the IV estimate loses significance when industry effects are added (column 4 of panel B) reflects the limitation of the leave-out instrumental variable approach discussed in footnote 13. Almost all of the first stage identifying variation from this approach is cross- rather than within-industry, meaning that it is nearly collinear with industry dummies.

Table 5a

The effect of industry and aggregate productivity growth on employment growth. Dependent variable: annual log change in employment by country-industry

	(1)	(2)	(3)	(4)	(5)
Δ ln productivity (cit)	-0.279** (0.027)	-0.280** (0.027)	-0.283** (0.027)	-0.256** (0.026)	-0.255** (0.026)
Δ ln productivity (c, j≠i, t)	0.212** (0.064)	0.190** (0.062)	0.136* (0.065)	0.116~ (0.063)	0.127* (0.061)
Δ ln productivity (c, j≠i, t-1)	0.166** (0.042)	0.152** (0.035)	0.104** (0.034)	0.098** (0.034)	0.108** (0.032)
Δ ln productivity (c, j≠i, t-2)	0.097* (0.042)	0.080* (0.036)	0.061~ (0.036)	0.057 (0.036)	0.056 (0.034)
Δ ln productivity (c, j≠i, t-3)	0.097* (0.039)	0.069* (0.031)	0.067* (0.032)	0.063* (0.031)	0.059~ (0.031)
Δ ln total population (ct)	-	-	-	-	1.113** (0.191)
Country fixed effects	*NO*	*YES*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*	*YES*
R2	0.142	0.174	0.206	0.312	0.320
N	17,858	17,858	17,858	17,858	17,858
Σk Δ ln productivity (c, j≠i, t-k)	0.573** (0.091)	0.491** (0.086)	0.369** (0.091)	0.333** (0.090)	0.350** (0.088)
Σk Δ ln productivity (c, j≠i, t-k) + Δ ln productivity (cit)	0.294** (0.093)	0.211* (0.088)	0.086 (0.094)	0.078 (0.094)	0.095 (0.091)

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is measured at the country-industry-year level; aggregate productivity is the country-year level productivity with the own industry netted out. All models estimated with OLS and weighted by industry employment shares within countries, averaged over the period. 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-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Consistent with the reasoning above, we find that labor productivity growth has strongly countervailing effects on employment at the industry and at the aggregate level. In the first row of estimates, we find an employment-productivity elasticity in the range of -0.26 to -0.28, which is nearly identical to the estimates in Table 4. Thus, the addition of aggregate productivity measures to the estimating equation has no impact on the industry-level inference. Accounting for aggregate population growth also leaves the estimates unaffected (column 5).

Rows two through five of Table 5a report coefficients on contemporaneous and lagged aggregate productivity growth, $\Delta \ln \widetilde{LP}_{ct,j\neq i}$. In all specifications, aggregate productivity growth occurring *outside* of each sector has strong predictive power for employment growth within the sector. Summing over the contemporaneous coefficient and the three lags (second to last row), we estimate that each percentage point rise in external (other-sector) productivity predicts an own-sector employment rise of between 0.3 and 0.6 percent. The final row of the table sums over the own-sector and other-sector productivity coefficients to estimate the *net* effect of a percentage point rise in own- and other-sector productivity occurring simultaneously.[20] This net effect is in all cases positive but is not statistically

[20] While the aggregate and own-sector productivity will not typically move in tandem in each sector, these terms *must* maintain equality on average in each year since arithmetically, the mean of the leave-out means of other-sector productivity growth equals the grand mean of own-sector productivity growth.

significant when year and industry trends are included (columns 3 and 4). In the most demanding specification (column 5), which includes country-, industry-, and year-specific common effects, and the contemporaneous change in national population, we find an insignificantly positive *net* employment-productivity elasticity of 0.095. These estimates imply that the positive external effect of productivity growth on employment fully offsets the negative internal effect of industry productivity growth on own-industry employment.

5.1 Robustness: Employment rates, business cycles, and productivity measures

Because the results in Table 5a ultimately prove central to our primary conclusions, we have performed an extensive set of tests to probe their robustness. A first test is whether our findings for the impact of productivity growth on industry employment levels also apply to industry employment to population rates—that is the (log) ratio of industry employment to working-age population in a country year.[21] Table 5b confirms that this is the case. Estimates in Table 5b for the effect of productivity on employment-to-population rates find almost identical results to those for employment levels, as in Table 5a. This result is sensible in light of our finding above that the aggregate elasticity of employment with respect to population is virtually indistinguishable from unity, and confirms that our findings apply with equal force to employment levels and employment rates.

A second concern with our estimates is that they do not account for the cyclical nature of productivity growth. If for example, productivity growth is generally pro-cyclical as argued by Basu and Fernald (2001), we could erroneously conclude that rising productivity causes rising aggregate employment simply because both tend to rise and fall with the business cycle—and not because productivity growth is employment-enhancing. Appendix Tables 5a through 5c confront this challenge. Table 5a reports the OECD designated peak and trough business cycle years for each of the 19 countries in our sample. Appendix Tables 5b and 5c, respectively, re-estimate equation (3) for the employment-productivity elasticity using only peak-to-peak and trough-to-trough changes in employment and productivity. Thus, the number of observations for these models is equal to the total number of peaks or troughs (minus one) in each country multiplied by the number of industries.[22] Surprisingly, the peak-to-peak and trough-to-trough estimates of the employment-productivity elasticity, both at the own-industry and aggregate levels, are highly comparable to our main estimates above. We conclude that cyclicality does not pose an important confound for our main analytic approach.

A third, and potentially more fundamental, limitation of our estimates so far is that our primary labor productivity measure, output per worker, makes no distinction between

21 The denominator of the country-industry-year employment-to-population rate is the working age population for the country-year. By construction, the sum of country-year industry employment-to-population rates is equal to the country-year employment-to-population ratio.

22 All measures are annualized to account for the uneven length of peak-to-peak and trough-to-trough intervals across countries and over time.

output growth arising from changes in quantities or prices of inputs, from changes in value-added, and from changes in total factor productivity. Appendix Tables 5d and 5e address this limitation by re-estimating equation (3) using industry-level value-added per worker and industry-level total factor productivity (TFP), respectively, in place of output per worker. Using value-added per worker as the productivity measure, we obtain estimates that are almost indistinguishable from our primary results. Specifically, we estimate an own-industry employment-productivity elasticity of -0.24, a cross-industry spillover elasticity of +0.36, and a net productivity-employment elasticity of 0.11. As with the prior estimates using output per worker, the aggregate elasticity estimate is positive but not statistically significant.

Appendix Table 5e reports estimates that use TFP in place of labor productivity. These estimates present an even stronger case that productivity growth is *not* employment reducing. We obtain an employment-productivity elasticity estimate of -0.08 at the industry level, which is only one-third as negative as the elasticity estimated using output per worker or value-added per worker. This finding implies that industry-level pure productivity growth (i.e., the Solow residual) is *less* employment-reducing than simple increases in labor productivity (which may arise from various technological and non-technological sources). Complementing this finding, Table 5e reveals that the estimated employment spillover effect of TFP growth is *nearly identical* to that for the spillover effects of conventional labor productivity. In net, the effect of rising TFP on aggregate employment is strongly positive: we estimate a highly significant aggregate employment-productivity elasticity of +0.29, implying that each percentage point rise in TFP (occurring notionally across all industries simultaneously) predicts a 0.3 percentage point rise in national employment.

Why does TFP growth have a less negative effect on *own-industry* employment growth than does labor-productivity but a comparable (i.e., equally positive) spillover effect on employment? One reason may be that, unlike labor productivity (equal to gross output or value-added, denominated by employment), the TFP variable does not suffer from simultaneity arising from measurement error. This simultaneity will tend to drive the employment-productivity estimates into negative territory, as discussed in Section 3.1. This issue does not apply to TFP since TFP is explicitly purged of measured fluctuations in inputs, including labor. In addition, this concern does not apply to the relationship between either labor-productivity or TFP and other-sector (spillover) employment because measurement variation in own-industry employment should not be correlated with measurement variation in other-industry employment. Jointly, these observations may explain why TFP growth has a less negative predictive relationship to own-industry employment but an equally positive spillover effect to other-industry employment, comparable to labor productivity growth—and hence a stronger net effect on employment.

We emphasize, however, that estimated TFP gains are typically one-tenth to one-half as large as gains in conventionally measured labor productivity during this period, and are in many cases negative even though labor productivity growth is positive (see Appendix Table 2). Thus, the larger aggregate employment-productivity elasticity found for TFP as compared to labor productivity does *not* imply a qualitatively larger effect of productivity growth on overall employment growth.[23] We are not inclined to put highest weight on the TFP-based findings because TFP is, after all, merely a regression residual that is potentially subject to numerous measurement and specification artifacts. Nevertheless, we view these TFP results as strong evidence that our main models are unlikely to *overstate* the net employment-augmenting effect of rising productivity.

Table 5b

The effects of industry and aggregate productivity growth on employment growth. Dependent variable: annual log change in employment to working age population by country-industry

	(1)	(2)	(3)	(4)
Δ ln productivity (cit)	-0.278** (0.027)	-0.279** (0.027)	-0.283** (0.027)	-0.255** (0.026)
Δ ln productivity (c, j≠i, t)	0.219** (0.061)	0.214** (0.062)	0.144* (0.063)	0.123* (0.061)
Δ ln productivity (c, j≠i, t-1)	0.163** (0.035)	0.160** (0.032)	0.105** (0.032)	0.099** (0.031)
Δ ln productivity (c, j≠i, t-2)	0.079* (0.035)	0.074* (0.033)	0.052 (0.033)	0.048 (0.033)
Δ ln productivity (c, j≠i, t-3)	0.065* (0.031)	0.056* (0.028)	0.052~ (0.029)	0.047 (0.029)
Country fixed effects	*NO*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*
R2	0.144	0.155	0.190	0.300
N	17,858	17,858	17,858	17,858
Σk Δ ln productivity (c, j≠i, t-k)	0.526** (0.081)	0.505** (0.085)	0.352** (0.088)	0.317** (0.087)
Σk Δ ln productivity (c, j≠i, t-k) + Δ ln productivity (cit)	0.247** (0.083)	0.226* (0.086)	0.070 (0.091)	0.062 (0.091)

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is measured at the country-industry-year level; aggregate productivity is the country-year level productivity with the own industry netted out. All models estimated with OLS and weighted by industry employment shares within countries, averaged over the period. 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-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

5.2 Does productivity growth raise consumption?

The robust finding that productivity growth is in net employment-augmenting implies that a combination of inter-industry output linkages and final demand effects fully offset the direct employment-reducing consequences of productivity growth. Thoroughly analyzing these linkages would require a cross-national input-output analysis as in Timmer et al. (2015), which is beyond the scope of this paper. As a small (tantalizing) step in this direction, we present evidence from consumption data that the conjectured linkage between productivity growth and consumption growth response is in fact evident. For this analysis, we draw on the World Input Output Database (discussed in Section 2). We estimate a variant of equation (3) in which we

23 Put simply, these estimates do not alter the conclusion that the net effects of productivity growth on aggregate employment (netting over internal and spillover effects) are quite small.

regress the log of domestic consumption by country-industry-year on the log of country-industry-year gross output per worker.[24] Because of the limited time interval available from the WIOD (1995 – 2009), we exclude productivity lags from the analysis.

Table 6

The effects of industry and aggregate productivity growth on domestic consumption growth. Dependent variable: Annual log change in domestic consumption by country-industry

	(1)	(2)	(3)	(4)	(5)
Δ ln productivity (cit)	0.406** (0.053)	0.410** (0.053)	0.408** (0.054)	0.455** (0.057)	0.455** (0.057)
Δ ln productivity (c, j≠i, t)	0.043 (0.283)	0.119 (0.313)	0.098 (0.348)	0.070 (0.348)	0.070 (0.348)
Δ ln total population (ct)	-	-	-	-	0.874 (1.543)
Country fixed effects	*NO*	*YES*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*	*YES*
R2	0.024	0.042	0.243	0.255	0.256
N	6,838	6,838	6,838	6,838	6,838

Notes: Source: WIOT, 1995-2009. Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is measured at the country-industry-year level; aggregate productivity is the country-year level productivity with the own industry netted out. All models estimated with OLS and weighted by industry employment shares within countries, averaged over the period. 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-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Estimates of these models reported in Table 6 detect a highly robust own-industry consumption response to labor productivity growth. The estimates imply that each percentage point increase in productivity gives rise to almost a half percentage point rise in consumption. This robust pattern suggests that final demand is considerably below unit elasticity, consistent with the fact that industry employment falls as productivity rises. [25]

The second row of each model in Table 6 tests for spillovers from own-industry productivity growth to consumption of other-industry outputs. Unlike for employment, however, we do not detect significant spillovers. Although the spillover coefficient is uniformly positive, it is economically small in magnitude and never statistically significant. Given the limitations of this analysis—especially the fact that we do not incorporate input-output linkages—we take the Table 6 evidence as corroborating the presence of a productivity-consumption link but providing limited information on its economic magnitude.

[24] The consumption data come from the World Input Output tables. We use the sum of final consumption by households, non-profit organizations serving households, and by governments. Labor productivity, equal to gross output divided by employment, is from the Socio-Economic Accounts of the World Input Output Database. Population counts by country-year are from the World Bank.

[25] Appendix Table 6a shows that this conclusion is unaffected by using the value-added based productivity measure, and Appendix Table 6b highlights that results are qualitatively robust to removing 2008 and 2009 (the start of the Great Recession) from the data.

6 Not all productivity growth is equivalent: Heterogeneity in sectoral spillovers

As countries have industrialized during the 20th and 21st centuries, the locus of employment has shifted secularly from primary and secondary sectors—agriculture, mining, utilities, construction, and manufacturing—towards tertiary sectors supplying services to businesses and consumers (e.g., education, healthcare, transportation, wholesale and retail trade, business services, hotels and restaurants). This secular transformation is plotted in Figure 2a for the 19 countries in our sample.[26] In this figure and the analysis that follows, we combine our 28 industries into five exhaustive and mutually exclusive 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.[27]

Over the comparatively short timespan between 1970 – 2007, the share of employment in manufacturing dropped by more than 15 percentage points while the share in mining, construction, and utilities fell by roughly three percentage points. Conversely, the share of employment in education and health rose by eight percentage points, the share in high-tech services rose by ten percentage points, and the share in low-tech services rose by a modest two percentage points. The six panels of Figure 2b document that this secular transformation has occurred simultaneously (though not identically) within each of the five largest OECD economies—France, Germany, Japan, the UK, and the US—as well as in the average of the remaining fourteen smaller economies.[28]

[26] Paralleling our regression analyses, the figure reports an unweighted average of sectoral employment shares across nineteen countries. Consequently, the cross-national means are not primarily driven by the employment movements of larger countries.

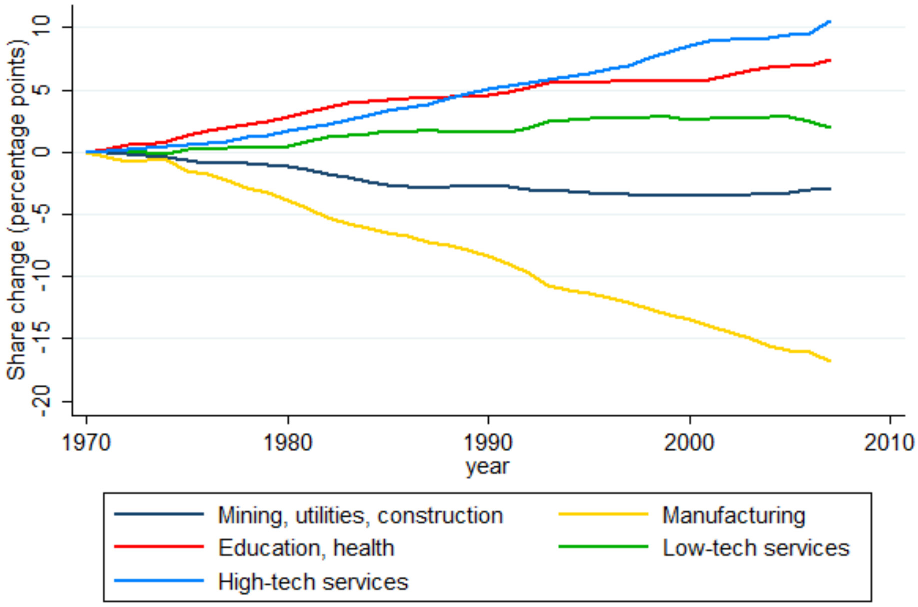
[27] Specifically: Mining, utilities, and construction corresponds to industries C, E and F; Manufacturing is industries 15 through 37; Education and health services are industries M and N; High-tech services are industries 64, J, and 71 to 74; and Low-tech services are industries 50 to 52, H, 60 to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

[28] For reference, Appendix Figures 2a and 2b present the corresponding employment *shares* by sector (overall and by major country) rather than the share *changes* reported in Figures 2a and 2b.

Figure 2a

Cumulative changes in employment shares by sector for nineteen countries, 1970 - 2007 (1970 = 0)

(x-axis: year; y-axis: share change (percentage points))

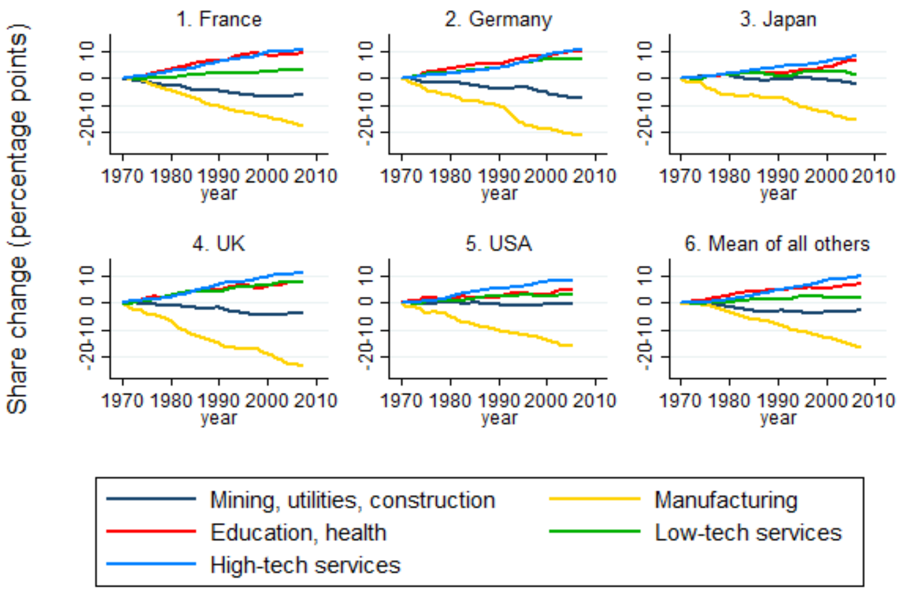


Shares normalized to 0 in 1970. Unweighted average across all 19 countries.

Figure 2b

Changes in employment shares by sector for the five largest economies in EUKLEMS, and for the average of the fourteen remaining economies, 1970 – 2007 (1970 = 0): Large countries

(x-axis: year; y-axis: share change (percentage points))



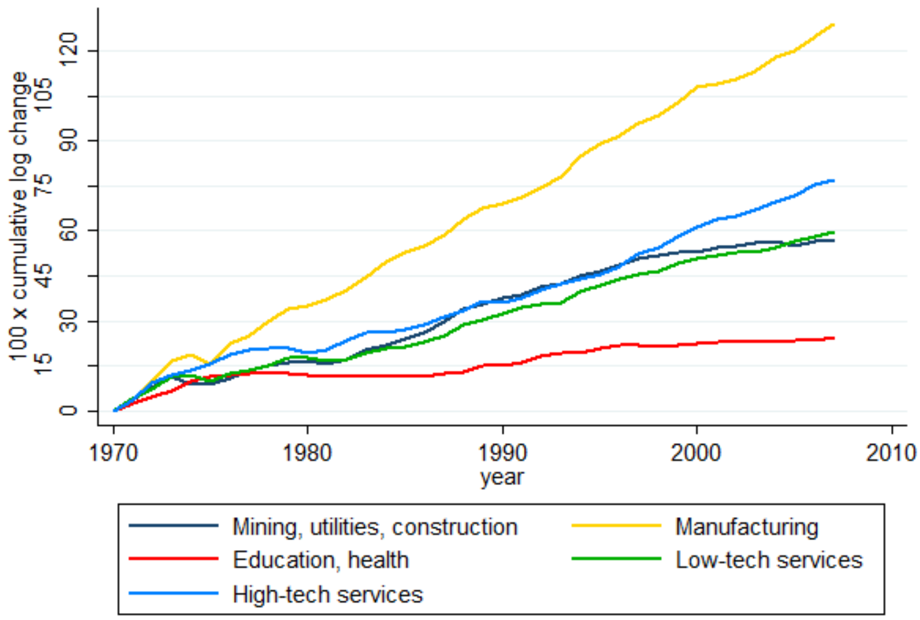
Shares normalized to 0 in 1970. Mean of all others is an unweighted average.

The substantial reallocation of employment across major sectors depicted in Figures 2a and 2b are inversely mirrored by trends in labor productivity growth across sectors. Figure 3a, which plots cumulative log labor productivity growth since 1970 by major sector, documents that productivity growth has been more than twice as rapid in manufacturing as in all other sectors while, conversely, productivity growth has been slowest—bordering on negligible—in education and health, and somewhat more rapid in high- and low-tech services, and in mining, utilities and construction.

Figure 3a

Cumulative log changes in labor productivity growth by sector for nineteen countries, 1970 – 2007 (1970 = 0)

(x-axis: year; y-axis: 100 x cumulative log change)



Unweighted average across all 19 countries. Productivity is gross output based.

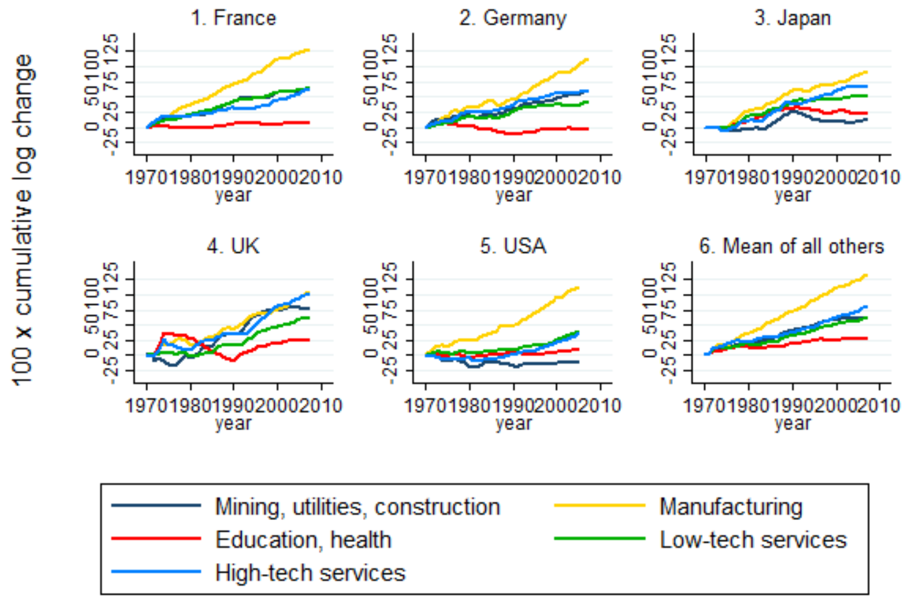
A qualitatively similar sectoral productivity pattern holds across all major countries, as documented in Figure 3b. In each of the five largest economies, manufacturing productivity growth has considerably outpaced that of all other major sectors. Education and health have experienced the lowest or second-lowest level of sectoral productivity growth in each of the big five economies, while productivity growth in high- and low-tech services has fallen somewhere in between these two extremes.[29] A comparison of the employment trends in Figure 2 with the productivity trends in Figure 3 highlights that, consistent with the Baumol (1967) hypothesis, sectors exhibiting more rapid productivity growth have contracted as a share of employment, while conversely those with slow productivity growth have expanded. The same conclusion emerges when using value-added rather than gross output per worker for our productivity measure, as reported in Appendix Figures 3a and 3b, respectively.

[29] Productivity growth in mining, utilities and construction has differed more substantially across countries.

Figure 3b

Cumulative log changes in labor productivity by sector for the five largest economies in EUKLEMS, and for the average of the fourteen remaining economies, 1970 - 2007 (1970 = 0): Large countries

(x-axis: year; y-axis: 100 x cumulative log change)



Mean of all others is an unweighted average. Productivity is gross output based.

The stark contrasts in employment and productivity growth across major sectors invite the question of whether our estimates above omit a critical interaction between productivity growth and employment growth. Implicitly, the models in Table 5 impose the restriction that the employment effect of productivity growth is symmetric across sectors: the employment-productivity elasticity is constrained to be identical across sectors; and, moreover, the external effects are similarly constrained, so that productivity growth in manufacturing must have the same external effect on employment in non-manufacturing as does productivity growth in non-manufacturing on employment in manufacturing.

These restrictions are unlikely to be realistic for several reasons. One is that the *external* effects of productivity gains in one sector on employment in others should depend, at least in part, on the economic heft of the sector experiencing the productivity gain. Concretely, a one percent productivity gain in services should have a larger impact on aggregate wealth—and hence likely aggregate employment—than a one percent productivity gain in agriculture simply because the service sector is so comparatively vast. Finally, these internal and external effects may change over time as incomes rise and as the demand for outputs of specific sectors saturates (as per Bessen 2017), or as sectors become increasingly integrated in international production chains.

A second reason why these restrictions may not hold is that own-productivity elasticities may differ across sectors for the reasons suggested by Bessen (2017): in sectors where demand is relatively saturated (e.g., agriculture), final demand may respond only weakly to price-reducing or quality-increasing productivity increases; in sectors that are less mature (e.g., healthcare), productivity gains may be met with a strong demand response. Furthermore, one might expect that sectors with more competitive output markets experience a stronger price response as a result of productivity enhancements, resulting in a larger demand response and hence a less negative own-productivity elasticity. Another possible reason why own-productivity effects may differ across sectors is that the labor-replacing versus labor-complementing properties of technologies are sector-specific. And finally, the degree of international tradability of sectoral outputs could affect the extent to which any final demand response from productivity growth is in part met by foreign rather than domestic producers, thereby impacting the own-industry employment effect of productivity growth.

We explore sectoral heterogeneity in the employment-productivity relationship by relaxing the symmetry restrictions imposed by our Table 5 estimates. Specifically, we augment equation (3) to allow both own-industry and cross-sector employment-productivity elasticities to differ across the five broad sectors plotted above. Following the lag specification in Table 5, we include three lags of other-sector productivity growth alongside the contemporaneous measure. We do not include lags of own-industry productivity growth since as reported above, these lags are never significant. Our estimating equation is:

$$\Delta \ln E_{ict} = \beta_0 + \sum_{s(i)=1}^{5} \beta_{1,s(i)} \Delta\ln LP_{ict} + \sum_{s(i)=1}^{5} \sum_{k=0}^{3} \beta_{2+k,s(i)} \Delta\ln\widetilde{LP}_{ct-k,j\neq i} \; [+\delta_t + \alpha_c + \gamma_i] + \varepsilon_{ict}, \tag{4}$$

where we denote sectors with the subscript $s(i)$ to emphasize the correspondence between industry and sector. In this equation, $\widetilde{LP}_{ct-k,j\neq i}$ is sectoral productivity with the own-industry component netted out: since the 5 sectors are aggregates of our 28 industries, $\beta_{2+k,s(i)}$ captures the impacts of productivity growth in sector s(i), onto all industries, where for industries belonging to sector s(i), the own-industry productivity increase is netted out. Table 7 presents estimates.

We find considerable heterogeneity in both the own-industry (internal) and cross-sector (external) productivity effects on employment. Focusing first on the internal effects, we find that three of five sectors have internal employment-productivity elasticities in the range of -0.35, while both manufacturing and high-tech services have smaller elasticities (estimated at -0.15 and -0.23, respectively), implying that equivalent productivity gains displace proportionately fewer workers (as a share of industry employment) in these sectors.

Table 7

The effect of industry and aggregate sectoral productivity growth on employment growth. Dependent variable: Annual log change in employment by country-industry

	(1)	(2)	(3)	(4)	(5)
Mining & utilities & construction					
Δ ln productivity (cit)	-0.324** (0.042)	-0.318** (0.042)	-0.323** (0.042)	-0.319** (0.042)	-0.317** (0.042)
Σk Δ ln productivity (c, j≠i, t-k)	0.007 (0.036)	0.036 (0.034)	0.010 (0.033)	0.002 (0.034)	0.007 (0.033)
Manufacturing					
Δ ln productivity (cit)	-0.127** (0.023)	-0.130** (0.023)	-0.134** (0.023)	-0.149** (0.023)	-0.148** (0.023)
Σk Δ ln productivity (c, j≠i, t-k)	0.220** (0.048)	0.131** (0.049)	0.043 (0.049)	0.053 (0.048)	0.054 (0.044)
Education & health					
Δ ln productivity (cit)	-0.360** (0.039)	-0.360** (0.039)	-0.355** (0.040)	-0.359** (0.040)	-0.359** (0.040)
Σk Δ ln productivity (c, j≠i, t-k)	0.121** (0.043)	0.099* (0.039)	0.119** (0.036)	0.122** (0.036)	0.089* (0.037)
Low-tech services					
Δ ln productivity (cit)	-0.351** (0.047)	-0.350** (0.046)	-0.353** (0.046)	-0.348** (0.048)	-0.347** (0.047)
Σk Δ ln productivity (c, j≠i, t-k)	0.106 (0.068)	0.133* (0.065)	0.132* (0.062)	0.138* (0.062)	0.167** (0.060)
High-tech services					
Δ ln productivity (cit)	-0.263** (0.044)	-0.264** (0.042)	-0.263** (0.043)	-0.227** (0.041)	-0.229** (0.042)
Σk Δ ln productivity (c, j≠i, t-k)	0.128** (0.025)	0.137** (0.028)	0.120** (0.026)	0.093** (0.026)	0.071** (0.022)
Δ ln total population (ct)	-	-	-	-	0.972** (0.190)
Nr of lags in ln productivity (c, j≠i)	*k=3*	*k=3*	*k=3*	*k=3*	*k=3*
Country fixed effects	*NO*	*YES*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*	*YES*
R2	0.239	0.272	0.303	0.331	0.336
N	17,858	17,858	17,858	17,858	17,858

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is measured at the country-industry-year level; aggregate productivity is the sector-year level productivity with the own industry netted out. All models estimated with OLS and weighted by industry employment shares within countries, averaged over the period. 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-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

More striking still is the heterogeneity in the estimated external effects of productivity. Productivity growth in mining, utilities, and construction has no measureable effect on employment growth in other industries. The external effect of productivity growth in manufacturing is also small in magnitude and statistically insignificant. Conversely, we estimate that productivity growth in high-tech services, and in health and education, raises other-industry employment with an elasticity of 0.07 to 0.09 (that is, a 10 percent productivity gain in these sectors raises economy-wide employment—excluding the source industry—by 0.7 to 0.9 percent). Finally, the external effects of productivity growth in low-tech services are roughly twice as large as any other sector, estimated at 0.17. This outsized spillover may stem from the fact that low-tech services is the largest sector in all major economies in our sample, typically encompassing 30 to 40 percent of employment (see Appendix Figure 2b), so that productivity gains in this sector may have a large positive effect on consumer purchasing power.

Summarizing, we find non-negligible sectoral heterogeneity in both the own- and cross-sector employment elasticities, indicating important roles for both Baumol effects—where productivity gains reduce own-sector employment—and positive demand linkages or income effects where rising sectoral productivity augments employment elsewhere in the economy. These findings are robust to alternatively using value added based productivity growth, as reported in Appendix Table 7a, or considering effects on the employment rate, shown in Appendix Table 7b.

To quantify what these statistical relationships imply for the net effect of productivity growth on employment, we consider the respective contributions to employment of productivity growth originating in each of these five broad sectors. These net effects will depend not only on the estimated own- and cross-sector elasticities, but also on the different productivity growth trajectories across industries and on their relative employment sizes. These relationships are formalized in equation (5):

$$\Delta\hat{E}_{ict} = \left\{E_{ic,t=base} \times 1(i \in s) \times \hat{\beta}_{1,s(i)} \times \Delta\ln LP_{ict}\right\} + \left\{E_{ic,t=base} \times \sum_{s(i)=1}^{5} \sum_{k=0}^{3} \hat{\beta}_{2+k,s(i)} \times \Delta\ln \widetilde{LP}_{ct-k,j\neq i}\right\} \quad [5]$$

In this equation, $\Delta\hat{E}_{ict}$ is the predicted employment change in industry i in country c and year t resulting from productivity growth occurring in i and in all other industries $j \neq i$. The first term in curly brackets represents the own-industry (internal) effect of labor productivity growth on employment, while the second term is the cross-industry (external or spillover) employment effect. The percentage annual employment change from the internal effect is given by the annual productivity growth in each industry multiplied by its sector-specific coefficient (denoted by the indicator function $1(i \in s)$ for the corresponding sector).[30] This annual percentage change is applied to base-year employment levels $E_{ic,t=base}$, where 1992, close to the midpoint of the sample period, serves as the base year.

Meanwhile, the percentage annual employment change resulting from the *external* productivity effect is given by the sum of productivity change in each sector *s* in the current and past three years–leaving out the industry's own productivity growth– multiplied by the respective sector-specific coefficients and their lags. This quantity is in turn multiplied by total country-level employment in the base year $E_{c,t=base}$, since these external effects operate on the entire economy. To obtain predicted employment changes by country and year, we sum each of these components across industries within countries for each time period. To abstract from differences in country size we scale predicted employment changes by countries' initial levels to obtain predicted percentage point changes. Equation (5) further allows us to study the separate contributions of the internal and external productivity effects to

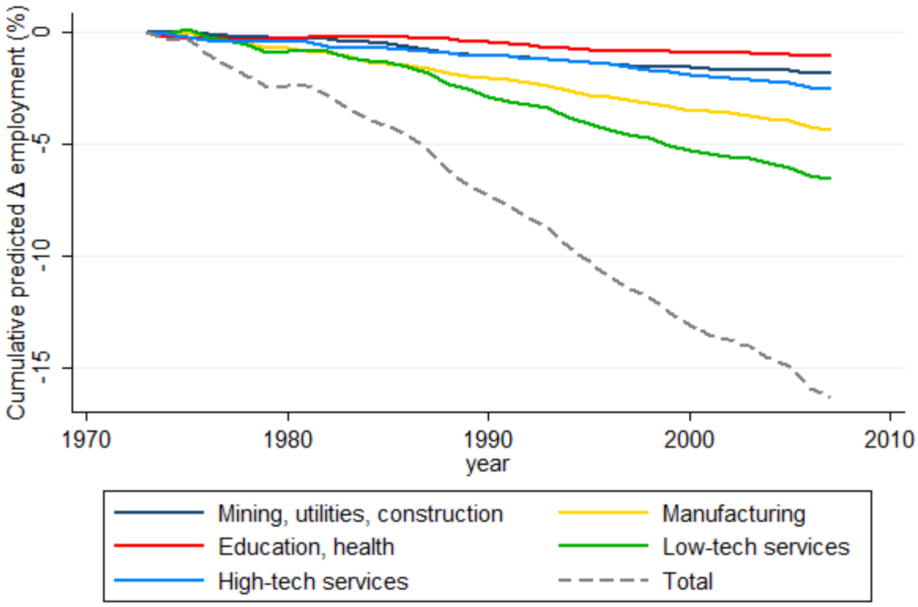
30 We exponentiate this term and subtract one to obtain percentage changes.

aggregate employment, as well as the separate contributions of productivity growth originating in any of the five broad sectors.

Figure 4a

Predicted cumulative percentage employment change from own-industry productivity growth originating in five sectors

(x-axis: year; y-axis: cumulative predicted Δ employment (%))



Based on model 5 from Table 7; prediction averaged across all 19 countries.
Productivity is gross output based.

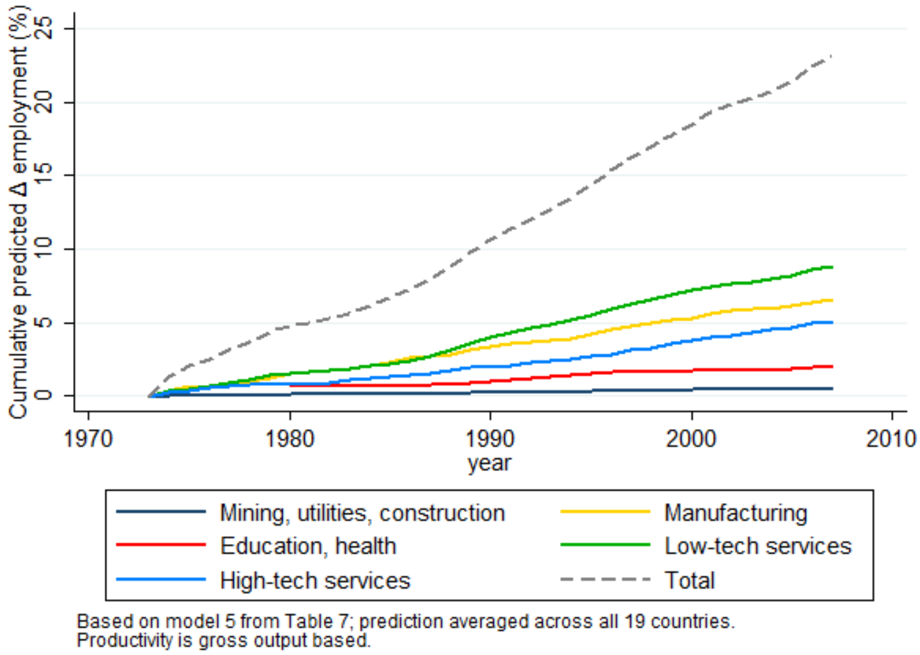
Starting with the internal effect, Figure 4a shows that the total effect of own-industry productivity growth (represented by the dashed gray line) is employment-reducing, amounting to a non-negligible decline in employment of more than 15 percent over the period. Although own-industry demand rises in response to a productivity increase (if not, the employment-productivity elasticity would equal negative one), this internal effect is insufficient to fully compensate the loss of employment from more efficient production. Of the total negative internal employment effect depicted by the gray dashed line, the largest contributions come from low-tech services and manufacturing. In the case of low-tech services, this is because it has one of the most negative own-industry employment elasticities, and a large share in total employment (see Appendix Figure 2a). Manufacturing, on the other hand, has a smaller negative own-industry employment elasticity but has witnessed outsized productivity growth, amplifying its contribution to the total effect. The smallest negative employment effect is due to productivity growth in education and health services. This is not because of an absence of Baumol effects or small sector size—indeed, this sector has the most negative own-industry employment elasticity and is among the largest in terms of employment size (see Appendix Figure 2a)—but because this sector has witnessed barely any productivity growth.

If these internal effects were the only channel through which productivity growth impacted labor demand, we would conclude technological progress *is* indeed inimical to employment. Yet our models show that there are spillovers accruing outside of the industry where the productivity growth originates. The contribution of these external effects to employment growth is plotted in Figure 4b. Here, we find that such effects have increased employment by over 20 percent over the period. Large positive contributions come from sectors that have a large heft in the economy (low-tech services) and those that have witnessed strong productivity growth (manufacturing, and to a lesser extent, high-tech services). On the other hand, productivity growth in mining, utilities, and construction has not produced an employment spillover at all, showing that the existence of these effects is not a given.

Figure 4b

Predicted cumulative percentage employment change from spillovers of productivity growth originating in five sectors

(x-axis: year; y-axis: cumulative predicted Δ employment (%))

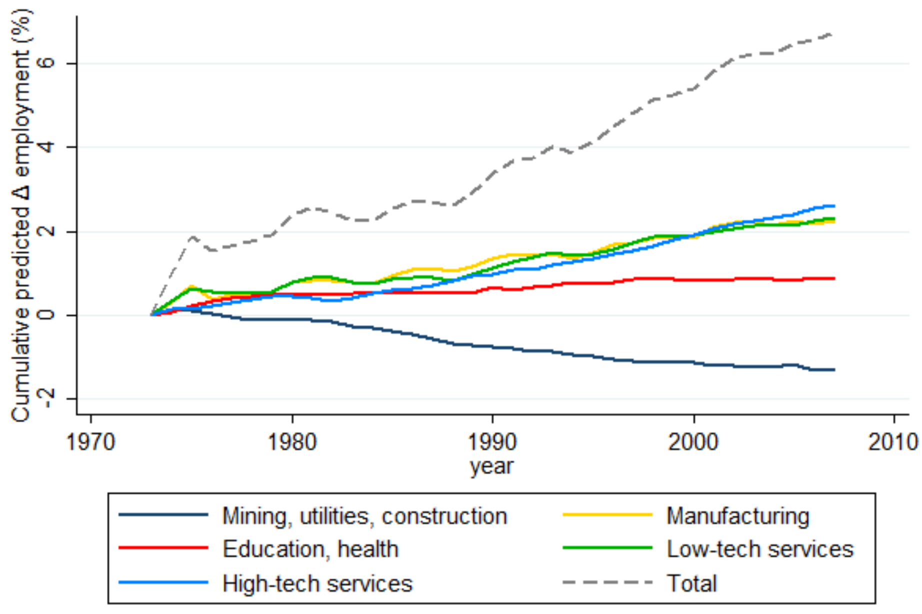


Summing these internal and external components in Figure 4c, we find that the net effect of productivity on employment is *positive*, as indicated by the gray dashed line. The contributions of productivity growth from these five sectors, however, differ markedly, highlighting the importance of considering the source of productivity growth. We calculate that productivity growth in mining, utilities and construction has been *employment-reducing* in net over 1970-2007, stemming from the joint impacts of a negative internal effect of sectoral productivity on sectoral employment and a zero external effect of sectoral productivity growth on aggregate employment. On the other hand, productivity growth in manufacturing appears to have made a modest positive contribution to aggregate employment, reflecting its comparatively small (negative) own-industry employment elasticity and its small (positive) external productivity-employment elasticity. By implication, productivity growth in manufacturing appears to reduce manufacturing's share of employment while raising aggregate employment slightly. Productivity growth in the education and health sector makes a contribution similar to manufacturing to aggregate employment growth, reflecting slower productivity growth in this sector but larger external employment effects. Finally, the two subsectors of other services, high-tech and low-tech, make positive contributions, albeit for different reasons. Reflecting its relatively large external elasticity and large relative size, productivity growth in low-tech services makes the largest contribution to aggregate employment growth. Conversely, despite being smaller in size and having a lower external elasticity, productivity growth in high-tech services still makes a positive, albeit smaller, contribution to aggregate employment growth, in part because it has witnessed higher productivity growth than low-tech services and, in part, because its internal elasticity is relatively small.

Figure 4c

Predicted cumulative percentage employment change from productivity growth originating in five sectors, summing own-industry and spillover effects

(x-axis: year; y-axis: cumulative predicted Δ employment (%))



Based on model 5 from Table 7; prediction averaged across all 19 countries.
Productivity is gross output based.

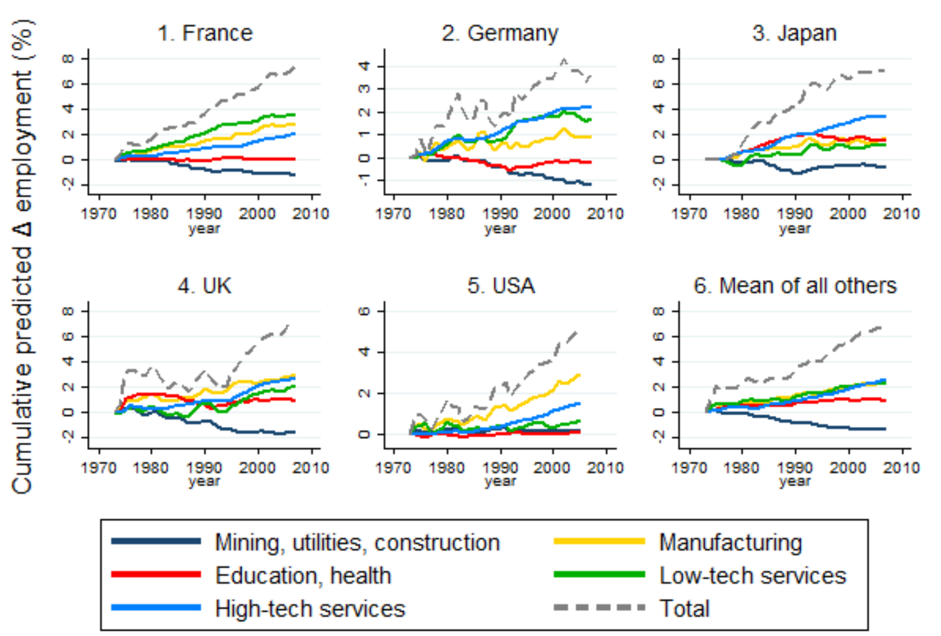
Thus, we estimate that labor productivity growth has generated net employment growth over the sample period for the countries considered. We note, however, that these net effects are modest in absolute magnitude—on the order of a few percentage points per decade—implying that the bulk of employment growth across countries and over time stems from other factors. Our conclusions are unaltered by alternatively considering value added per worker as a measure of labor productivity, as reported in Appendix Figure 4.

A central implication from the three panels of Figure 4 is that not all productivity growth is created equal. Despite the overall positive effect of economy-wide productivity growth uncovered by our country-level analyses, the sectoral sources of such productivity gains are non-neutral for their aggregate consequences. We should expect productivity growth to be less employment-augmenting in net if it is concentrated in sectors which do not produce a spillover onto employment growth elsewhere, such as mining, utilities, and construction. On the other hand, sectors with a relatively small spillover, such as manufacturing, can still produce a large positive external employment effect based on the sheer size of their productivity increase. In that sense, technological advances—say, assistive robots that raise productivity in health services, and other high- or low-tech services—may be a boon for employment growth since these sectors produce stronger spillovers.

Of course, these pooled cross-national estimates may not be representative of the experience of any one country. Although the estimated elasticities are constrained to be identical across countries—essentially assuming similar inter-industry or consumption linkages across each of these developed economies—this does not mean that the implied effects are homogeneous across countries. Because countries differ in both their sectoral productivity trajectories and cross-industry employment shares, productivity growth may make distinct contributions to aggregate employment in each country.

Figure 5
Predicted cumulative percentage employment change from productivity growth originating in five sectors, summing own-industry and spillover effects: Large countries

(x-axis: year; y-axis: cumulative predicted Δ employment (%))



Based on model 5 from Table 7. Productivity is gross output based.

We explore these differences in Figure 5 for the five largest economies in our sample, and for the average of the remaining fourteen. We estimate that labor productivity growth contributes positively in net to employment growth in all 'big 5' countries as well as across the other 14. Indeed, in all countries but the US, productivity growth in high- or low-tech services has had the strongest employment-increasing effects. For the US, however, productivity growth in services has been quite sluggish, rising a modest +25 percent over nearly forty years, as compared to something in excess of +50 percent for other major countries (see Figure 3b). In Japan, relatively strong productivity growth in high-tech services and health and education has contributed to aggregate employment growth. Similarly, in France, the UK, as well as other smaller countries, service economy productivity growth has been instrumental in driving a positive aggregate productivity-employment relationship. Appendix Figure 5 highlights that these conclusions are unaffected by using value-added as a base for calculating productivity.

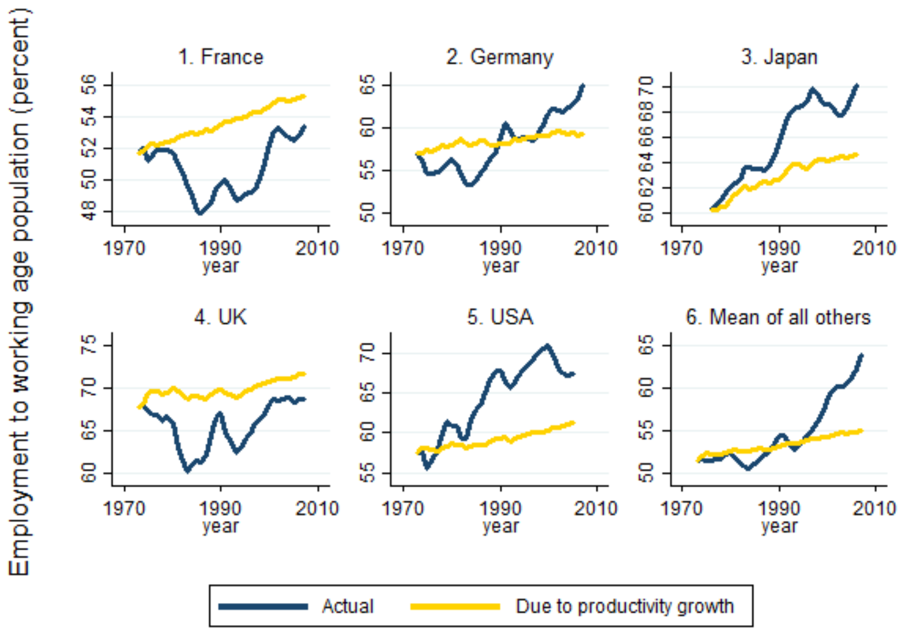
We further consider how sectoral productivity growth may have impacted employment to working age population ratios across economies by taking predictions from the companion set of models reported in Appendix Table 7b, where the dependent variable is employment-to-population (rather than employment as in Table 7). The implied contribution of productivity to the evolution of employment-to-population is plotted in Figure 6a for the five largest economies in our sample and the mean of all others, together with the actually observed employment rate evolution over this period. On average across these countries, our models imply that holding all else equal, productivity growth has raised the employment rate by some 3.6 percentage points, though this varies between 1 to 6 percentage points depending on the country.[31] These differences arise because of variation across countries in cumulative productivity growth and in the distribution of that growth (and of employment) across sectors. A key takeaway from these figures is that although productivity growth supplies an impetus for rising employment-to-population rates across most countries throughout this period, it is clearly not the predominant determinant of the differential evolution of employment rates across countries.

[31] As reported in Appendix Figure 6a, results are robust to instead using real value added per worker as a measure of productivity. Appendix Figure 6b shows predictions separately by country. The employment rate increase from productivity growth is predicted to be lowest in Greece and Spain, and highest in Denmark, Finland, Portugal, South Korea, and Sweden.

Figure 6a

Predicted cumulative percentage employment to working age population change from productivity growth originating in five sectors, summing own-industry and spillover effects: Large countries

(x-axis: year; y-axis: employment to working age population (percent))



Figures are for the total economy, excluding agriculture, public administration, private households and extraterritorial organizations. Productivity is gross output per worker.

Finally, we put the magnitude of the employment effects of productivity growth in perspective by considering their role relative to population growth. A consistent finding from our models above is that population growth and employment growth move close to equiproportionally, suggesting a large role for changes in population in determining employment. Figure 6c compares the contribution of these two forces, productivity growth and population growth, to the overall employment growth across the ‘big 5’ economies and all other countries.[32] Not surprisingly, the contribution of productivity growth to employment growth is minute relative to the contribution of population growth (see also Appendix Figure 6c, which reports this for each of the 19 countries separately, and Appendix Figure 6d, which presents highly comparable findings using value-added based labor productivity growth rather than output-based labor productivity growth). The realized employment trajectories of these countries (in navy) are typically closely matched by the predicted trajectory coming from population growth alone (in red), with productivity growth (in gold) contributing much less. The extent of this contribution does vary somewhat across countries: in Germany, Japan and the UK, productivity growth has a larger impact than in France and the US. Furthermore, some countries’ employment performance has been worse

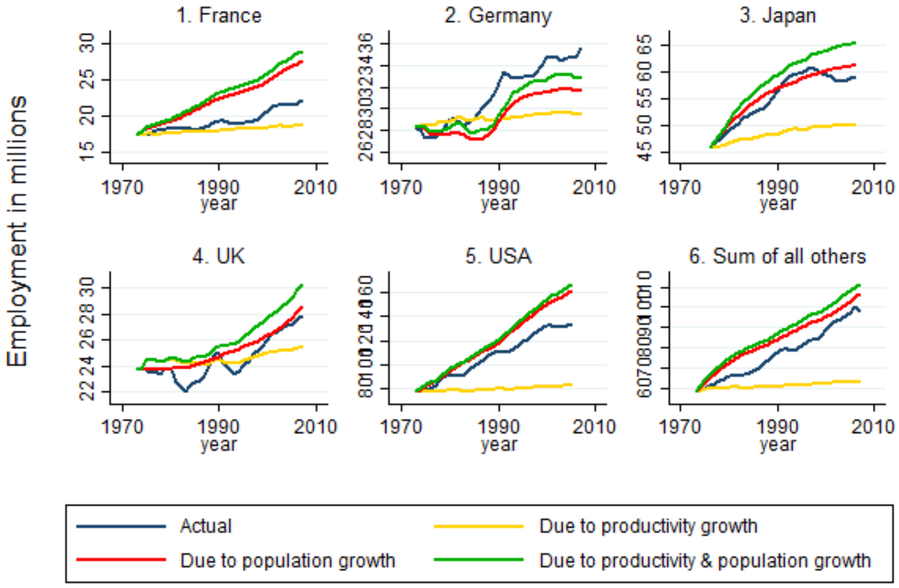
[32] The predictions for population growth are obtained in an analogous manner to those for productivity growth (as shown in equation 5), by multiplying the product of percentage changes in population and the exponentiated coefficient from model 5 of Table 7 (which also controls for productivity growth) with countries’ base year population.

than is suggested by the combined forces of population growth and employment growth (shown as the green line)—this is the case in France, and to a lesser extent also the US and in more recent years, the UK. Germany, on the other hand, has performed better than its productivity and population growth would suggest. This implies these countries face other headwinds, or tailwinds as the case may be, from forces impacting employment growth (e.g labor supply, population aging, or international trade).

Figure 6b

Comparing the estimated effects of productivity growth and population growth to the evolution of employment by country, 1970 – 2007: Large countries

(x-axis: year; y-axis: employment in millions)



Figures are for the total economy, excluding agriculture, public administration, private households and extraterritorial organizations. Productivity is gross output based.

Of course, the ‘result’ that population growth is a central determinant of employment growth borders on self-evident—akin to the observation that large countries have more jobs. We nevertheless report this result to highlight that while productivity growth is central to rising living standards, it is not a primary driver of employment growth.

7 Is this time (period) different?

A noteworthy pattern evidenced by Figure 1 is that employment growth in several countries—the US, Japan, and the UK—appears to decouple from productivity growth during the 2000s. Thus, productivity growth appears less positive for employment growth, and productivity stagnation appears less adverse for employment growth, in this decade than in earlier periods. This pattern could suggest that the virtuous relationship between productivity growth and employment growth has begun to break down. This might occur, for example, if demand for any one industry's output becomes saturated as its most productive uses are exhausted (Bessen 2017). Secondly, as the relative weight of sectors in the economy changes, so do the relative contributions on their internal versus external employment-productivity elasticities. Finally, changes in production technologies or the rising integration of production chains across countries may alter the nature of productivity-employment linkages. To explore these possibilities, we modify equation (3) to allow for decade-specific effects of both own-industry and net aggregate productivity:

$$\Delta \ln E_{ict} = \beta_0 + \sum_d \beta_{1,d(t)} \Delta \ln LP_{ict} + \sum_d \sum_k \beta_{2,d(t),k} \Delta \ln \widetilde{LP}_{ct-k,j\neq i} \; [+ \delta_t + \alpha_c + \gamma_i] + \varepsilon_{ict}, \quad [6]$$

where we use subscript $d(t)$ for decades (1970s, 1980s, 1990s, 2000s) to emphasize the correspondence between decade and year. Estimates of this model, where year, country, and industry fixed effects are cumulatively added across columns, are reported in the top panel of Table 8.

As a final refinement of our model, we also include a full set of decade interactions in equation (4):

$$\Delta \ln E_{ict} = \beta_0 + \sum_d \sum_s \beta_{1,s(i),d(t)} \Delta \ln LP_{ict} + \sum_d \sum_s \sum_k \beta_{2,s(i),d(t),k} \Delta \ln \widetilde{LP}_{ct-k,j\neq i} + \delta_t + \alpha_c + \gamma_i + \varepsilon_{ict}, \quad [7]$$

This specification, our most flexible one, allows both own-productivity (e.g. from demand saturation) and cross-productivity (e.g. from changing sector shares) effects to differ across sectors over time. Estimates of this model, with a full set of year, country, and industry fixed effects, are reported in Table 8.

Starting with the top panel of Table 8 with the specification where elasticities are common across sectors but differ across decades (equation 6), two main results emerge. First, own-industry productivity effects have become more negative over time: this is most pronounced when comparing the 1970s with any of the other three decades. This is consistent with saturation effects, though alternative interpretations are possible, such as a shift in the nature of technological progress (to become more labor-replacing), or an increase in trade openness which has led part of the increased domestic demand following productivity growth to be met by foreign producers. Regardless of the underlying cause, this result suggests that over-time changes in the own-sector price elasticity may play an important role in the evolving employment effects of labor productivity growth. Over (even) the relatively short data span considered here, we find that own-sector price elasticities have risen, suggesting it could be misleading to assume a stable employment-productivity relationship.

Secondly, the estimates indicate that the external effect of productivity growth on employment has varied considerably over time. It was seemingly strongest in the

1970s and 1990s, and weakest in the 2000s. Taking both internal and external effects together, the 2000s stand out as the decade when the virtuous relationship between productivity growth and employment growth was weakest. Indeed, our estimates suggest that the relationship was weakly negative (though this estimate is not statistically significant). This contrasts with the preceding decade, when the relationship was positive (though also statistically insignificant). These results therefore again serve to qualify our finding of an overall positive relationship between productivity growth and employment growth that prevailed *on average* across the four decades of our sample.

The bottom panel of Table 8 investigates to what extent these decadal changes in the employment-productivity relationship are driven by different effects emanating from the five broad sectors, by estimating of equation (7), where the internal and external effects of productivity growth are allowed to vary both by broad sectoral group and by decade. These estimates show that across sectors, the own employment-productivity elasticity has become more pronounced over successive decades. This is most pronounced in manufacturing, where the own-industry employment-productivity elasticity fell from close to zero to -0.29. Furthermore, manufacturing has experienced a decline in its external effect over time: this used to be positive in the 1970s but turned slightly negative since. The external effects for mining, utilities, and construction have remained constant at around zero over time, whereas the spillovers from services and health and education do not show a particular pattern over time and are positive and significant in most cases.

Taken together, the evidence reported in this section indicates that the virtuous productivity-employment relationship looks weaker in the 2000s than in prior decades. Specifically, the net productivity-employment effect is least positive in the most recent decade. This finding is reinforced by robustness checks reported in Appendix Tables 8a and 8b, which respectively use value-added based productivity measures, and consider the effect of productivity growth on employment rates rather than employment levels.

Figure 7 reports predictions separately by decade based on applying equation (7) to the estimates reported in Table 8. In all four decades of the sample, the internal effect of productivity growth on employment is significantly *negative* while in three of four decades—all but the 2000s—the external effect is significantly *positive*. Putting these pieces together, the net effect of productivity growth on employment growth has indeed fluctuated over time. It was strongly and significantly positive in the 1970s, small and statistically insignificant in the 1980s and 1990s, and—surprisingly—significantly negative in the 2000s, reflecting the absence of positive external employment effects in this decade.

Appendix Figure 7 shows corresponding results for value-added based productivity growth. As for gross output based productivity growth, we find a statistically significant positive net effect for the 1970s, insignificant net effects for the 1980s and 1990s, and statistically significant negative net effect for the 2000s. Unlike for gross output, however, the estimated net employment effects for value-added based productivity are monotonically decreasing across time periods.

Table 8

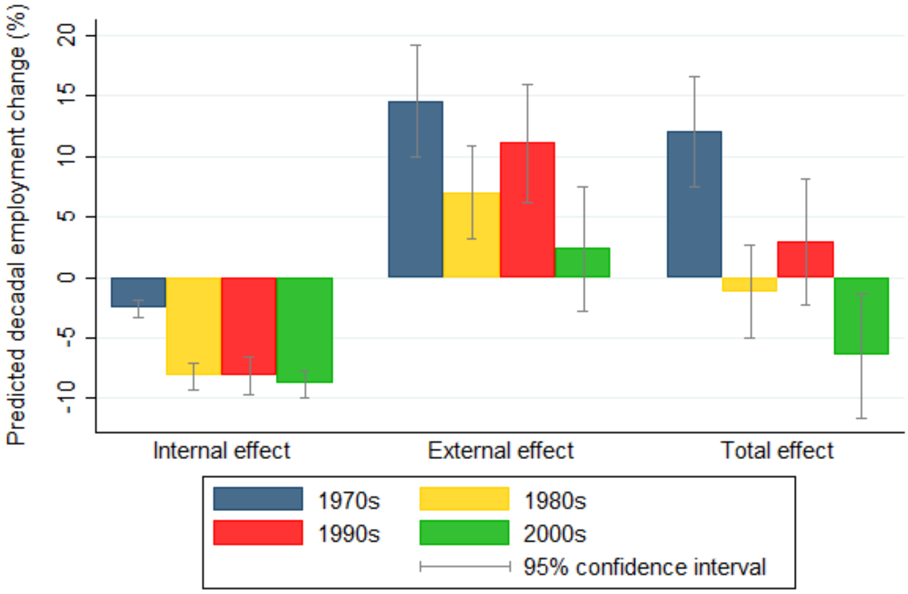
The decadal effects of industry and aggregate sectoral productivity growth on employment growth. Dependent variable: Annual log change in employment by country-industry

	1970s	1980s	1990s	2000s
All sectors				
Δ ln productivity (cit)	-0.151** (0.047)	-0.322** (0.052)	-0.255** (0.039)	-0.301** (0.034)
Σk Δ ln productivity (c, j≠i, t-k)	0.567** (0.136)	0.211 (0.147)	0.424** (0.121)	0.092 (0.142)
Σk Δ ln productivity (c, j≠i, t-k) + Δ ln productivity (ict)	0.416** (0.124)	-0.112 (0.161)	0.168 (0.116)	-0.210 (0.142)
Mining & utilities & construction				
Δ ln productivity (ict)	-0.185** (0.057)	-0.351** (0.062)	-0.457** (0.093)	-0.297** (0.054)
Σk Δ ln productivity (c, j≠i, t-k)	-0.027 (0.050)	0.066 (0.054)	-0.061 (0.084)	0.057 (0.041)
Manufacturing				
Δ ln productivity (cit)	-0.037 (0.039)	-0.138** (0.031)	-0.156** (0.033)	-0.292** (0.056)
Σk Δ ln productivity (c, j≠i, t-k)	0.235** (0.074)	0.024 (0.089)	-0.047 (0.092)	-0.056 (0.075)
Education & health				
Δ ln productivity (cit)	-0.257** (0.082)	-0.399** (0.060)	-0.303** (0.072)	-0.482** (0.079)
Σk Δ ln productivity (c, j≠i, t-k)	0.097* (0.039)	-0.010 (0.068)	0.261~ (0.142)	0.241** (0.087)
Low-tech services				
Δ ln productivity (cit)	-0.270** (0.074)	-0.495** (0.072)	-0.284** (0.075)	-0.268** (0.030)
Σk Δ ln productivity (c, j≠i, t-k)	0.232** (0.079)	0.129 (0.110)	0.235* (0.104)	0.019 (0.072)
High-tech services				
Δ ln productivity (cit)	-0.146* (0.062)	-0.270** (0.091)	-0.236** (0.047)	-0.278** (0.031)
Σk Δ ln productivity (c, j≠i, t-k)	0.053~ (0.032)	0.071* (0.035)	0.184** (0.052)	0.082 (0.051)
Δ ln total population (ct)	0.900** (0.160)			
Nr of lags in ln productivity (c, j≠i)	k=3			
Country fixed effects	YES			
Year fixed effects	YES			
Industry fixed effects	YES			
R2	0.365			
N	17,858			

Figure 7

Predicted cumulative percentage employment change by decade from productivity growth originating in five sectors

(y-axis: predicted decadal employment change (%))



Based on sector-specific model from Table 8. Predictions for the 1970s and 2000s scaled up to be comparable to the 1980s and 1990s. Confidence interval constructed by bootstrapping predictions (1,000 repetitions). Productivity is gross output per worker.

We note this development without drawing a strong conclusion since it may be transitory, especially considering the unusual economic conditions leading up to the global financial crisis at the end of 2007 (which is also the last year of our data).[33] Indeed, the 1980s exhibited the second weakest productivity-employment relationship of the four decades in our sample, and it was followed immediately by the decade of the 1990s that exhibited a stronger net productivity-employment relationship. These observations underscore that the positive relationship between productivity and employment appears to fluctuate over time, as both the distribution of productivity growth across sectors and its employment elasticities may change over time. Our analysis does not shed light on why these fluctuations occur.

8 Employment growth for whom? The impacts of sectoral productivity growth on skill demands

The evidence presented here indicating that productivity growth has made a modest positive contribution to aggregate employment growth over three and a half decades

[33] Note that we scale our predictions proportionately for the 1970s and 2000s to reflect the incomplete data span for these decades, in order to make their size comparable to model predictions for the other two decades. In follow-up work, we will use a separate EUKLEMS release for 1995-2014 to consider whether this development has persisted or reversed course in the post-crisis years. Preliminary results suggest it may be the latter—though these results are subject to change.

does not imply that these positive employment effects have been evenly distributed across all groups of workers. An uneven distribution of these effects across skill groups can occur for two main reasons. First, it could be that productivity growth leads to a change in the relative demand for skill *within* industries. This could for instance be the case if productivity growth stems from new production techniques or other work practices that skew labor requirements towards more or less skilled workers. Second, sectoral reallocations stemming from unbalanced productivity growth across industries could spur changes in aggregate labor demand by skill group. Because skill-intensity differs substantially across sectors, this reallocation effect on skill demands operates *between* industries. We investigate these two mechanisms in turn.

Table 9 relates changes in countries' industry-level employment shares by skill type (high, medium, and low) to these industries' productivity growth.[34] Our estimates here are akin to those in estimating equation (2), but with the change in skill *shares* as the dependent variables rather than the log change in employment. Like in its counterpart, Table 4, we report both OLS and IV results. We do not find any evidence that productivity growth is skill-biased at the industry level: all estimates are economically small and statistically insignificant. This does not imply that there has been no skill upgrading over the period—indeed, there has been a sizable increase in the share of workers who are high-skilled within *all* industries. Rather, Table 9 indicates that industries experiencing more rapid productivity growth are not differentially changing their skill composition relative to lagging industries.[35]

[34] Although these skill definitions are country-specific, 'high-skilled' broadly corresponds to college graduates, and 'low-skilled' to high-school dropouts (but including high school graduates in some countries), with 'medium-skilled' making up the intermediate range of secondary and lower tertiary degrees in between these two groups. Skill share coverage is lower than overall employment coverage in EU KLEMS, with only Finland, Italy, South Korea, the UK, and the US starting in 1970 (and most other countries starting data coverage around 1980 instead). Table 9 accordingly has fewer observations than found in other tables.

[35] Appendix Table 9a shows that we obtain near-identical results for skill shares when using value-added based labor productivity rather than output-based labor productivity.

Table 9

The effect of productivity growth on employment share by skill type. Dependent variable: Annual change in skill group employment share by country-industry

	A. OLS		
Δ ln productivity (cit)	-0.003 (0.003)	0.005~ (0.003)	-0.003 (0.002)
Country fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES
Industry fixed effects	YES	YES	YES
R2	0.068	0.154	0.145
N	13,875	13,875	13,875
	B. IV		
Δ ln productivity (cit)	0.016 (0.018)	0.014 (0.024)	-0.031 (0.023)
Country fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES
Industry fixed effects	YES	YES	YES
Sanderson-Windmeijer F-statistic	41.2	41.2	41.2
N	13,875	13,875	13,875
	First stage for Δ ln productivity		
Mean Δ ln productivity (it) in other countries	0.270*** (0.042)	0.270*** (0.042)	0.270*** (0.042)

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is measured at the country-industry-year level. All models weighted by industry employment shares within countries, averaged over the period. 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-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

We next assess how industry productivity growth affects the skill composition of employment by inducing employment shifts across sectors. Since we find unambiguously large and negative Baumol effects in every sector—whereby industry productivity growth reduces own-industry employment—our estimates imply that sectoral productivity growth will be non-neutral for employment by skill group: productivity growth in relatively low-skill intensive sectors will diminish economy-wide relative demand for low-skill workers, while productivity growth in relatively high-skill intensive sectors will reduce economy-wide demand for high-skill workers.[36] Appendix Table 9a shows that different sectors are indeed differently skill intensive, with education and health, and high-tech services having the highest shares of high-skilled workers, and low-tech services relying more on low-skilled workers. Such skill-biases can potentially be quite large, even when the net employment implications of productivity growth are modest.

To quantify the non-neutrality of productivity growth for employment by skill, we calculate a variant of equation (5) above where we scale predicted employment growth by industry as a function of both internal and external productivity growth by

[36] A second source of non-neutrality results from the fact that sectoral productivity growth is calculated as a leave-out mean that excludes own-industry productivity growth for industries within the sector. This means that the external effects of productivity growth from a given sector will depend in part on which industries within the sector contribute most or least to sectoral productivity growth. In practice, this non-neutrality makes little difference for our calculations; almost the entirety of the estimated non-neutrality stems from the internal rather than external effects of productivity growth.

the average share of industry employment comprised by low-, middle-, and high-education workers, indexed below by the superscript q:

$$\Delta\hat{E}^q_{ict} = \{E^q_{ic,t=base} \times 1(i \in s) \times \hat{\beta}_{1,s(i)} \times \Delta\ln LP_{ict}\} + \left\{E^q_{ic,t=base} \times \sum_{s(i)=1}^{5} \sum_{k=0}^{3} \hat{\beta}_{2+k,s(i)} \times \Delta\ln\widetilde{LP}_{ct-k,j\neq i}\right\} \quad [8]$$

Paralleling our earlier calculations for aggregate employment, we normalize these predicted employment impacts by the base employment level of each skill group in each country to obtain implied proportional impacts. This scaling also accounts for the fact that the three major skill groups are not typically equally large, so for example, a projected employment gain of one million workers in each skill category would imply larger proportional growth for smaller skill groups.

Results averaged across all 19 countries are shown in Figure 8. Employment growth has been strongly skill-biased, with productivity-driven employment growth for high-skilled workers substantially exceeding that for both medium- and low-skill workers since 1980. This diverging pattern shows no signs of abatement in the later years of our sample and is equally visible when using value-added per worker as a productivity measure (see Appendix Figure 8).

Considering these predictions separately for the 'big 5' countries, reported in Figure 9, we find that this pattern is near-universal, with two exceptions: Japan, which based on its skill shares has (by our calculations) witnessed a strong increase in low-skilled work; and the US, where high- and low-skilled workers have seen almost identical percentage increases in demand whereas middle-skill demand has lagged, consistent with employment polarization. Appendix Figure 9 reports qualitatively identical results for value-added based productivity growth. Thus, despite productivity growth not being inimical to employment in net, it has been decidedly friendlier towards high-skilled employment than towards low- or middle-skill employment.

Figure 8

Predicted cumulative percentage employment change by skill group from productivity growth originating in five sectors

(x-axis: year; y-axis: cumulative predicted change (%))

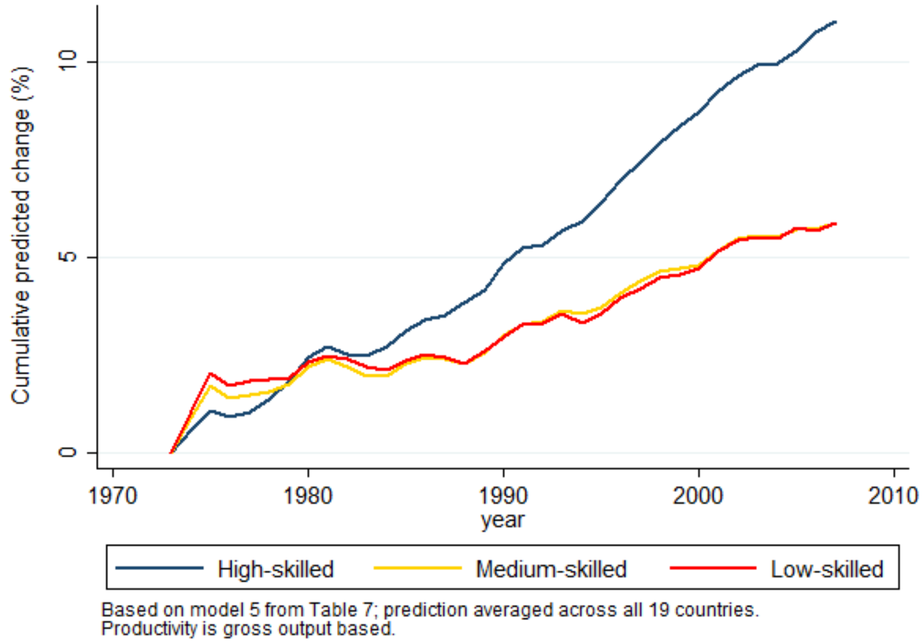
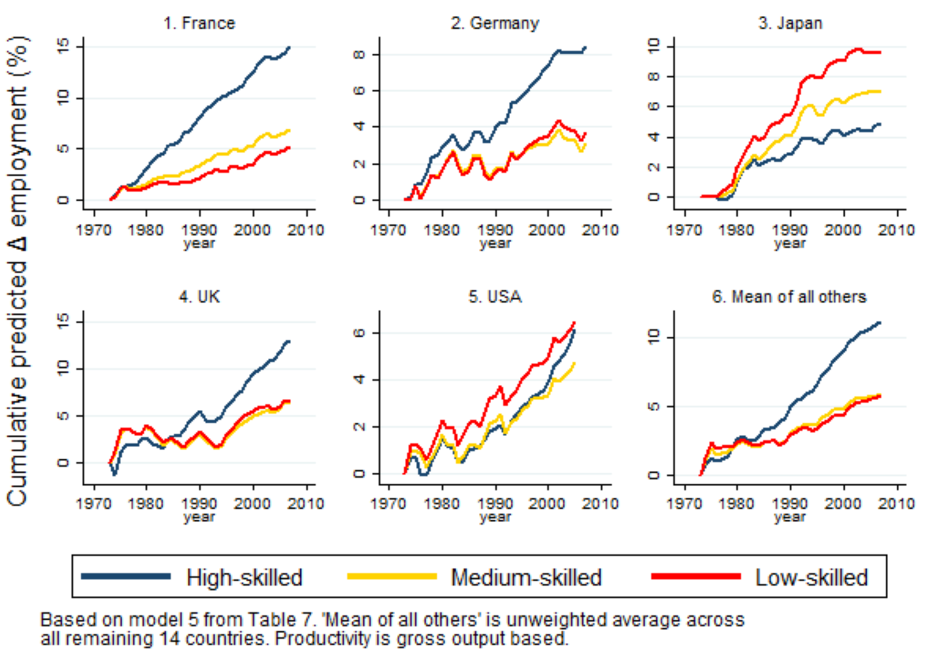


Figure 9

Predicted cumulative percentage employment change by skill group from productivity growth originating in five sectors: Results by country

(x-axis: year; y-axis: cumulative predicted Δ employment (%))



9 Concluding remarks

Has productivity growth threatened employment? Over the 35-year period we considered, the answer has been no—or perhaps more memorably, ‘Robocalypse *no*.’ Aggregate productivity growth has been employment-augmenting in this period. This is true despite robust evidence—consistent with popular perceptions—that industries experiencing rising labor productivity exhibit falling employment. As such, the evidence does not support the optimistic scenario in which industry-level productivity gains *raise* own-industry employment—though this optimistic scenario has doubtless been true in specific sectors and time periods (Bessen, 2017). Yet, this case is neither necessary nor sufficient for industry- or sector-level productivity gains to be employment-augmenting in net. Provided that productivity growth in one sector generates sufficiently large positive spillovers to employment growth elsewhere in the economy—operating through what is likely a combination of income effects and inter-industry demand linkages—then this productivity growth can still be employment-augmenting, even if it reduces employment in the sector in which it occurs. This latter scenario is supported by our analysis: over the nearly four decades that we study, the external effects of sectoral productivity growth on aggregate employment have been sufficiently powerful to more than fully offset employment contractions occurring in sectors making strong productivity gains.

Sectoral productivity growth does, however, have strongly heterogeneous external employment effects, with the most positive stemming from productivity growth in health, education, and the other services, and the least positive effects emanating from productivity growth in utilities, mining, and construction. The source of productivity growth therefore matters for its aggregate employment consequences. Given that service sector productivity growth in particular appears to have strong employment spillovers, our findings suggest that the spread of robotics and other productivity-augmenting technologies into services may prove a *net positive* for employment growth.

Two observations temper this conclusion, however: first, productivity growth is slower in services than outside of it; second, the own-sector effects of productivity growth on sectoral employment have become more negative in recent decades while the external effects of productivity growth on other-sector employment have become less positive. This suggests a weakening of the virtuous relationship between productivity growth and employment growth. This weakening is most pronounced in the manufacturing sector, suggesting the possibility that increased trade openness has led part of the increased domestic demand following productivity growth to be met by foreign producers—thus moderating the positive domestic employment response from increased product demand. This is a hypothesis we will explore in future work.

Lastly, we establish that for understanding countries’ employment trajectories, population growth is a much more important contributor to employment growth than is productivity growth. Yet the profound sectoral reallocations implied by productivity growth—away from high-productivity sectors such as utilities and manufacturing, and towards tertiary sectors—have important consequences for the distribution of employment growth, and likely also the gains from employment. Specifically, these productivity-induced sectoral shifts are shown to be sharply biased in favor of skilled workers. In this respect, our analysis underscores a central insight of much recent work on the labor market impacts of technological progress: the primary societal challenge posed so far by these advances far is not falling aggregate labor demand but, rather, an increasingly skewed distribution of employment—and ultimately earnings—favoring highly educated workers.

References

Acemoglu, Daron, and David Autor. 2011. “Skills, Tasks and Technologies: Implications for Employment and Earnings.” in O. Ashenfelter and D. Card, eds., *The Handbook of Labor Economics Volume IV*, Amsterdam: Elsevier.

Acemoglu, Daron, and Veronica Guerrieri. 2008. “Capital Deepening and Nonbalanced Economic Growth.” Journal of Political Economy 116 (3): 467–98.

Acemoglu, Daron and Pascual Restrepo. 2016. “The Race Between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment.” NBER Working Paper No. 23077, May.

Acemoglu, Daron and Pascual Restrepo. 2017. “Robots and Jobs: Evidence from U.S. Labor Markets.” NBER Working Paper No. 23285, March.

Akerman, Anders, Ingvil Gaarder, and Magne Mogstad. 2015. “The Skill Complementarity of Broadband Internet.” *Quarterly Journal of Economics* 130(4): 1781–1824.

Alexopoulos, Michelle, and Jon Cohen. 2016. “The Medium Is the Measure: Technical Change and Employment, 1909–1949.” *Review of Economics and Statistics* 98(4): 792–810.

Autor, David. 2015. “Why Are There Still So Many Jobs? The History and Future of Workplace Automation.” *Journal of Economic Perspectives* 29(3), 3 – 30.

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen. 2017. “The Fall of the Labor Share and the Rise of Superstar Firms.” NBER Working Paper No. 23396, May.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. “Trends in US Wage Inequality: Revising the Revisionists.” *Review of Economics and Statistics* 90(2): 300-323.

Autor, David, and Melanie Wasserman. 2013. *Wayward Sons: The Emerging Gender Gap in Education and Labor Markets*. Washington, DC.

Barkai, Simcha. 2016. “Declining Labor and Capital Shares.” Working Paper, University of Chicago.

Basu, Susanto, and John Fernald. 2001. "Why is Productivity Procyclical? Why Do We Care?" In Charles R. Hulten, Edwin R. Dean and Michael J. Harper, eds., *New Developments in Productivity Analysis*, Chicago: Univ of Chicago Press, 225–302.

Baumol, William J. 1967. "Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis." *American Economic Review* 57(3): 415–26.

Berg, Andrew, Edward F. Buffie, and Luis-Felipe Zanna. 2017. "Robots, Growth, and Inequality: Should We Fear the Robot Revolution? (The Correct Answer is Yes)." IMF Working Paper WP/17/XX, February.

Bessen, James. 2017. "Automation and Jobs: When Technology Boosts Employment." Boston University School of Law: Law & Economics Paper No. 17-09, April.

Blundell, Richard. 2016. "Labour Markets and Inclusive Growth" Presentation to the U.K. Growth Commission, Nov. 17.

Brynjolfsson, Erik, and Andrew McAfee. 2014. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York and London: W.W. Norton & Company.

Dao, Mai, Mitali Das, Zsoka Koczan, and Weicheng Lian. 2017. "Why is Labor Receiving a Smaller Share of Global Income? Theory and Empirical Evidence," IMF Working Paper.

Elsby, Mike, Bart Hobijn, and Aysegul Sahin. 2013. "The Decline of the U.S. Labor Share." *Brookings Papers on Economic Activity*, 1-42.

Dustmann, Christian, Bernd Fitzenberger, Uta Schönberg, and Alexandra Spitz-Oener. 2014. "From Sick Man of Europe to Economic Superstar: Germany's Resurgent Economy." *Journal of Economic Perspectives* 28(1): 167–188.

Ford, Martin. 2015. *Rise of the Robots: Technology and the Threat of a Jobless Future.* New York: Basic Books.

Frey, Carl Benedikt, and Michael A. Osborne. 2015. "The Future of Employment: How Susceptible are Jobs to Computerisation?" *Technological Forecasting and Social Change* 114: 254–280.

Goos, Maarten, Alan Manning, and Anna Salomons. 2009. "Job Polarization in Europe." *American Economic Review Papers and Proceedings* 99(2): 58-63.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review* 104(8): 2509–26.

Goos, Maarten, Emile Rademakers, Anna Salomons, and Marieke Vandeweyer. 2015. "Routinization, Between-Sector Job Polarization, Deindustrialization and Baumol's Cost Disease." Utrecht School of Economics Working Paper 15-15, December.

Graetz, Georg, and Guy Michaels. 2015. “Robots at work.” CEP Discussion No. 1335.

Gregory, Terry, Anna Salomons, and Ulrich Zierahn. 2016. “Racing With or Against the Machine? Evidence from Europe.” Utrecht School of Economics, Tjalling C. Koopmans Research Institute, Discussion Paper Series 16-05, July.

Herald Press, The. 1966. “Skirting the Automation Question.” February 7, p. 2. (The Herald Press of St. Joseph, Michigan.)

Hogan, Andrew and Brian Roberts. 2015. “Occupational Employment Projections to 2024.” *Monthly Labor Review*, U.S. Bureau of Labor Statistics, 2015.

Johnston, Louis. 2001. “The Growth of the Service Sector in Historical Perspective: Explaining Trends in U.S. Sectoral Output and Employment, 1840-1990.” St. John’s University Working Paper.

Jones, Charles I, and Paul Romer. 2010. “The New Kaldor Facts: Ideas, Institutions, Population, and Human Capital.” *American Economic Journal: Macroeconomics* 2: 224–45.

Kaldor, Nicholas. 1961. “Capital Accumulation and Economic Growth.” in *The Theory of Capital*, ed. F. A. Lutz and D. C. Hague, 177–222. New York: St. Martins Press.

Karabarbounis, Loukas and Brent Neiman. 2014. “The Global Decline of the Labor Share.” *Quarterly Journal of Economics*, 129(1), 61-103.

Katz, Lawrence, and David Autor. 1999. “Changes in the Wage Structure and Earnings Inequality.” in O. Ashenfelter and D. Card, eds., *The Handbook of Labor Economics Volume III*, Amsterdam: Elsevier.

Keynes, John Maynard, 1939. “Relative Movements of Real Wages and Output.” *Economic Journal* 49, 34-51

Leontief, Wassily. 1983. “National Perspective: The Definition of Problem and Opportunity,” in National Academies, *The Long-term Impact of Technology on Employment and Unemployment: A National Academy of Engineering Symposium*, June 30, p3.

Matsuyama, Kiminori. 2002. “The Rise of Mass Consumption Societies.” *Journal of Political Economy* 110(5): 1035–1070.

Michaels, Guy, Ashwini Natraj, and John Van Reenen. 2013. “Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years.” *Review of Economics and Statistics* 96 (1): 60–77.

Moulton, Brent R. 1986. “Random Group Effects and the Precision of Regression Estimates.” *Journal of Econometrics* 32(3): 385-397.

New York Times, The. 1927. “Davis Says Labor Needs New Outlet.” September 5.

Ngai, L. Rachel, and Christopher A. Pissarides. 2007. “Structural Change in a Multisector Model of Growth.” *American Economic Review* 97(1): 429-443.

Ngai, L, and C Pissarides. 2008. “Trends in Hours and Economic Growth.” Review of Economic Dynamics 11 (2): 239–256.

Nordhaus, William D. 2015. “Are We Approaching an Economic Singularity? Information Technology and the Future of Economic Growth.” NBER Working Paper No. 21547, September.

O’Mahony, Mary and Marcel Timmer. 2009. “Output, Input and Productivity Measures at the Industry Level: the EU KLEMS Database,” *Economic Journal* 119(538), F374-503.

Piketty, Thomas. 2014. *Capital in the Twenty-First Century*. Harvard University Press.

Rognlie, Matthew. 2015. “Deciphering the Fall and Rise in the Net Capital Share: Accumulation or Scarcity?” *Brookings Papers on Economic Activity*, 1-69.

Sachs, Jeffrey D., and Laurence J. Kotlikoff. 2012. “Smart Machines and Long-Term Misery.” NBER Working Paper 18629, December.

Sanderson, Eleanor, and Frank Windmeijer. 2016. “A Weak Instrument F-test in Linear IV Models with Multiple Endogenous Variables.” *Journal of Econometrics* 190(2): 212–221.

Solow, Robert M. 1956. “A Contribution to the Theory of Economic Growth.” *Quarterly Journal of Economics* 70 (1): 65–94.

Susskind, Daniel. 2017. “A Model of Technological Unemployment.” Oxford University Working Paper, April.

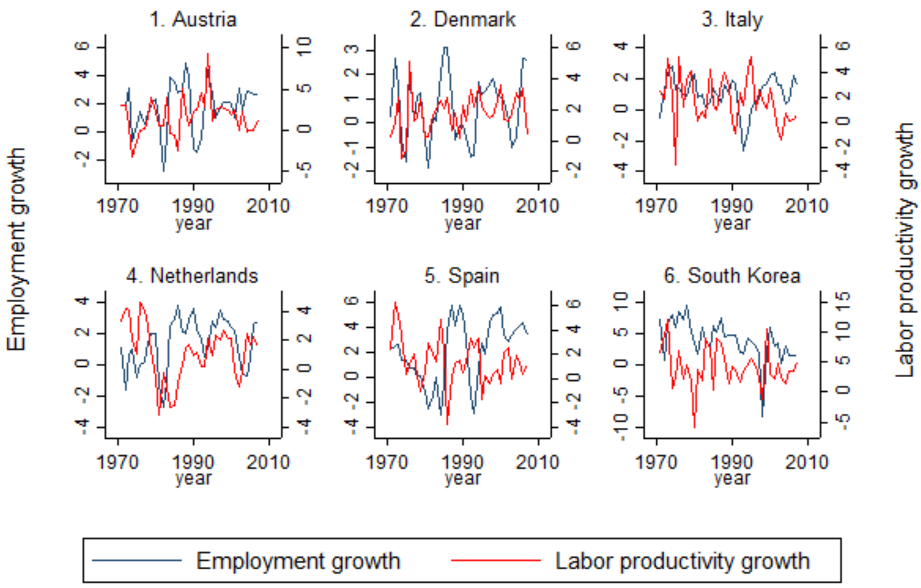
Timmer, Marcel P., Erik Dietzenbacher, Bart Los, Robert Stehrer, and Gaaitzen J. de Vries. 2015. “An Illustrated User Guide to the World Input–Output Database: The Case of Global Automotive Production,” *Review of International Economics* 23: 575–605.

10 Appendix Figures

Figure A1a

Employment and productivity growth, 1970 – 2007: Results for additional countries

(x-axis: year; y-axis: employment growth (left-hand scale), labor productivity growth (right-hand scale))

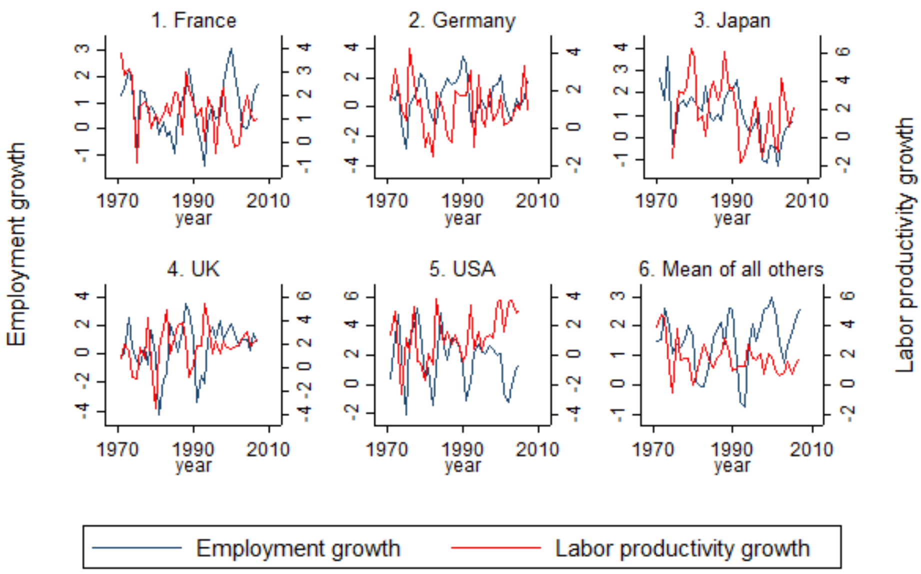


Figures are for the total economy, excluding agriculture, public administration, private households and extraterritorial organizations.
All growth rates obtained as log changes x 100. Productivity is gross output per worker.

Figure A1b

Employment and value-added based productivity growth, 1970 – 2007

(x-axis: year; y-axis: employment growth (left-hand scale), labor productivity growth (right-hand scale))

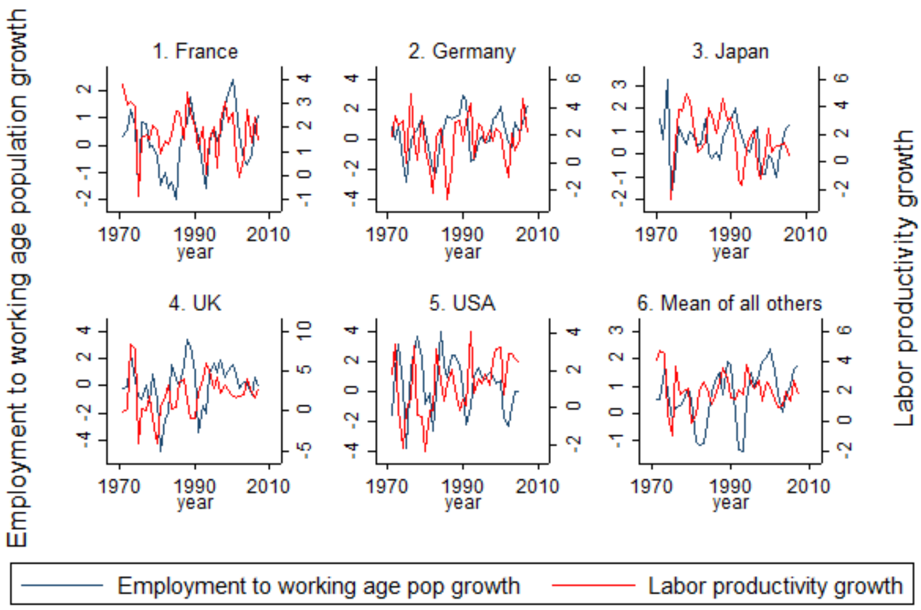


Figures are for the total economy, excluding agriculture, public administration, private households and extraterritorial organizations.
All growth rates obtained as log changes x 100. Graph 6 reports unweighted mean growth rates across the remaining 14 countries.
Productivity is value added per worker.

Figure A1c

Employment rate and productivity growth, 1970 – 2007

(x-axis: year; y-axis: employment to working age population growth (left-hand scale), labor productivity growth (right-hand scale))

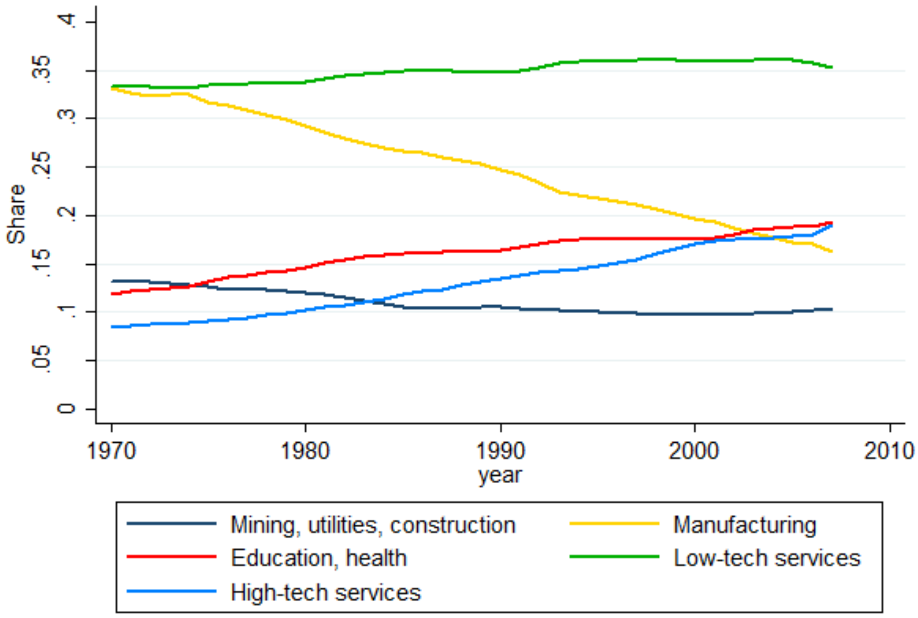


Figures are for the total economy, excluding agriculture, public administration, private households and extraterritorial organizations. All growth rates obtained as log changes x 100. Graph 6 reports unweighted mean growth rates across the remaining 14 countries. Productivity is gross output per worker.

Figure A2a

Employment shares by sector, 1970 -2007

(x-axis: year; y-axis: share)



Unweighted average across all 19 countries.

Figure A2b

Employment shares by sector, 1970 -2007: Large countries

(x-axis: year; y-axis: share)

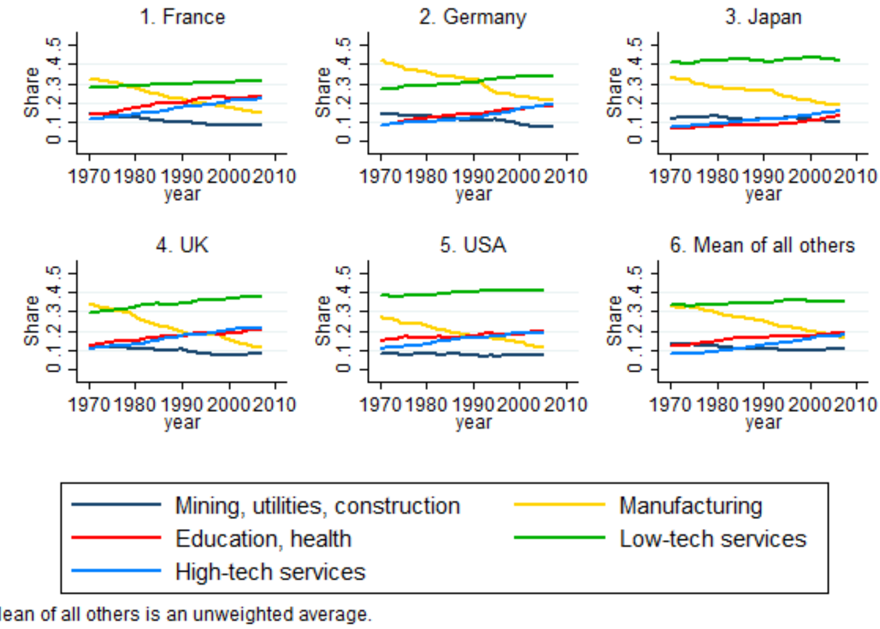


Figure A3a

Cumulative log value-added based labor productivity growth by sector, 1970 -2007

(x-axis: year; y-axis: 100 x cumulative log change)

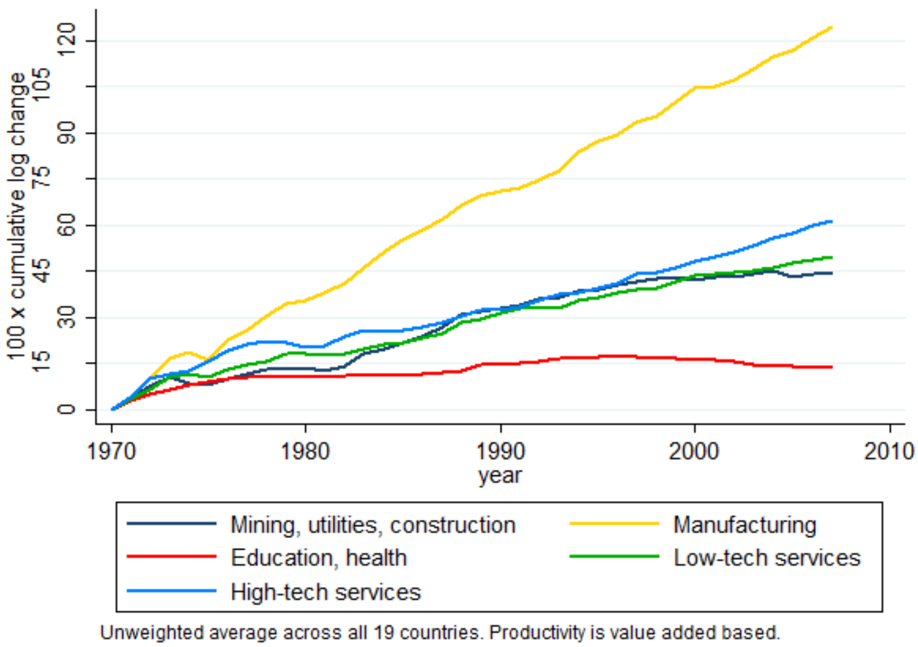
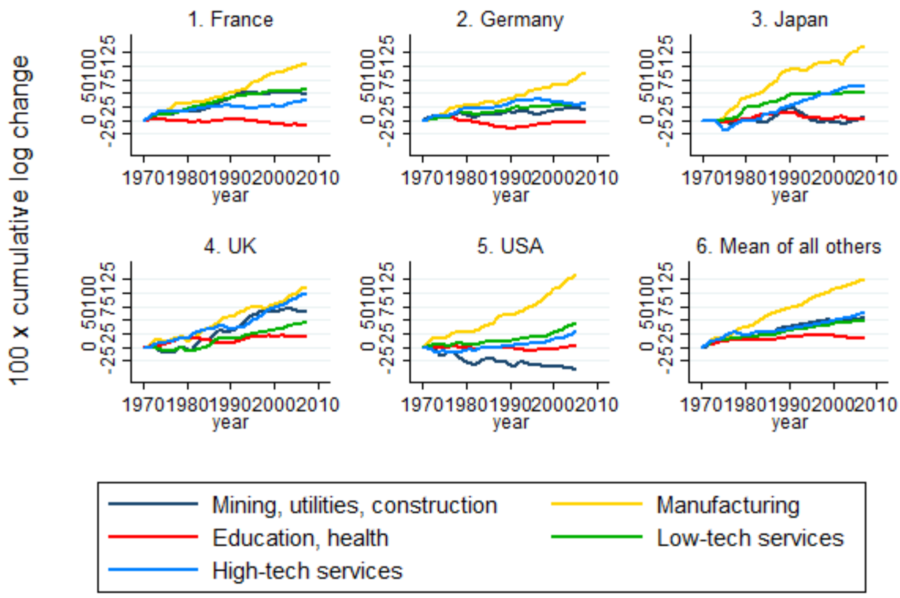


Figure A3b

Cumulative log value-added based labor productivity growth by sector, 1970 -2007: Large countries

(x-axis: year; y-axis: 100 x cumulative log change)

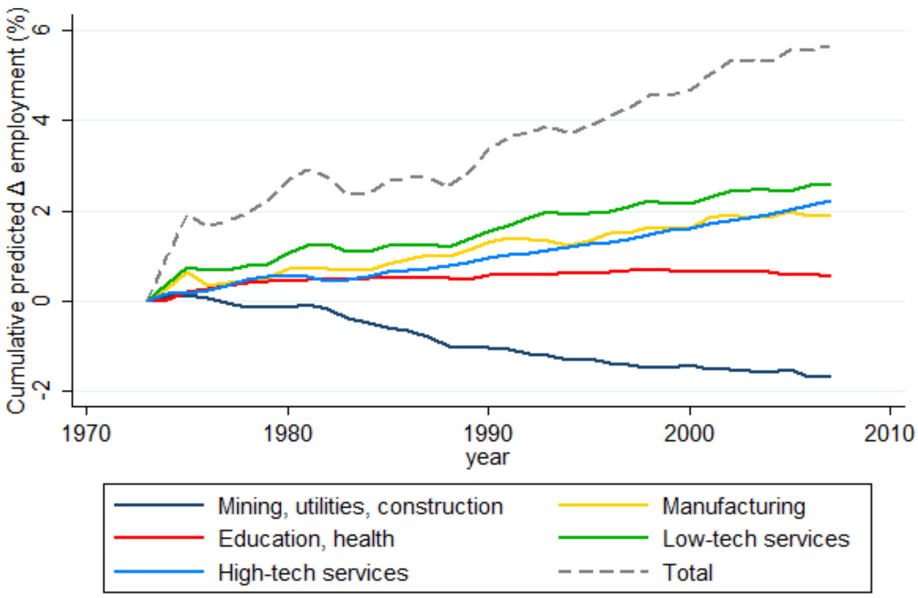


Mean of all others is an unweighted average. Productivity is value added based.

Figure A4

Predicted cumulative percentage employment change from value-added based productivity growth originating in five sectors, summing own-industry and spillover effects

(x-axis: year; y-axis: cumulative predicted Δ employment (%))

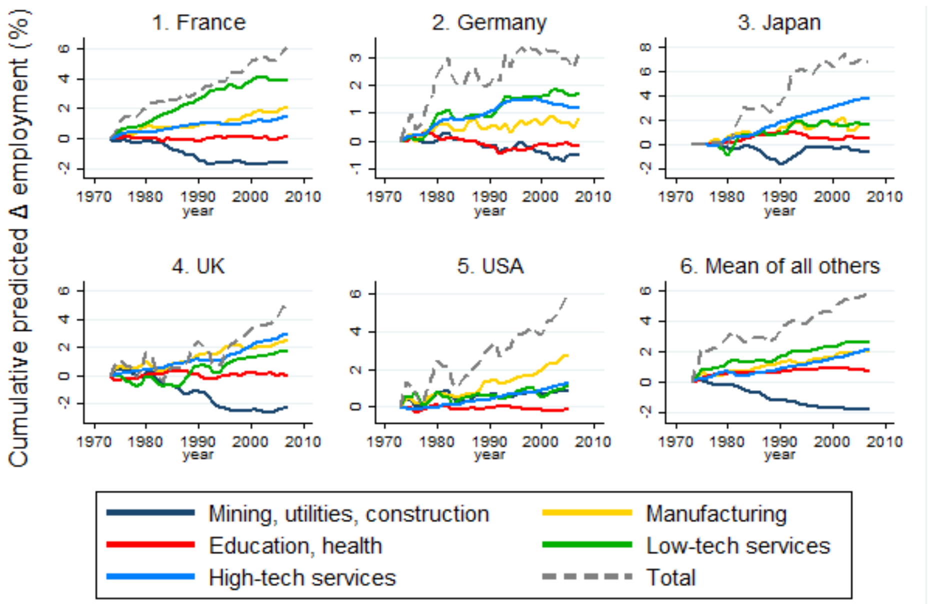


Based on model 5 from Table 7; prediction averaged across all 19 countries.
Productivity is value added based.

Figure A5

Predicted cumulative percentage employment change from value-added based productivity growth originating in five sectors, summing own-industry and spillover effects: Large countries

(x-axis: year; y-axis: cumulative predicted Δ employment (%))

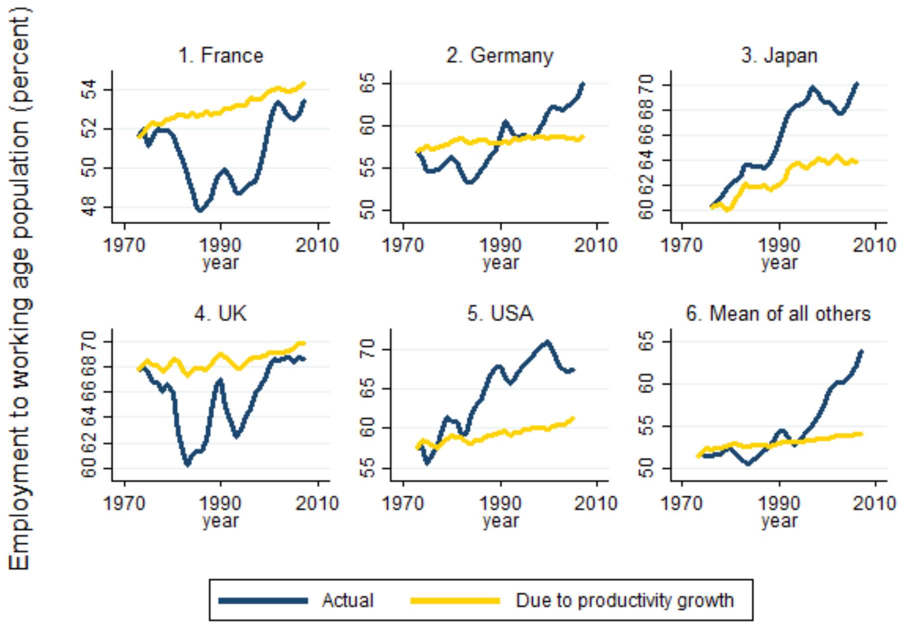


Based on model 5 from Table 7. Productivity is value added based.

Figure A6a

Comparing the estimated effects of value-added based productivity growth on employment rate growth to the evolution of employment rates by country, 1970 – 2007: Large countries

(x-axis: year; y-axis: employment to working age population (percent))

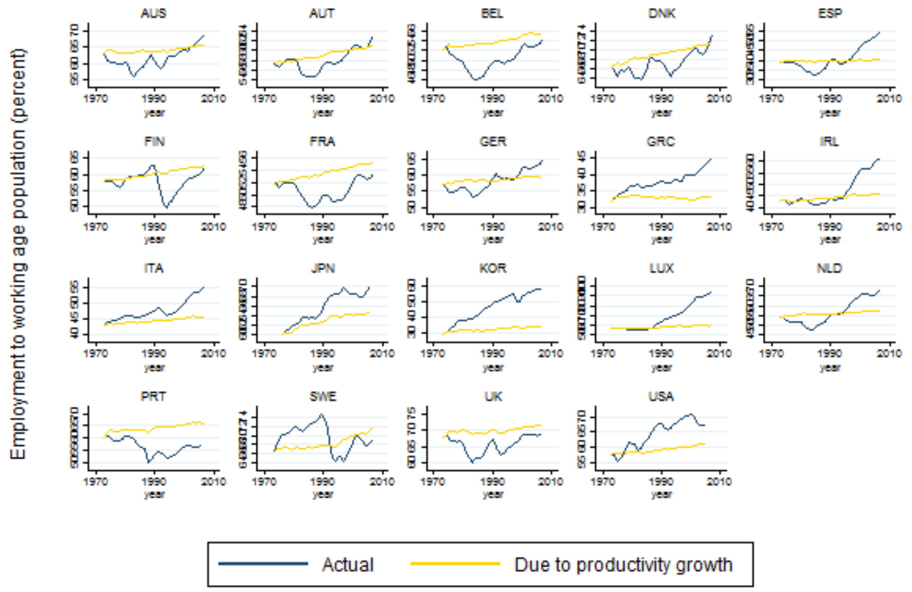


Figures are for the total economy, excluding agriculture, public administration, private households and extraterritorial organizations. Productivity is value added per worker.

Figure A6b

Comparing the estimated effects of productivity growth on employment rate growth to the evolution of employment rates by country, 1970 – 2007: Individual countries

(x-axis: year; y-axis: employment to working age population (percent))

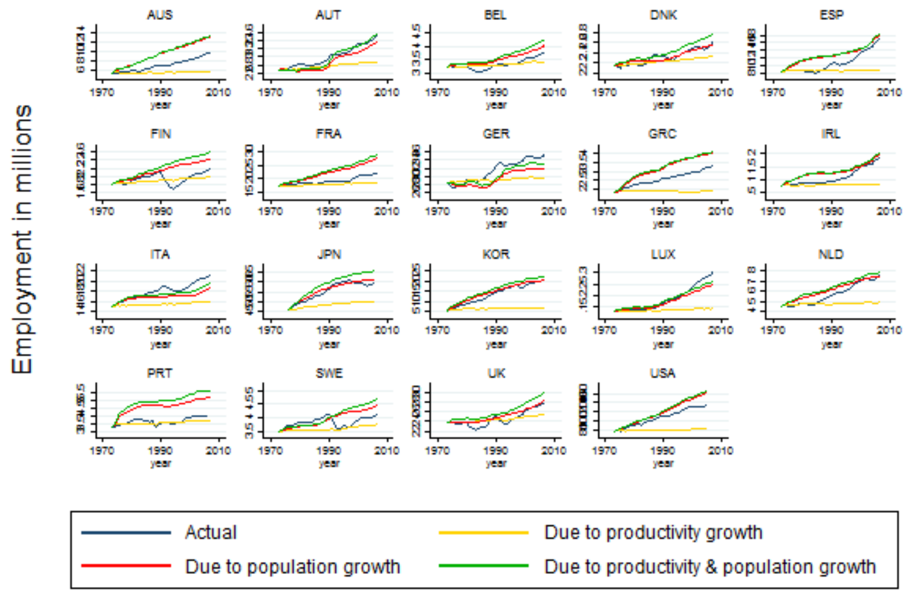


Figures are for the total economy, excluding agriculture, public administration, private households and extraterritorial organizations.
Productivity is gross output per worker.

Figure A6c

Comparing the estimated effects of productivity growth and population growth to the evolution of employment by country, 1970 – 2007: Individual countries

(x-axis: year; y-axis: employment in millions)

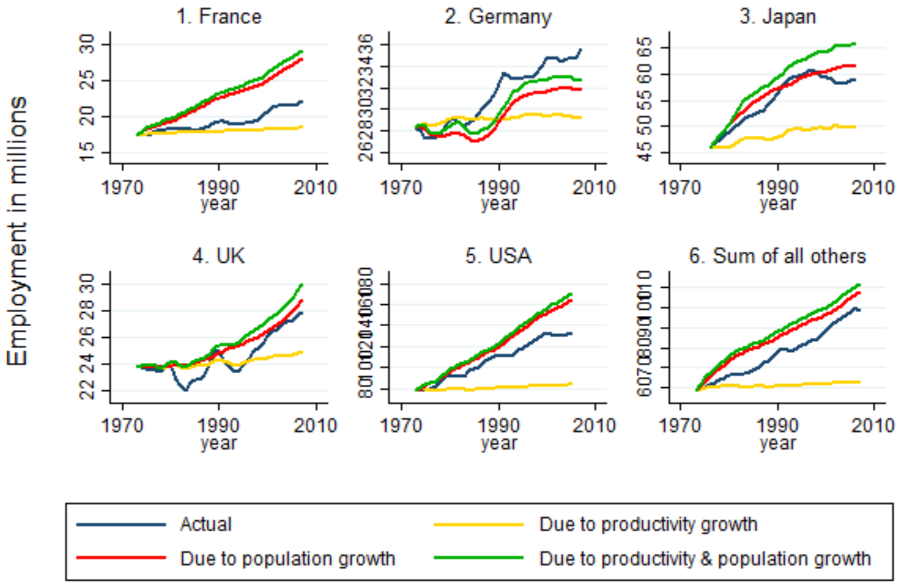


Figures are for the total economy, excluding agriculture, public administration, private households and extraterritorial organizations.
Productivity is gross output based.

Figure A6d

Comparing the estimated effects of value-added based productivity growth and population growth to the evolution of employment by country, 1970 – 2007: Large countries

(x-axis: year; y-axis: employment in millions)

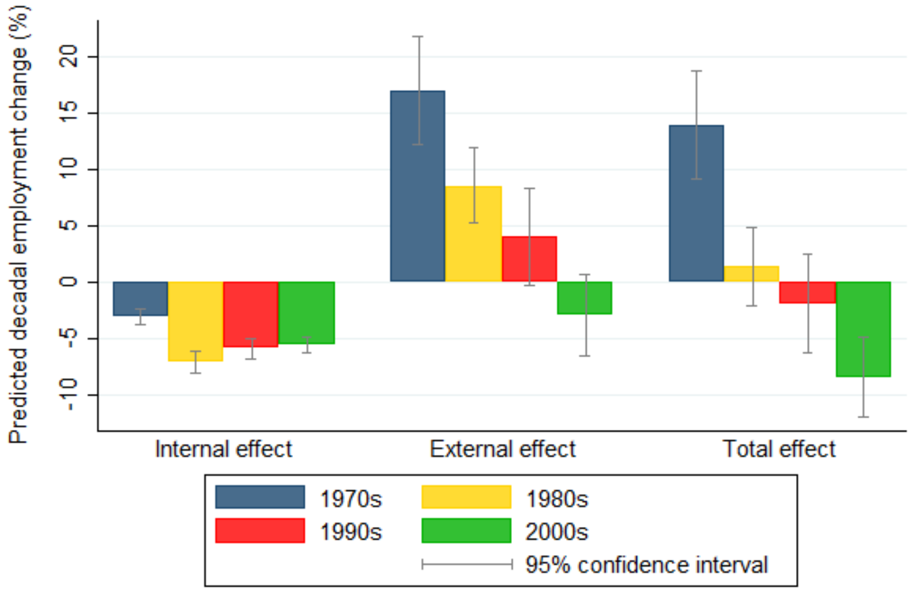


Figures are for the total economy, excluding agriculture, public administration, private households and extraterritorial organizations. Productivity is value added based.

Figure A7

Predicted cumulative percentage employment change by decade from value-added based productivity growth originating in five sectors

(y-axis: predicted decadal employment change (%))



Based on sector-specific model from Table 8. Predictions for the 1970s and 2000s scaled up to be comparable to the 1980s and 1990s. Confidence interval constructed by bootstrapping predictions (1,000 repetitions). Productivity is value added per worker.

Figure A8

Predicted cumulative percentage employment change by skill group from value-added based productivity growth originating in five sectors

(x-axis: year; y-axis: cumulative predicted change (%))

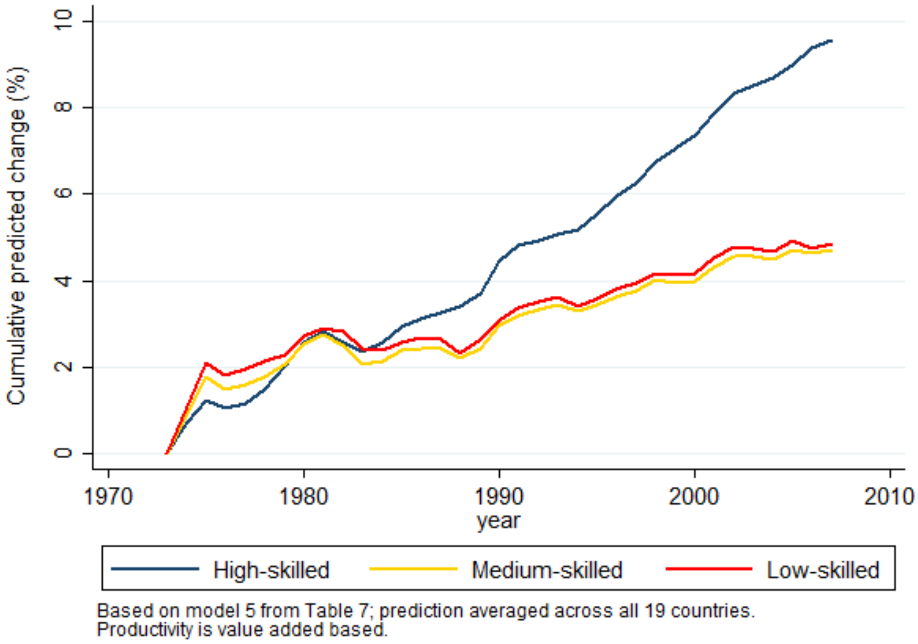
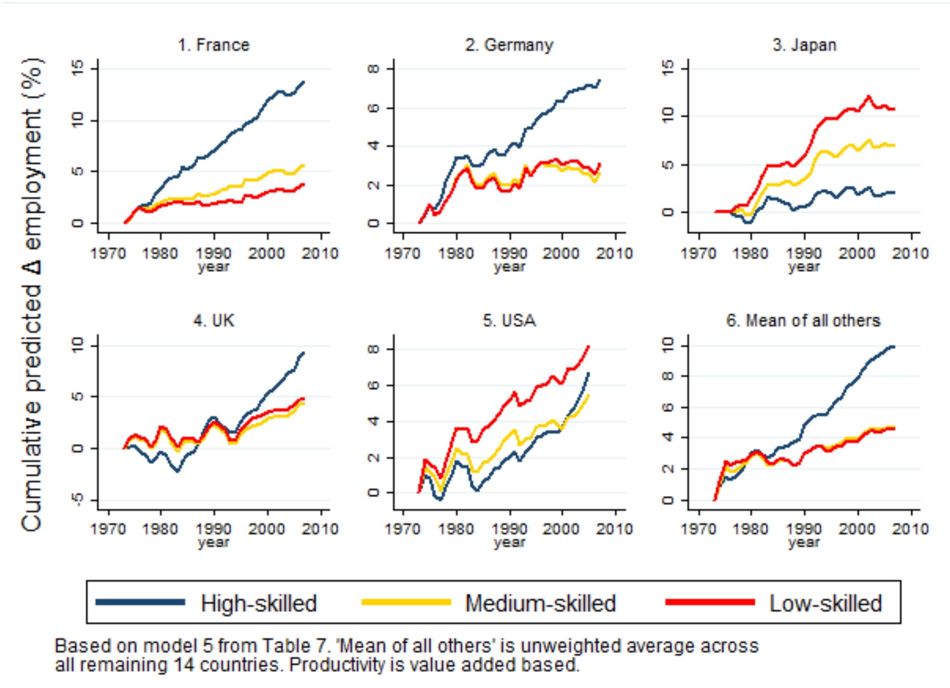


Figure A9

Predicted cumulative percentage employment change by skill group from value-added based productivity growth originating in five sectors: Large countries

(x-axis: year; y-axis: cumulative predicted Δ employment(%))



11 Appendix Tables

Table A1

EUKLEMS data coverage: Industries

ISIC code	Description
AtB	Agriculture, hunting, forestry, and fishing
C	Mining and quarrying
15t16	Food, beverages, and tobacco
17t19	Textiles, textile, leather, and footwear
20	Wood and wood products
21t22	Pulp, paper, paper, printing, and publishing
23	Coke, refined petroleum and nuclear fuel
24	Chemicals and chemical products
25	Rubber and plastics
26	Other non-metallic mineral
27t28	Basic metals and fabricated metal
29	Machinery, not elsewhere classified
30t33	Electrical and optical equipment
34t35	Transport equipment
36t37	Manufacturing not elsewhere classified; recycling
E	Electricity, gas, and water supply
F	Construction
50	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel
51	Wholesale trade and commission trade, except of motor vehicles and motorcycles
52	Retail trade, except of motor vehicles and motorcycles; repair of household goods
H	Hotels and restaurants
60t63	Transport and storage
64	Post and telecommunications
J	Financial intermediation
70	Real estate activities
71t74	Renting of machinery & equipment and other business activities
L	Public admin and defense; compulsory social security
M	Education
N	Health and social work
O	Other community, social and personal service activities
P	Private households with employed persons
Q	Extra-territorial organizations and bodies

Notes: ISIC revision 3 codes. We exclude agriculture (industry AtB), public administration (industry L), and private households (P) and extra-territorial organizations (Q) from our analyses. Industries 15t16 through 36t37 are manufacturing industries.

Table A2

Average annualized growth in employment and productivity by industry

ISIC code	Description	Δ log employment	Δ log gross output per worker	Δ log value added per worker	Δ Total Factor Productivity
C	Mining and quarrying	-2.47	3.67	3.61	0.18
15t16	Food, beverages, and tobacco	-0.44	2.33	2.22	0.53
17t19	Textiles, textile, leather, and footwear	-3.57	3.27	3.14	1.68
20	Wood and wood products	-0.60	2.75	2.92	1.96
21t22	Pulp, paper, paper, printing, and publishing	-0.20	3.12	2.76	0.83
23	Coke, refined petroleum and nuclear fuel	-0.79	2.95	3.69	-2.87
24	Chemicals and chemical products	-0.20	4.42	4.80	2.24
25	Rubber and plastics	0.52	3.51	3.63	2.16
26	Other non-metallic mineral	-1.00	3.16	3.02	1.41
27t28	Basic metals and fabricated metal	-0.39	3.01	2.82	1.24
29	Machinery, not elsewhere classified	-0.05	3.38	3.09	1.58
30t33	Electrical and optical equipment	0.20	5.64	6.08	5.98
34t35	Transport equipment	-0.02	3.69	3.31	2.31
36t37	Manufacturing not elsewhere classified; recycling	-0.22	2.80	2.30	1.08
E	Electricity, gas, and water supply	0.08	3.82	3.58	1.06
F	Construction	0.85	1.19	0.83	0.08
50	Sale, maintenance and repair of motor vehicles; retail sale of fuel	1.32	1.91	1.35	0.16
51	Wholesale trade and commission trade, except of motor vehicles	1.31	2.11	2.18	0.98
52	Retail trade, except of motor vehicles; repair of household goods	1.31	1.71	1.59	1.11
H	Hotels and restaurants	2.13	0.37	-0.21	-0.80
60t63	Transport and storage	1.11	2.78	2.38	1.01
64	Post and telecommunications	0.85	6.03	5.62	3.39
J	Financial intermediation	2.20	3.05	2.56	1.16
70	Real estate activities	3.50	-0.13	-0.14	-0.42
71t74	Renting of machinery & equipment and other business activities	5.03	0.39	0.02	-1.61
M	Education	2.09	0.58	0.37	-0.23
N	Health and social work	3.12	0.84	0.49	-0.42
O	Other community, social and personal service activities	2.48	0.73	0.29	-1.28

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

Table A3

First stages for Instrumental Variables models in Tables 3a and 3b

	(1)	(2)	(3)	(4)	(5)	(6)
			First stage for Δ ln productivity (c, t)			
Mean Δ ln productivity (t) in other countries	0.758** (0.080)	0.781** (0.077)	0.641** (0.102)	0.686** (0.099)	0.639** (0.103)	0.673** (0.099)
Mean Δ ln productivity (t-1) in other countries	-	-	-0.013 (0.092)	0.012 (0.089)	-0.013 (0.092)	0.013 (0.089)
Mean Δ ln productivity (t-2) in other countries	-	-	-0.093 (0.092)	-0.071 (0.089)	-0.093 (0.092)	-0.068 (0.088)
Mean Δ ln productivity (t-3) in other countries	-	-	-0.053 (0.085)	-0.025 (0.082)	-0.051 (0.085)	-0.011 (0.082)
Δ ln population (ct)	-	-	-	-	-0.052 (0.170)	-0.403~ (0.221)
			First stage for Δ ln productivity (c, t-1)			
Mean Δ ln productivity (t) in other countries	-	-	-0.099 (0.106)	-0.053 (0.102)	-0.101 (0.106)	-0.064 (0.102)
Mean Δ ln productivity (t-1) in other countries	-	-	0.719** (0.095)	0.746** (0.092)	0.719** (0.095)	0.746** (0.092)
Mean Δ ln productivity (t-2) in other countries	-	-	0.001 (0.095)	0.024 (0.091)	0.001 (0.095)	0.027 (0.091)
Mean Δ ln productivity (t-3) in other countries	-	-	-0.080 (0.088)	-0.050 (0.085)	-0.079 (0.088)	-0.039 (0.085)
Δ ln population (ct)	-	-	-	-	-0.038 (0.175)	-0.328 (0.228)
			First stage for Δ ln productivity (c, t-2)			
Mean Δ ln productivity (t) in other countries	-	-	-0.123 (0.106)	-0.077 (0.103)	-0.116 (0.107)	-0.076 (0.103)
Mean Δ productivity (t-1) in other countries	-	-	-0.013 (0.096)	0.014 (0.092)	-0.013 (0.096)	0.014 (0.092)
Mean Δ ln productivity (t-2) in other countries	-	-	0.719** (0.096)	0.743** (0.092)	0.718** (0.096)	0.743** (0.092)
Mean Δ ln productivity (t-3) in other countries	-	-	0.004 (0.089)	0.035 (0.085)	-0.003 (0.089)	0.034 (0.086)
Δ ln population (ct)	-	-	-	-	0.211 (0.177)	0.053 (0.230)
			First stage for Δ ln productivity (c, t-3)			
Mean Δ ln productivity (t) in other countries	-	-	-0.087 (0.109)	-0.040 (0.105)	-0.074 (0.109)	-0.034 (0.105)
Mean Δ ln productivity (t-2) in other countries	-	-	-0.077 (0.098)	-0.049 (0.095)	-0.077 (0.098)	-0.050 (0.095)
Mean Δ ln productivity (t-2) in other countries	-	-	0.002 (0.098)	0.026 (0.094)	0.000 (0.098)	0.024 (0.094)
Mean Δ ln productivity (t-3) in other countries	-	-	0.734** (0.091)	0.766** (0.087)	0.723** (0.091)	0.760** (0.088)
Δ ln population (ct)	-	-	-	-	0.342~ (0.181)	0.183 (0.236)

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. All models estimate stacked annual differences over 1970-2007 for the total economy. The number of observations is equal to the number of countries multiplied by the number of years. Standard errors in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table A4

The contemporaneous and lagged effects of productivity growth on employment growth at the industry level. Dependent variable: Annual log change in employment by country-industry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. OLS							
Δ ln productivity (ci, t)	-0.254** (0.025)	-0.263** (0.025)	-0.276** (0.026)	-0.251** (0.025)	-0.255** (0.026)	-0.263** (0.025)	-0.274** (0.026)	-0.249** (0.026)
Δ ln productivity (ci, t-1)	0.035** (0.012)	0.026* (0.011)	0.013 (0.011)	0.037** (0.010)	0.033** (0.012)	0.026* (0.011)	0.014 (0.011)	0.037** (0.010)
Δ ln productivity (ci, t-2)	-	-	-	-	-0.001 (0.012)	-0.010 (0.011)	-0.016 (0.011)	0.008 (0.010)
Country fixed effects	*NO*	*YES*	*YES*	*YES*	*NO*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*	*NO*	*NO*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*	*NO*	*NO*	*NO*	*YES*
R2	0.113	0.154	0.200	0.302	0.112	0.155	0.200	0.306
N	18,920	18,920	18,920	18,920	18,389	18,389	18,389	18,389
	B. IV							
Δ ln productivity (ci, t)	-0.264** (0.069)	-0.265** (0.061)	-0.333** (0.096)	0.026 (0.109)	-0.268** (0.071)	-0.267** (0.062)	-0.262** (0.096)	0.003 (0.109)
Δ ln productivity (ci, t-1)	-0.076 (0.061)	-0.078 (0.054)	-0.260** (0.088)	0.078 (0.091)	0.065 (0.081)	0.063 (0.071)	-0.032 (0.120)	0.113 (0.099)
Δ ln productivity (ci, t-2)	-	-	-	-	-0.241** (0.070)	-0.242** (0.063)	-0.371** (0.096)	-0.097 (0.083)
Country fixed effects	*NO*	*YES*	*YES*	*YES*	*NO*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*	*NO*	*NO*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*	*NO*	*NO*	*NO*	*YES*
Sanderson-Windmeijer F-stat	127.8	127.1	37.5	46.4	136.1	135.3	41.4	47.6
N	18,920	18,920	18,920	18,920	18,389	18,389	18,389	18,389

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is measured at the country-industry-year level. All models weighted by industry employment shares within countries, averaged over the period. The number of observations is equal to the number of country-industry cells multiplied by the number of years. Standard errors reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table A5a

Cyclical peaks and troughs for the 19 countries in our sample, 1970 – 2007

	Peaks	Troughs
AUS	1970, 1973, 1976, 1981, 1985, 1989, 1994, 2000, 2002	1972, 1975, 1978, 1983, 1986, 1991, 1996, 2001, 2003
AUT	1970, 1974, 1977, 1980, 1983, 1986, 1991, 1995, 2000	1971, 1975, 1978, 1981, 1984, 1988, 1993, 1997, 2003
BEL	1970, 1974, 1976, 1980, 1984, 1990, 1994, 1997, 2000, 2004	1971, 1975, 1977, 1983, 1987, 1993, 1996, 1998, 2003, 2005
DNK	1973, 1976, 1979, 1986, 1989, 1992, 1994, 1997, 2000, 2006	1971, 1975, 1978, 1981, 1987, 1991, 1993, 1995, 1998, 2003
ESP	1974, 1978, 1980, 1983, 1991, 1995, 2000	1971, 1975, 1979, 1981, 1986, 1993, 1996, 2004
FIN	1970, 1973, 1980, 1985, 1990, 1995, 1998, 2000, 2007	1971, 1978, 1984, 1987, 1993, 1996, 1999, 2003
FRA	1971, 1974, 1979, 1982, 1990, 1995, 2000, 2007	1972, 1975, 1981, 1987, 1993, 1997, 2003
GER	1970, 1973, 1979, 1985, 1991, 1995, 2001	1972, 1975, 1982, 1987, 1993, 1996, 2005
GRC	1973, 1979, 1985, 1989, 1991, 1994, 1998, 2004	1974, 1983, 1987, 1990, 1993, 1996, 2002, 2005
IRL	1972, 1975, 1978, 1982, 1985, 1990, 1995, 2000, 2007	1971, 1974, 1976, 1980, 1983, 1986, 1994, 1996, 2003
ITA	1970, 1974, 1976, 1979, 1985, 1989, 1995, 2001	1972, 1975, 1977, 1983, 1987, 1993, 1999, 2003
JPN	1973, 1979, 1982, 1985, 1990, 1997, 2001	1975, 1980, 1983, 1987, 1994, 1999, 2002
KOR	1971, 1973, 1979, 1984, 1988, 1991, 1997, 2000, 2002, 2007	1972, 1975, 1980, 1986, 1989, 1992, 1998, 2001, 2005
LUX	1974, 1979, 1984, 1986, 1989, 1991, 1994, 2000, 2007	1971, 1975, 1983, 1985, 1987, 1990, 1992, 1996, 2005
NLD	1970, 1974, 1976, 1979, 1986, 1990, 1994, 2000	1972, 1975, 1977, 1982, 1987, 1993, 1996, 2005
PRT	1970, 1973, 1977, 1980, 1983, 1990, 2001, 2004	1972, 1975, 1978, 1981, 1984, 1993, 2003, 2005
SWE	1970, 1974, 1980, 1984, 1990, 1995, 2000, 2007	1972, 1977, 1983, 1986, 1993, 1997, 2003
UK	1973, 1979, 1983, 1988, 1994, 1997, 2000, 2003	1970, 1975, 1981, 1984, 1992, 1996, 1999, 2002, 2004
USA	1973, 1978, 1985, 1989, 1994, 2000	1970, 1975, 1982, 1987, 1991, 1995, 2003

Notes: Based on OECD data.

Table A5b

The effects of industry and aggregate productivity growth on employment growth over the business cycle. Dependent variable: Annual log peak-to-peak change in employment by country-industry

	(1)	(2)	(3)	(4)	(5)
Δ ln productivity (cit)	-0.317** (0.030)	-0.325** (0.029)	-0.329** (0.029)	-0.247** (0.027)	-0.244** (0.027)
Δ ln productivity (c, j≠i, t)	-0.098 (0.196)	-0.257 (0.159)	-0.073 (0.142)	-0.113 (0.138)	-0.038 (0.121)
Δ ln productivity (c, j≠i, t-1)	0.350* (0.155)	0.366** (0.129)	0.020 (0.162)	0.014 (0.160)	-0.009 (0.162)
Δ ln productivity (c, j≠i, t-2)	0.261~ (0.134)	0.284~ (0.149)	0.203 (0.174)	0.183 (0.174)	0.161 (0.163)
Δ ln productivity (c, j≠i, t-3)	0.144 (0.116)	0.057 (0.102)	0.182~ (0.106)	0.182~ (0.098)	0.179~ (0.094)
Δ ln total population (ct)	-	-	-	-	1.257** (0.382)
Country fixed effects	*NO*	*YES*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*	*YES*
R2	0.148	0.209	0.258	0.474	0.485
N	3,520	3,520	3,520	3,520	3,520
Σk Δ ln productivity (c, j≠i, t-k)	0.658** (0.154)	0.449** (0.120)	0.332** (0.108)	0.265* (0.104)	0.293** (0.098)
Σk Δ ln productivity (c, j≠i, t-k) + Δ ln productivity (cit)	0.340** (0.161)	0.124 (0.126)	0.003 (0.112)	0.018 (0.111)	0.048 (0.104)

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is measured at the country-industry-year level; aggregate productivity is the country-year level productivity with the own industry netted out. All models estimated with OLS and weighted by industry employment shares within countries, averaged over the period. The number of observations is equal to the number of country-industry cells multiplied by the number of peak-to-peak periods. Standard errors are clustered by country-year and reported in parentheses, ~ $p<0.10$, * $p<0.05$, ** $p<0.01$.

Table A5c

The effects of industry and aggregate productivity growth on employment growth over the business cycle. Dependent variable: Annual log trough-to-trough change in employment by country-industry

	(1)	(2)	(3)	(4)	(5)
Δ ln productivity (cit)	-0.328** (0.036)	-0.333** (0.035)	-0.333** (0.036)	-0.225** (0.036)	-0.225** (0.036)
Δ ln productivity (c, j≠i, t)	-0.016 (0.253)	-0.031 (0.173)	0.169 (0.233)	0.084 (0.231)	-0.034 (0.213)
Δ ln productivity (c, j≠i, t-1)	0.765* (0.321)	0.705** (0.195)	0.328 (0.315)	0.326 (0.305)	0.523~ (0.280)
Δ ln productivity (c, j≠i, t-2)	-0.371~ (0.213)	-0.405** (0.135)	-0.240 (0.197)	-0.237 (0.192)	-0.311~ (0.171)
Δ ln productivity (c, j≠i, t-3)	0.273~ (0.162)	0.183 (0.111)	0.246~ (0.138)	0.232~ (0.138)	0.206~ (0.119)
Δ ln total population (ct)	-	-	-	-	1.477** (0.387)
Country fixed effects	*NO*	*YES*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*	*YES*
R2	0.156	0.217	0.251	0.475	0.485
N	3,353	3,353	3,353	3,353	3,353
Σk Δ ln productivity (c, j≠i, t-k)	0.651** (0.141)	0.451** (0.101)	0.503** (0.104)	0.406** (0.103)	0.384** (0.096)
Σk Δ ln productivity (c, j≠i, t-k) + Δ ln productivity (cit)	0.323* (0.148)	0.119 (0.112)	0.170 (0.118)	0.181 (0.119)	0.160 (0.112)

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is measured at the country-industry-year level; aggregate productivity is the country-year level productivity with the own industry netted out. All models estimated with OLS and weighted by industry employment shares within countries, averaged over the period. The number of observations is equal to the number of country-industry cells multiplied by the number of trough-to-trough periods. Standard errors are clustered by country-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table A5d

The effects of industry and aggregate value-added based productivity growth on employment growth. Dependent variable: Annual log change in employment by country-industry

	(1)	(2)	(3)	(4)	(5)
Δ ln productivity (cit)	-0.265** (0.023)	-0.266** (0.023)	-0.269** (0.023)	-0.243** (0.023)	-0.243** (0.023)
Δ ln productivity (c, j≠i, t)	0.163* (0.069)	0.140* (0.066)	0.083 (0.064)	0.062 (0.063)	0.076 (0.061)
Δ ln productivity (c, j≠i, t-1)	0.177** (0.046)	0.160** (0.038)	0.102** (0.036)	0.094** (0.035)	0.109** (0.034)
Δ ln productivity (c, j≠i, t-2)	0.131** (0.046)	0.111** (0.039)	0.092* (0.038)	0.087* (0.037)	0.086* (0.036)
Δ ln productivity (c, j≠i, t-3)	0.130** (0.041)	0.100** (0.034)	0.096** (0.033)	0.090** (0.033)	0.085** (0.032)
Δ ln total population (ct)	-	-	-	-	1.104** (0.197)
Country fixed effects	*NO*	*YES*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*	*YES*
R2	0.147	0.178	0.209	0.315	0.322
N	17,858	17,858	17,858	17,858	17,858
Σk Δ ln productivity (c, j≠i, t-k)	0.601** (0.097)	0.511** (0.095)	0.373** (0.090)	0.333** (0.089)	0.356** (0.086)
Σk Δ ln productivity (c, j≠i, t-k) + Δ ln productivity (cit)	0.336** (0.099)	0.245* (0.098)	0.104 (0.094)	0.089 (0.093)	0.113 (0.089)

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is measured at the country-industry-year level; aggregate productivity is the country-year level productivity with the own industry netted out. All models estimated with OLS and weighted by industry employment shares within countries, averaged over the period. 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-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table A5e

The effects of industry and aggregate TFP productivity growth on employment growth. Dependent variable: Annual log change in employment by country-industry

	(1)	(2)	(3)	(4)	(5)
Δ ln productivity (cit)	-0.106** (0.014)	-0.105** (0.014)	-0.108** (0.015)	-0.077** (0.012)	-0.076** (0.012)
Δ ln productivity (c, j≠i, t)	0.159* (0.069)	0.177* (0.077)	0.129~ (0.074)	0.094 (0.073)	0.104 (0.072)
Δ ln productivity (c, j≠i, t-1)	0.190** (0.064)	0.213** (0.053)	0.159** (0.050)	0.137** (0.049)	0.147** (0.049)
Δ ln productivity (c, j≠i, t-2)	0.087 (0.063)	0.094~ (0.050)	0.073 (0.047)	0.055 (0.046)	0.067 (0.044)
Δ ln productivity (c, j≠i, t-3)	0.065 (0.055)	0.054 (0.044)	0.061 (0.039)	0.038 (0.038)	0.050 (0.038)
Δ ln total population (ct)	-	-	-	-	1.079** (0.224)
Country fixed effects	*NO*	*YES*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*	*YES*
R2	0.040	0.078	0.114	0.269	0.274
N	12,981	12,981	12,981	12,981	12,981
Σk Δ ln productivity (c, j≠i, t-k)	0.501** (0.095)	0.538** (0.105)	0.422** (0.100)	0.324** (0.097)	0.368** (0.096)
Σk Δ ln productivity (c, j≠i, t-k) + Δ ln productivity (cit)	0.395** (0.092)	0.433** (0.104)	0.314** (0.100)	0.247** (0.098)	0.292** (0.097)

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is value added based TFP is measured at the country-industry-year level; aggregate productivity is the country-year level productivity with the own industry netted out. All models estimated with OLS and weighted by industry employment shares within countries, averaged over the period. 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-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table A6a

The effects of industry and aggregate value-added based productivity growth on domestic consumption growth. Dependent variable: Annual log change in domestic consumption by country-industry

	(1)	(2)	(3)	(4)	(5)
Δ ln productivity (cit)	0.274** (0.048)	0.280** (0.049)	0.262** (0.050)	0.300** (0.052)	0.301** (0.052)
Δ ln productivity (c, j≠i, t)	0.323 (0.288)	0.446 (0.314)	0.023 (0.326)	-0.009 (0.326)	0.006 (0.324)
Δ ln total population (ct)	-	-	-	-	1.025 (1.528)
Country fixed effects	*NO*	*YES*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*	*YES*
R2	0.015	0.033	0.230	0.241	0.241
N	6,838	6,838	6,838	6,838	6,838

Notes: Source: WIOT, 1995-2009. Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is value added based and measured at the country-industry-year level; aggregate productivity is the country-year level productivity with the own industry netted out. All models estimated with OLS and weighted by industry employment shares within countries, averaged over the period. 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-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table A6b

The effects of industry and aggregate based productivity growth on domestic consumption growth, dropping Great Recession years 2008 and 2009. Dependent variable: Annual log change in domestic consumption by country-industry

	(1)	(2)	(3)	(4)	(5)
Δ ln productivity (cit)	0.418** (0.064)	0.413** (0.069)	0.437** (0.062)	0.513** (0.068)	0.512** (0.068)
Δ ln productivity (c, j≠i, t)	-0.313 (0.462)	-0.398 (0.587)	0.136 (0.442)	0.099 (0.440)	0.088 (0.448)
Δ ln total population (ct)	-	-	-	-	0.778 (1.669)
Country fixed effects	*NO*	*YES*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*	*YES*
R2	0.022	0.052	0.278	0.296	0.296
N	5,860	5,860	5,860	5,860	5,860

Table A7a

The effect of industry and aggregate sectoral value-added based productivity growth on employment growth. Dependent variable: Annual log change in employment by country-industry

	(1)	(2)	(3)	(4)	(5)
Mining & utilities & construction					
Δ ln productivity (cit)	-0.307** (0.039)	-0.306** (0.039)	-0.307** (0.038)	-0.301** (0.039)	-0.301** (0.038)
Σk Δ ln productivity (c, j≠i, t-k)	0.014 (0.034)	0.016 (0.032)	-0.003 (0.031)	-0.011 (0.032)	-0.009 (0.032)
Manufacturing					
Δ ln productivity (cit)	-0.098** (0.016)	-0.101** (0.017)	-0.104** (0.017)	-0.117** (0.017)	-0.117** (0.017)
Σk Δ ln productivity (c, j≠i, t-k)	0.191** (0.046)	0.120** (0.044)	0.040 (0.042)	0.049 (0.041)	0.045 (0.038)
Education & health					
Δ ln productivity (cit)	-0.419** (0.037)	-0.417** (0.037)	-0.417** (0.038)	-0.419** (0.038)	-0.418** (0.037)
Σk Δ ln productivity (c, j≠i, t-k)	0.132** (0.043)	0.125** (0.041)	0.133** (0.040)	0.134** (0.039)	0.091* (0.041)
Low-tech services					
Δ ln productivity (cit)	-0.373** (0.041)	-0.372** (0.041)	-0.378** (0.041)	-0.374** (0.042)	-0.373** (0.042)
Σk Δ ln productivity (c, j≠i, t-k)	0.128 (0.078)	0.160* (0.073)	0.151* (0.068)	0.155* (0.068)	0.191** (0.066)
High-tech services					
Δ ln productivity (cit)	-0.282** (0.051)	-0.283** (0.049)	-0.279** (0.049)	-0.242** (0.047)	-0.242** (0.048)
Σk Δ ln productivity (c, j≠i, t-k)	0.115** (0.027)	0.121** (0.030)	0.112** (0.027)	0.086** (0.027)	0.076** (0.023)
Δ ln total population (ct)	-	-	-	-	1.008** (0.193)
Nr of lags in ln productivity (c, j≠i)	*k=3*	*k=3*	*k=3*	*k=3*	*k=3*
Country fixed effects	*NO*	*YES*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*	*YES*
R2	0.251	0.286	0.316	0.343	0.348
N	17,858	17,858	17,858	17,858	17,858

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is measured at the country-industry-year level; aggregate productivity is the sector-year level productivity with the own industry netted out. All models estimated with OLS and weighted by industry employment shares within countries, averaged over the period. 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-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table A7b

The effect of industry and aggregate sectoral productivity growth on employment to working age population. Dependent variable: Annual log change in employment to working age population by country-industry

	(1)	(2)	(3)	(4)
Mining & utilities & construction				
Δ ln productivity (cit)	-0.320** (0.041)	-0.316** (0.042)	-0.323** (0.041)	-0.318** (0.041)
Σk Δ ln productivity (c, j≠i, t-k)	0.031 (0.033)	0.045 (0.032)	0.016 (0.032)	0.007 (0.032)
Manufacturing				
Δ ln productivity (cit)	-0.128** (0.023)	-0.129** (0.023)	-0.132** (0.023)	-0.148** (0.023)
Σk Δ ln productivity (c, j≠i, t-k)	0.174** (0.041)	0.147** (0.044)	0.058 (0.042)	0.068 (0.042)
Education & health				
Δ ln productivity (cit)	-0.359** (0.039)	-0.359** (0.039)	-0.357** (0.040)	-0.360** (0.040)
Σk Δ ln productivity (c, j≠i, t-k)	0.058 (0.039)	0.053 (0.037)	0.073* (0.035)	0.076* (0.035)
Low-tech services				
Δ ln productivity (cit)	-0.348** (0.046)	-0.347** (0.046)	-0.352** (0.046)	-0.347** (0.047)
Σk Δ ln productivity (c, j≠i, t-k)	0.149* (0.062)	0.163* (0.063)	0.149* (0.060)	0.156* (0.060)
High-tech services				
Δ ln productivity (cit)	-0.266** (0.044)	-0.267** (0.043)	-0.267** (0.044)	-0.230** (0.042)
Σk Δ ln productivity (c, j≠i, t-k)	0.111** (0.021)	0.115** (0.026)	0.086 (0.022)	0.058 (0.022)
Nr of lags in ln productivity (c, j≠i)	k=3	k=3	k=3	k=3
Country fixed effects	*NO*	*YES*	*YES*	*YES*
Year fixed effects	*NO*	*NO*	*YES*	*YES*
Industry fixed effects	*NO*	*NO*	*NO*	*YES*
R2	0.240	0.255	0.288	0.317
N	17,858	17,858	17,858	17,858

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is measured at the country-industry-year level; aggregate productivity is the sector-year level productivity with the own industry netted out. All models estimated with OLS and weighted by industry employment shares within countries, averaged over the period. 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-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table A8a

The decadal effects of industry and aggregate sectoral value-added based productivity growth on employment growth. Dependent variable: Annual log change in employment by country-industry

	1970s	1980s	1990s	2000s
All sectors				
Δ ln productivity (cit)	-0.161** (0.048)	-0.295** (0.046)	-0.250** (0.030)	-0.252** (0.026)
Σk Δ ln productivity (c, j≠i, t-k)	0.666** (0.140)	0.332* (0.151)	0.322* (0.127)	-0.003 (0.100)
Σk Δ ln productivity (c, j≠i, t-k) + Δ ln productivity (ict)	0.505** (0.128)	0.037 (0.166)	0.072 (0.124)	-0.255** (0.101)
Mining & utilities & construction				
Δ ln productivity (cit)	-0.189** (0.052)	-0.322** (0.054)	-0.451** (0.090)	-0.269** (0.059)
Σk Δ ln productivity (c, j≠i, t-k)	-0.060 (0.043)	0.072 (0.044)	-0.044 (0.064)	-0.031 (0.048)
Manufacturing				
Δ ln productivity (cit)	-0.040 (0.032)	-0.109** (0.024)	-0.117** (0.025)	-0.201** (0.040)
Σk Δ ln productivity (c, j≠i, t-k)	0.266** (0.074)	0.072 (0.071)	-0.145 (0.101)	-0.038 (0.053)
Education & health				
Δ ln productivity (cit)	-0.327** (0.087)	-0.427** (0.064)	-0.406** (0.071)	-0.530** (0.064)
Σk Δ ln productivity (c, j≠i, t-k)	0.128** (0.049)	0.048 (0.068)	0.236 (0.163)	0.154~ (0.089)
Low-tech services				
Δ ln productivity (cit)	-0.313** (0.070)	-0.477** (0.074)	-0.349** (0.064)	-0.264** (0.026)
Σk Δ ln productivity (c, j≠i, t-k)	0.270** (0.091)	0.109 (0.109)	0.305* (0.120)	0.039 (0.079)
High-tech services				
Δ ln productivity (cit)	-0.167* (0.075)	-0.278** (0.093)	-0.257** (0.052)	-0.307** (0.026)
Σk Δ ln productivity (c, j≠i, t-k)	0.061 (0.039)	0.096* (0.039)	0.213** (0.049)	-0.002 (0.051)
Δ ln total population (ct)	0.948**			
	(0.164)			
Nr of lags in ln productivity (c, j≠i)	*k=3*			
Country fixed effects	*YES*			
Year fixed effects	*YES*			
Industry fixed effects	*YES*			
R2	0.374			
N	17,858			

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is measured at the country-industry-year level; aggregate productivity is the country-year level productivity for the total economy with the own industry netted out. All models estimated with OLS and weighted by industry employment shares within countries, averaged over the period. 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-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table A8b

The decadal effects of industry and aggregate sectoral productivity growth on employment to working age population. Dependent variable: Annual log change in employment to working age population by country-industry

	1970s	1980s	1990s	2000s
All sectors				
Δ ln productivity (cit)	-0.151** (0.047)	-0.323** (0.052)	-0.255** (0.039)	-0.302** (0.033)
Σk Δ ln productivity (c, j≠i, t-k)	0.523** (0.126)	0.173 (0.145)	0.402** (0.116)	0.080 (0.139)
Σk Δ ln productivity (c, j≠i, t-k) + Δ ln productivity (ict)	0.372** (0.114)	-0.150 (0.160)	0.147 (0.110)	-0.222 (0.139)
Mining & utilities & construction				
Δ ln productivity (ict)	-0.184** (0.056)	-0.353** (0.062)	-0.454** (0.092)	-0.296** (0.054)
Σk Δ ln productivity (c, j≠i, t-k)	-0.021 (0.050)	0.059 (0.054)	-0.061 (0.082)	0.065 (0.040)
Manufacturing				
Δ ln productivity (ict)	-0.037 (0.039)	-0.138** (0.031)	-0.155** (0.033)	-0.289** (0.056)
Σk Δ ln productivity (c, j≠i, t-k)	0.210** (0.071)	0.067 (0.084)	-0.021 (0.089)	-0.026 (0.073)
Education & health				
Δ ln productivity (ict)	-0.257** (0.082)	-0.404** (0.060)	-0.305** (0.073)	-0.490** (0.080)
Σk Δ ln productivity (c, j≠i, t-k)	0.095** (0.033)	-0.046 (0.066)	0.214 (0.137)	0.213* (0.085)
Low-tech services				
Δ ln productivity (ict)	-0.270** (0.074)	-0.497** (0.072)	-0.283** (0.075)	-0.271** (0.030)
Σk Δ ln productivity (c, j≠i, t-k)	0.238** (0.076)	0.123 (0.106)	0.219* (0.102)	-0.009 (0.071)
High-tech services				
Δ ln productivity (ict)	-0.147* (0.062)	-0.272** (0.091)	-0.236** (0.047)	-0.285** (0.032)
Σk Δ ln productivity (c, j≠i, t-k)	0.033 (0.032)	0.049 (0.034)	0.201** (0.052)	0.039 (0.046)
Nr of lags in ln productivity (c, j≠i)	*k=3*			
Country fixed effects	*YES*			
Year fixed effects	*YES*			
Industry fixed effects	*YES*			
R2				
N	17,858			

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is measured at the country-industry-year level; aggregate productivity is the country-year level productivity for the total economy with the own industry netted out. All models estimated with OLS and weighted by industry employment shares within countries, averaged over the period. 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-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table A9a

The effect of value-added based productivity growth on employment share by skill type. Dependent variable: Annual change in skill group employment share by country-industry

	High-skilled	Medium-skilled	Low-skilled
		A. OLS	
Δ ln productivity (cit)	-0.002 (0.002)	0.003 (0.003)	-0.001 (0.002)
Country fixed effects	*YES*	*YES*	*YES*
Year fixed effects	*YES*	*YES*	*YES*
Industry fixed effects	*YES*	*YES*	*YES*
R2	0.068	0.154	0.145
N	13,875	13,875	13,875
		B. IV	
Δ ln productivity (cit)	0.026 (0.017)	0.001 (0.023)	-0.027 (0.022)
Country fixed effects	*YES*	*YES*	*YES*
Year fixed effects	*YES*	*YES*	*YES*
Industry fixed effects	*YES*	*YES*	*YES*
Sanderson-Windmeijer F-statistic	37.1	37.1	37.1
N	13,875	13,875	13,875
		First stage for Δ ln productivity	
Mean Δ ln productivity (it) in other countries	0.248*** (0.041)	0.248*** (0.041)	0.248*** (0.041)

Notes: Excludes agriculture, public administration, private households, and extra-territorial organizations. Productivity is value added based and measured at the country-industry-year level. All models weighted by industry employment shares within countries, averaged over the period. 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-year and reported in parentheses, ~ p<0.10, * p<0.05, ** p<0.01.

Table A9b

High-, medium-, and low-skill employment shares by sector: Five largest countries and fourteen remaining countries

	High-skilled	Medium-skilled	Low-skilled	High-skilled	Medium-skilled	Low-skilled
	1. France			2. Germany		
Mining & utilities & construction	6.6	65.5	28.0	5.4	64.5	30.1
Manufacturing	6.2	56.0	37.8	5.8	61.1	33.1
Education & health	24.6	58.8	16.6	21.0	59.5	19.6
Low-tech services	7.8	60.7	31.5	5.6	65.0	29.3
High-tech services	15.0	68.1	16.9	8.2	68.1	23.7
	3. Japan			4. UK		
Mining & utilities & construction	14.9	59.5	25.6	9.9	71.7	18.4
Manufacturing	14.1	58.9	27.0	6.8	62.3	30.9
Education & health	33.5	60.4	6.1	24.2	55.5	20.3
Low-tech services	16.4	68.2	15.4	8.2	65.0	26.8
High-tech services	26.7	66.1	7.2	15.5	67.8	16.6
	5. USA			6. Mean of all others		
Mining & utilities & construction	18.9	67.8	13.3	9.4	49.8	40.8
Manufacturing	18.2	65.5	16.3	7.5	48.6	43.9
Education & health	48.3	45.8	5.9	37.3	43.7	19.0
Low-tech services	20.2	66.3	13.5	10.6	50.9	38.5
High-tech services	35.7	59.5	4.8	18.6	52.9	28.5

Notes: All shares are for 1992. 6. is the unweighted mean across all 14 remaining countries.