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Theory and Evidence

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U.S.E. Discussion Paper Series nr: 15-15

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December 2015

Abstract

This paper examines three empirical phenomena that have recently been discussed in the literature: job polarization, deindustrialization and Baumol's cost disease. Although assumed to be driven by the same process of recent technological change, each of these phenomena is explained differently by existing models and empirical analyses. Building on the existing literature, this paper therefore presents a unifying framework to derive critical assumptions that are consistent with all three stylized facts. Moreover, the paper presents empirical evidence for the US and 12 European countries in support of the hypothesis that job polarization, deindustrialization and Baumol's cost disease are intrinsically related phenomena following from ongoing technological progress.

Keywords: Labor Demand, Technology, Sector Employment

JEL classification: J21, J23, J24

Acknowledgements :
We thank numerous seminar participants for feedback on earlier drafts. Emilie Rademakers thanks the Research Foundation Flanders (scholarship Aspirant Onderzoeker) for financial support.

1 Introduction

This paper examines three empirical phenomena that have recently been discussed in the literature: job polarization, deindustrialization and Baumol's cost disease. Although assumed to be driven by the same process of recent technological change, each of these phenomena is explained differently by existing models and empirical analyses. Building on the existing literature, this paper therefore presents a unifying framework to derive critical assumptions that are consistent with all three stylized facts. Moreover, the paper presents empirical evidence for the US and 12 European countries in support of the hypothesis that job polarization, deindustrialization and Baumol's cost disease are intrinsically related phenomena following from ongoing technological progress.

Firstly, it has been documented for advanced economies that employment in both high- and low-skilled jobs is becoming increasingly important, at the expense of middling jobs. This phenomenon is known as *job polarization* [Goos, Manning and Salomons 2009a, 2014; Autor and Dorn 2013; Acemoglu and Autor 2011; Goos and Manning 2007; Autor, Katz and Kearney 2006].[2] Job polarization poses a puzzle to the canonical labor market model that assumes that innovation increases the productivity of skilled workers more than of unskilled workers, i.e. that there is Skill-Biased Technological Change (SBTC) leading to skill-upgrading rather than job polarization [Goldin and Katz 2008; Autor, Katz and Kearney 2008; Card and Lemieux 2001; Autor and Katz 1999; Katz and Murphy 1992]. In response to this puzzle, the task approach to labor markets has emerged arguing that job tasks can be done either by workers or by computer capital, leading to the hypothesis of Routine-Biased Technological Change (RBTC) [see Autor, Levy and Murnane 2003 for early work and Autor 2013 for a recent overview of the task approach to labor markets]. Routine tasks are structured and can therefore be increasingly codified in software and embodied in capital, whereas non-routine tasks are harder to automate. As a result, capital accumulation leads to an increase in the amount of routine tasks in the economy – hence the term RBTC – while decreasing the demand for routine relative to non-routine labor tasks done by workers.[3] Because routine labor tasks are concentrated in middling-paid jobs,

[2] Although almost all evidence unambiguously supports the existence of job polarization, some studies have questioned this result. However, these studies are typically confounding the notion of job polarization, i.e. differences in employment growth across occupations or industries, with notions of changes in wage inequality such as wage polarization, i.e. differences in wage growth across occupations or industries. Moreover, confusion results from differences in data analysis and interpretation. For example, Mishel, Shierholz, and Smith [2013] argue that the growth of low-wage service jobs does not commence in the US until the 2000s. However, Autor [2015] argues that this is at odds with all existing work because the adjustments that Mishel et al. [2013] apply to the data generate occupational patterns that appear anomalous. For Europe, Fernández-Macías [2012] claims that job polarization is not pervasive across countries. However, Goos, Manning and Salomons [2009b] show that this result is entirely driven by the unusual data methodology and interpretation of results.

[3] Note the difference in our terminology between *tasks* that can be done by either capital or labor and *labor tasks* than can only done by workers. In particular, this paper argues that there is a relative increase in routine

RBTC leads to a hollowing out of labor demand or job polarization. This paper builds on this literature by formally deriving critical assumptions in a more realistic framework that not only predicts job polarization but also deindustrialization and Baumol's cost disease.

Secondly, this paper suggests a more nuanced view about the process of *deindustrialization* that has recently been discussed in the literature [Rodrik 2015; Felipe, Mehta and Rhee 2014, Lawrence and Edwards 2013]. In particular, Rodrik [2015] argues that in advanced economies SBTC is leading to a decline of manufacturing employment but not of manufacturing real output. This paper shows that this outcome is also consistent with the more nuanced hypothesis of RBTC. The intuition for this is simple. Innovation in manufacturing leads to an accumulation of capital and hence of routine tasks. Consequently, manufacturing real output increases despite the displacement of routine labor tasks from manufacturing – i.e. there is deindustrialization in terms of employment but not real output. In line with Rodrik [2015], our framework also predicts that employment deindustrialization mainly displaces unskilled workers because routine labor tasks in manufacturing are mainly done by those workers. But our framework also goes beyond Rodrik [2015] in that strong innovation in some fast growing high-tech sectors both within but also outside manufacturing will attract skilled workers doing non-routine labor tasks. In sum, unskilled workers reallocate to less innovative sectors outside manufacturing, whereas skilled workers reallocate towards high-tech sectors within and outside manufacturing where innovation is strongest, i.e. there is not only employment deindustrialization but also between-sector job polarization following RBTC.[4]

Thirdly, following the seminal work by Baumol and Bowen [1965] and Baumol [1967], a literature has emerged examining the phenomenon of *Baumol's cost disease*. Baumol's [1967] original thesis stated that, if productivity growth is unbalanced across sectors, sectors with lower productivity growth will see their relative output price as well as their share in total employment increase.[5] An alternative view, and the one that we take in this paper, is that Baumol's cost disease does not result from unbalanced productivity growth across sectors but from differences in capital intensities between sectors. In particular, Acemoglu and Guerrieri [2008] assume that productivity grows the same in all sectors but that structural change results from faster capital

tasks done in the economy – i.e. there is routinization in the economy as a defining result of RBTC – because capital doing routine tasks accumulates faster than the decrease in routine labor tasks done by workers.

[4]The empirical relevance of *between-sector* job polarization is analyzed in Goos, Manning and Salomons [2014] who show that job polarization between occupations has an economically meaningful between-sector component following RBTC. However, their main level of analysis is the level of occupations, and not the level of sectors as is the focus in this paper.

[5]Moreover, Baumol [1967] argued that unbalanced productivity growth would lead to an increasing share in GDP for less innovative sectors, and thus to a slowdown in sector-weighted aggregate growth. Because this is inconsistent with Kaldor facts, more recent work has shown how unbalanced productivity growth can lead to structural changes between sectors while still predicting constant aggregate growth. See, for example, Ngai and Pissarides [2007].

accumulation in sectors that are more capital intensive. Building on Acemoglu and Guerrieri [2008], the framework presented in this paper assumes that sectors are more capital intensive if they are more routine task intensive. Consequently, consistent with Baumol's cost disease, more capital intensive sectors will innovate more to see their relative marginal costs and therefore their relative output price decrease. Also consistent with Baumol's cost disease, the least capital intensive sectors experience both increasing relative prices and relative employment.[6] Moreover, this paper assumes that unskilled workers doing routine tasks are displaced towards the least capital intensive sectors, whereas skilled workers doing non-routine tasks reallocate towards the most capital intensive sectors. This is consistent with job polarization into the least and most capital intensive sectors, and with employment deindustrialization if manufacturing sectors are not the least nor exclusively the most capital intensive sectors in the economy.

The remainder of this paper is organized as follows. Section 2 presents our framework and the parameters restrictions under which it predicts between-sector job polarization, deindustrialization and Baumol's cost disease. Section 3 explains our data and Section 4 presents our estimations. Finally, Section 5 concludes.

2 A Model

If job polarization, deindustrialization and Baumol's cost disease result from the same process of innovation, all three phenomena must be intrinsically related. Therefore, this section presents a framework to derive a consistent set of critical assumptions that jointly predicts all three stylized facts. The section first outlines the set-up of the model (how we model innovation, sector-specific production functions, consumption and labor supply) in subsection 2.1. It then discusses critical assumptions under which the model predicts between-sector job polarization, deindustrialization as well as Baumol's cost disease in subsection 2.2.

[6] Young [2014] also predicts Baumol's cost disease while assuming that innovation is balanced across sectors. However, his explanation for the existence of Baumol's cost disease is not that sectors differ in their capital intensity but that a) individual workers differ in their sector-specific productivity and that b) preferences are nonhomothetic. In particular, assume that technological progress leads to a rise in real income. If the income elasticities differ between sectors, relative product and therefore labor demand increases for sectors with higher income elasticities. Consequently, the least productive workers will reallocate towards those sectors, thereby decreasing their average labor productivity and increasing their relative output price. In sum, relative employment as well as relative output prices increase in sectors with lower productivity growth which is observationally identical to Baumol's cost disease. Although the main text below assumes that workers with identical skills (i.e. either unskilled or skilled) also have identical labor productivities, Appendix A allows for heterogeneity in labor productivity within skill types to show that this does not qualitatively change our results. However, in contrast to Young [2014] it is assumed throughout this paper that preferences are homothetic.

2.1 Set Up

2.1.1 Routinization

Following Autor and Dorn [2013][7], assume that efficiency units of computer capital used in Sector j at time t, $K_j(t)$, result from:

$$K_j\left(t\right) = Y_{kj}(t)e^{\delta t} \tag{1}$$

where δ captures the speed of digital innovation and where $Y_{kj}(t)$ is output that is not consumed but reinvested in capital production.

Competitive capital and output markets imply that marginal revenue must equal marginal cost in each sector j:

$$p_k(t) = p_j(t)\frac{\partial Y_{kj}(t)}{\partial K_j(t)} = p_j(t)e^{-\delta t} \tag{2}$$

where p_k is the unique price per efficiency unit of computer capital and p_j the price of good j produced by sector j. Defining $\mathbf{p}_k(t) \equiv p_k(t)/p_j(t)$, equation (2) can be written as:

$$\mathbf{p}_k(t) = e^{-\delta t} \tag{3}$$

Consistent with Moore's Law[8], technological progress is captured by an exponential decrease over time in the relative price per efficiency unit of computer capital limiting to zero asymptotically: $\mathbf{p}_k = e^{-\delta t} \rightarrow 0$ as $t \rightarrow \infty$. For simplicity, we drop the time indicator and denote efficiency units of computer capital simply by "capital".

2.1.2 Services

Assume that there is a sector in the economy providing Services, Y_s:

$$Y_s = L_m \tag{4}$$

[7]The framework presented below can be seen as a modification of the spatial model developed in Autor and Dorn [2013] who derive critical assumptions about production and consumption elasticities to predict rising employment shares for the least capital intensive sectors (providing in-person services) in the economy following RBTC. This paper extends their two-sector model into a three-sector model to derive critical assumptions that can predict job polarization, i.e. a model that not only predicts rising employment shares for the least but also for the most capital intensive sectors in the economy.

[8]In 1965, Intel cofounder Gordon Moore posited that innovation in microprocessors would lead to a doubling of the number of transistors in a dense integrated circuit every two years, implying a corresponding exponential decrease in their unit cost. This has become known as Moore's Law and its predictions, by and large, seem to capture reasonably well the observed speed of technological progress in computing hardware as well as a wider range of digital technologies [Nagy, Farmer, Bui and Trancik 2013; Nordhaus 2007; Koh and Magee 2006]. The estimated magnitude of this progress is also remarkable. Nordhaus [2007] estimates that between 1980 and 2006 the real costs of performing a standard set of computations measured by the cost expressed in constant dollars or relative to labor costs, has fallen by 60 to 75 percent annually.

with L_m workers performing manual labor tasks. The manual labor tasks done in these jobs mainly are an end-product in themselves such as assisting or caring for others, in the way receptionists, waiters in restaurants or other in-person services do. Typically, these jobs are low-paid because they are easy to do for humans and do not require much capital, schooling or experience.[9]

2.1.3 Goods producing sectors

In contrast to Autor and Dorn [2013], assume that there is not one but that there are two additional sectors in the local economy, Sector 1 and Sector 2. Sector 1 produces good Y_{g1} by combining abstract and routine tasks. Abstract tasks can only be performed by labor, whereas routine tasks are performed by labor and capital:

$$Y_{g1} = L_{a1}^{1-\beta_1} X^{\beta_1} \text{ with } X \equiv [L_r^{\mu} + K_1^{\mu}]^{\frac{1}{\mu}} \tag{5}$$

with L_{a1} abstract labor tasks, X total input of routine tasks consisting of L_r routine labor tasks and K_1 capital tasks. Assuming that $0 < \mu < 1$ implies that the elasticity of substitution between routine labor and capital tasks is larger than unity, i.e. $1/[1-\mu] > 1$, and therefore also larger than the elasticity of substitution between abstract labor and routine tasks (which equals unity given the Cobb-Douglas specification in equation (5)).

Sector 2 produces Y_{g2} by combining abstract labor tasks and capital:

$$Y_{g2} = L_{a2}^{1-\beta_2} K_2^{\beta_2} \tag{6}$$

with L_{a2} abstract labor tasks and K_2 capital.

A difference between equations (5) and (6) is the assumption that in Sector 1 routine tasks are performed by both labor and capital whereas in Sector 2 routine tasks are performed solely by capital. Moreover, following Acemoglu and Guerrieri [2008], the assumption is made that $\beta_2 > \beta_1$ or that Sector 2 is more routine-task intensive than Sector 1. The intuition for these assumptions is that routine tasks are more important in Sector 2 and that the routine tasks done in Sector 2 are more susceptible to automation.[10]

Equations (5) and (6) together with the assumption that $\beta_2 > \beta_1$ also imply that Sector 2 is

[9] Paradoxically, many of these manual tasks are, as of yet, difficult to automate. For example, most of us know how to be a good waiter but none of us knows how to write this down in software code. Autor [2014] refers to this paradox as Polanyi's paradox, arguing that tacit knowledge – i.e. knowledge that cannot be easily formalized or put into exact words – is important because we know more than we can tell and this poses significant hurdels to automization.

[10] For example, sending text messages between any two persons involves a larger fraction of routine tasks than determining a person's right to benefits through social security. Moreover, the routine tasks involved in text messaging have been entirely automated, whereas social security counselors still perform various routine activities (e.g. filling in the standardized information of new requests for benefits).

more capital intensive than Sector 1. To see this, define the capital intensity of Sector $j = 1, 2$, CAP_j, as the ratio of rents paid out to capital over total output value. Assuming perfectly competitive labor, capital and output markets gives:

$$CAP_1 \equiv \frac{\mathbf{p}_k K_1}{Y_{g1}} = \frac{\partial Y_{g1}}{\partial K_1}\frac{K_1}{Y_{g1}} = \beta_1 \frac{K_1^{\mu}}{L_r^{\mu} + K_1^{\mu}} \leq \beta_1 \tag{7}$$

$$CAP_2 \equiv \frac{\mathbf{p}_k K_2}{Y_{g2}} = \frac{\partial Y_{g2}}{\partial K_2}\frac{K_2}{Y_{g2}} = \beta_2 \tag{8}$$

such that $\beta_2 > \beta_1$ implies that $CAP_2 > CAP_1$. Also note that the capital intensity of Services is $CAP_s = 0$. That is, we can rank sectors by their capital intensity as is done in column (1a) of Table 1 and use this ranking as an identification strategy in our empirical analysis below.

2.1.4 Consumption

Assume that consumers maximize utility by consuming Services, C_s, Sector 1 goods, C_{g1}, and Sector 2 goods, C_{g2}, according to:

$$U = \left[C_s^{\frac{\sigma-1}{\sigma}} + C^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \text{ with } C \equiv \left[C_{g1}^{\frac{\theta-1}{\theta}} + C_{g2}^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} \tag{9}$$

with σ the elasticity of substitution between Services and other goods and with θ the elasticity of substitution between Sector 1 and Sector 2 goods. We assume that $\theta > 1$ and that $0 < \sigma < \theta$, or that Sector 1 and 2 goods are more substitutable in consumption than Services. This assumption implies that the demand for Services will be relatively price inelastic. The intuition for this assumption is that Services are not readily dispensable as their relative prices increase.[11]

Also note that preferences are assumed to be homothetic to maintain the independence of preferences on the demand side and technological progress on the supply side, as is most standard in recent work (see, for example, Goos, Manning and Salomons [2014], Autor and Dorn [2013], Acemoglu and Guerrieri [2008] and Ngai and Pissarides [2007]). Finally, since a fraction of final goods produced is allocated towards capital production, consumption equals: $C_{gj} = Y_{gj} - Y_{kj} = Y_{gj} - \mathbf{p}_k K_j$ for $j = 1, 2$ and $C_s = Y_s$.

2.1.5 Labor Supply

Assume that there is a continuum of skilled as well as of unskilled workers, each normalized to unity.[12] Each skilled worker has a single unit of labor which can be supplied to perform

[11] For example, the demand for child care by parents or for hotels and catering by business travelers is unlikely to dissipate even as their relative prices increase.

[12] We assume that workers are identical within skill groups. Appendix A solves the model assuming that workers within each skill group are heterogenous, as is assumed in Young [2014], Autor and Dorn [2013], Acemoglu and Autor [2011] and Autor, Levy and Murnane [2003]. This does not qualitatively change our results presented in the main text.

abstract labor tasks in Sector 1 or 2. The masses of skilled workers employed in Sectors 1 and 2 are denoted by $L_{a1} \in [0,1]$ and $L_{a2} = 1 - L_{a1} \in [0,1]$ respectively. Similarly, an unskilled worker has a single unit of labor which can be supplied to perform manual labor tasks in Services or routine labor tasks in Sector 1. The masses of unskilled workers employed in Services and Sector 1 are denoted by $L_m \in [0,1]$ and $L_r = 1 - L_m \in [0,1]$ respectively.

Skilled workers are perfectly mobile between Sectors 1 and 2 but are not employed in Services. Unskilled workers are perfectly mobile between Services and Sector 1 but are not employed in Sector 2. The reason for these simplifying assumptions are given in columns (3a) and (4a) of Table 1: Column (3a) shows that skilled workers appear to be concentrated in sectors with the highest capital intensity, whereas column (4a) shows that unskilled workers appear to be concentrated in sectors with the lowest capital intensity. For example, the probability to be employed in the bottom quintile of sectors (based on their overall employment shares given in column (2a)) is 8% for skilled workers and 22% for unskilled workers, whereas the probability to be employed in the top quintile of sectors is 32% for skilled workers and 17% for unskilled workers. By completely barring skilled workers from Services and unskilled workers from Sector 2, we retain the minimum amount of heterogeneity among workers needed to create sorting based on comparative advantage. This clearly is a formal simplification of these numbers, but this simplification is not critical to our results. Finally, note that we do not assume any shocks in labor supply (for example, an increase over time in the number of skilled relative to unskilled workers) such that all labor reallocation in our model will be driven by routinization only.

2.1.6 Assumptions made so far

Before we discuss the equilibrium in this model, this section summarizes the restrictions imposed so far. Besides the assumption that $0 < \beta_1 < \beta_2 < 1$, i.e. Sector 2 is more routine task intense than Sector 1, the following assumptions have been made about elasticities of substitution:

$1/[1-\mu] > 1$:	Capital most easily substitutes for routine labor tasks in production
$0 < \sigma < \theta$:	Services are less substitutable than Sector 1 or 2 goods in consumption
$\theta > 1$:	The substitutability between Sector 1 and 2 goods in consumption exceeds unity

The next section will return to these restrictions when the critical assumptions to predict between-sector job polarization, deindustrialization and Baumol's cost disease are discussed.

2.2 Equilibrium

Since all markets are assumed to be perfectly competitive, the second welfare theorem implies that the equilibrium is characterized by solving the social planner's problem of maximizing utility of the representative household:

$$\max_{K_1,K_2,L_r,L_{a1}} U = \left[C_s^{\frac{\sigma-1}{\sigma}} + C^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \text{ with } C \equiv \left[C_{g1}^{\frac{\theta-1}{\theta}} + C_{g2}^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} \tag{10}$$

where:

$$C_s = Y_s = L_m = 1 - L_r \tag{11}$$

$$C_{gj} = Y_{gj} - Y_{kj} \text{ with } Y_{kj} = \mathbf{p}_k K_j \text{ for } j = 1, 2 \tag{12}$$

$$Y_{g1} = L_{a1}^{1-\beta_1} X^{\beta_1} \text{ with } X = [L_r^\mu + K_1^\mu]^{\frac{1}{\mu}} \tag{13}$$

$$Y_{g2} = L_{a2}^{1-\beta_2} K_2^{\beta_2} = [1 - L_{a1}]^{1-\beta_2} K_2^{\beta_2} \tag{14}$$

Efficient allocations of K_1, K_2, L_r and L_{a1} are given by the first-order conditions:

$$\mathbf{p}_k = \beta_1 L_{a1}^{1-\beta_1} X^{\beta_1-\mu} K_1^{\mu-1} \tag{15}$$

$$\mathbf{p}_k = \beta_2 [[1 - L_{a1}]/K_2]^{1-\beta_2} \tag{16}$$

$$L_r^{1-\mu}[1 - L_r]^{-\frac{1}{\sigma}} = C^{\frac{\sigma-\theta}{\theta\sigma}} C_{g1}{}^{-\frac{1}{\theta}} \beta_1 L_{a1}^{1-\beta_1} X^{\beta_1-\mu} \tag{17}$$

$$L_{a1}^{-\beta_1}[1 - L_{a1}]^{\beta_2} = [C_{g1}/C_{g2}]^{1/\theta}[[1 - \beta_2]/[1 - \beta_1]] X^{-\beta_1} K_2^{\beta_2} \tag{18}$$

Note that equations (15)-(18) also give the equilibrium allocations over time for $\mathbf{p}_k \to 0$ because it is implicitly assumed above that income can be saved but not for future consumption and that the capital stock can increase every period – i.e. there is capital accumulation – but fully depreciates between periods. The remainder of this section shows the conditions under which these efficient allocations are consistent with between-sector job polarization, deindustrialization and Baumol's cost disease.

2.2.1 Job Polarization

Job polarization between sectors requires that unskilled workers move to less capital intensive sectors, i.e. from Sector 1 to Services, and skilled workers move to more capital intensive sectors, i.e. from Sector 1 to Sector 2. Asymptotically, we must have that $L_r \to 0$ and that $L_{a1} \to 0$ which is now shown to be the case under some additional parameter restrictions.

Unskilled labor reallocates from Sector 1 to Services Since the relative price of capital falls to zero in each sector, capital in each sector will accumulate and limit to infinity: $K_1 \to \infty$ and $K_2 \to \infty$ if $\mathbf{p}_k \to 0$. Because $K_1 \to \infty$ and L_r is bounded, X will essentially be determined by K_1 in the limit or $K_1/X \to 1$ such that $X \to \infty$. Consequently, $X + K_2 \to \infty$ or the amount of routine tasks done in the economy will limit to infinity, i.e. there is routinization through capital accumulation in the economy.[13]

Given that capital accumulates in Sectors 1 and 2, equation (17) gives the conditions needed for $L_r \to 0$. To see this, first consider the consumption terms C_{g1} and C_{g2} (which are included in C) that occur in the expression. Making use of equations (15) and (16) gives:

$$C_{g1} = Y_{g1} - \mathbf{p}_k K_1 = [1 - \beta_1 [K_1/X]^{\mu}] L_{a1}^{1-\beta_1} X^{\beta_1} \tag{19}$$

$$C_{g2} = Y_{g2} - \mathbf{p}_k K_2 = [1 - \beta_2][1 - L_{a1}]^{1-\beta_2} K_2^{\beta_2} \tag{20}$$

which shows that the limits for C_{g1} and C_{g2} depend on the limit for L_{a1}. If $L_{a1} \to 0$, we get that the limit for C_{g1} is undetermined but that $C_{g2} \to \infty$. If $L_{a1} \to 1$, we get that $C_{g1} \to \infty$ whereas the limit for C_{g2} remains unspecified. However, note that in any case it must be true that $C \to \infty$ because either $C_{g1} \to \infty$ or $C_{g2} \to \infty$.

Substituting equation (19) into equation (17) gives:

$$L_r^{1-\mu}[1 - L_r]^{-\frac{1}{\sigma}} = C^{\frac{\sigma-\theta}{\theta\sigma}} [1 - \beta_1 [K_1/X]^{\mu}]^{-\frac{1}{\theta}} \beta_1 L_{a1}^{\frac{[\theta-1][1-\beta_1]}{\theta}} X^{\beta_1 - \mu - \frac{1}{\theta}\beta_1} \tag{21}$$

Given that $\mu < 1$, a sufficient condition for $L_r \to 0$ on the left-hand side of equation (21) is that the right-hand side of equation (21) is zero asymptotically: (i) $C \to \infty$ implies that $C^{\frac{\sigma-\theta}{\theta\sigma}} \to 0$ if $\sigma < \theta$; (ii) $K_1/X \to 1$ implies that $(1 - \beta_1 [K_1/X]^{\mu})^{-\frac{1}{\theta}}$ converges to some finite number; (iii) $L_a \in [0, 1]$ implies that $L_{a1}^{[\theta-1][1-\beta_1]/\theta}$ converges to some finite number given that $\theta > 1$; (iv) Given that $X \to \infty$, sufficient conditions for the right-hand side of equation (21) to go to zero and therefore $L_r \to 0$ are the assumptions summarized in subsection 2.1.6 above together with:

$$L_r \to 0 \text{ if } \frac{1}{\theta} > \frac{\beta_1 - \mu}{\beta_1} \tag{22}$$

Equation (22) has a straightforward interpretation. For given β_1, $L_r \to 0$ if μ is sufficiently large relative to θ and therefore also relative to σ (given that $\sigma < \theta$). Said differently, the elasticity of substitution between routine labor tasks and capital in production, $1/[1 - \mu]$, must be sufficiently large compared to the elasticities of substitution in consumption, θ and σ. On the one hand, a large elasticity of substitution between routine labor tasks and capital in production implies a large decrease in the demand for routine relative to manual labor tasks – this is a substitution effect. On the other hand, the decrease in the capital price will also lead to a fall in the output price of Sector 1 goods relative to Services (see section 2.2.3 below), thereby increasing the demand for routine relative to manual labor tasks – this is a scale effect. But if θ and σ are small relative to $1/[1 - \mu]$, this scale effect will not dominate the substitution effect and $L_r \to 0$. The role played by β_1 in equation (22) also has a straightforward interpretation.

[13] Moreover, given that the amount of manual and abstract tasks are bounded by L_m and L_a respectively, $X + K_2 \to \infty$ implies that the *share* of routine tasks done in the economy converges to unity.

All else equal, a smaller β_1 implies that the inequalities in equation (22) are more likely to hold or that it is more likely that unskilled workers will reallocate from Sector 1 to Services. The reason for this is that a smaller β_1 means that a smaller fraction of the gains from technological progress accrue to routine tasks, such that unskilled workers are more likely to reallocate from Sector 1 to Services.[14]

Skilled labor reallocates from Sector 1 to Sector 2 Because Sector 2 is more routine task intense than Sector 1 given that $\beta_2 > \beta_1$, a uniform decline in the price of capital across both sectors leads to a greater adoption of routine tasks in Sector 2 than in Sector 1. So we not only have that routine tasks accumulate in both sectors, i.e. $X \to \infty$ and $K_2 \to \infty$, but also that routine tasks accumulate faster in Sector 2 than in Sector 1, i.e. $X/K_2 \to 0$.

Given that $X/K_2 \to 0$, equation (18) gives the asymptotic allocation of skilled labor. Substituting equations (19) and (20) into equation (18) gives:

$$L_{a1}^{\beta_1+\frac{1}{\theta}(1-\beta_1)}\left[1-L_{a1}\right]^{\frac{1}{\theta}(\beta_2-1)-\beta_2} = \left[1-\beta_1\right]\left[\beta_2-1\right]^{\frac{\theta-1}{\theta}}\left[1-\beta_1\left[K_1/X\right]^{\mu}\right]^{-1/\theta}\left[X^{\beta_1}/K_2^{\beta_2}\right]^{\frac{\theta-1}{\theta}} \quad (23)$$

showing that a sufficient condition for $L_{a1} \to 0$ on the left-hand side of equation (23) is that its right-hand side is zero asymptotically: (i) $K_1/X \to 1$ such that $\left[1-\beta_1\left[K_1/X\right]^{\mu}\right]^{-1/\theta}$ converges to $\left[1-\beta_1\right]^{-1/\theta}$; (ii) $X/K_2 \to 0$ implies that $\left[X^{\beta_1}/K_2^{\beta_2}\right]^{\frac{\theta-1}{\theta}} \to 0$ given that $\beta_2 > \beta_1$ and $\theta > 1$. Consequently, the right-hand side of equation (23) converges to zero such that $L_{a1} \to 0$ if the assumptions summarized in subsection 2.1.6 above hold.

That skilled workers reallocate from Sector 1 to Sector 2 if $\theta > 1$ also has a straightforward interpretation. For given relative output prices, $\beta_2 > \beta_1$ implies that a smaller fraction of the gains from technological progress accrue to abstract labor tasks in Sector 2 compared to Sector 1. Consequently, skilled workers would reallocate from Sector 2 to Sector 1. However, because a fall in the price of capital also leads to a decrease in the output price of Sector 2 relative to Sector 1 goods (see section 2.2.3 below), the demand for abstract labor tasks increases in

[14] In the RBTC literature, a similar intuition for critical assumptions about production and consumption functions can be found in, for example, Goos, Manning and Salomons [2014]; Autor and Dorn [2013]; Acemoglu and Autor [2011]; and Autor, Levy and Murnane [2003]. Critical assumptions also exist in the SBTC literature. For example, in the canonical model, the demand for skilled relative to unskilled workers increases – i.e. there is SBTC – only if the elasticity of substitution between skilled and unskilled workers in aggregate output exceeds unity. Another example is Rodrik [2015] who provides critical assumptions about aggregate production and consumption functions to predict deindustrialization in terms of employment following SBTC. He assumes that innovation directly displaces labor from manufacturing – this is a substitution effect. However, as manufacturing is more susceptible to innovation, the relative output price of manufacturing goods decreases which increases its relative demand for output and therefore labor – this is a scale effect that counter-balances the substitution effect. In net, for the relative demand for manufacturing workers to fall – i.e. to get deindustrialization in terms of employment – the scale effect must be sufficiently small relative to the substitution effect. This will be the case if the elasticity of substitution between capital and labor in production is sufficiently large relative to the price elasticity of demand for manufacturing goods in consumption.

Sector 2 relative to Sector 1. Because the substitutability in consumption between Sector 1 and 2 goods is larger than unity, i.e. $\theta > 1$, this increase in the demand for abstract labor tasks in Sector 2 relative to Sector 1 dominates and $L_{a1} \to 0$. More generally, skilled workers doing abstract labor tasks reallocate towards the most capital intensive sectors in the economy. This is because these sectors will see their relative output price decrease, thereby increasing their demand for skilled abstract labor tasks the more substitutable their goods are in consumption.

In sum, given that $\beta_2 > \beta_1$, we have that there is between sector job polarization if (i) $1/[1-\mu] > 1$; (ii) $0 < \sigma < \theta < \beta_1/[\beta_1 - \mu]$; and (iii) $\theta > 1$. A similar intuition to explain job polarization is given in Autor [2015] and the inequalities in (i), (ii) and (iii) can therefore be seen as a formalization of the arguments made therein.[15]

The next two subsections show that these restrictions are also sufficient to predict the phenomena of deindustrialization and Baumol's cost disease.

2.2.2 Deindustrialization

Rodrik [2015] argues that, in advanced economies, SBTC is leading to deindustrialization in terms of employment but not real output. Moreover, Rodrik [2015] shows that especially unskilled workers are displaced from manufacturing. However, this paper argues that this process of deindustrialization is also consistent with the more nuanced RBTC hypothesis.

For simplicity, define goods producing Sectors 1 and 2 as the manufacturing sector. Employment in manufacturing is then given by $(1 + L_r)$. Deindustrialization in terms of unskilled employment implies that $1 + L_r \to 1$ which requires $L_r \to 0$. Therefore, the assumptions discussed above to predict that unskilled workers move from Sector 1 to Services are also sufficient to predict deindustrialization in terms of unskilled employment, and the intuition of both phenomena is the same. Finally, our model predicts that $C \to \infty$ which implies an increase over time in manufacturing real output.

However, the first column of Table 1 lists all sector by their ICT capital intensity and indicates manufacturing sectors in bold.[16] What is clear from this ranking is that manufacturing sectors can be found at varying levels of capital intensity. Also note that relatively large sectors with high ICT capital intensities, namely "Transport and Storage", "Wholesale Trade and Commission Trade" and "Renting of Machinery & Equipment and Other Business Activities",

[15] One difference between this paper and the discussion in Autor [2015] is that our formal model assumes that preferences are homothetic, thereby excluding the possibility that job polarization is driven by income elasticities that are larger than unity for goods and services produced by the least and most capital intensive sectors.

[16] In the list of sectors reported in Table 1, those printed in bold are considered to be manufacturing sectors by ISIC defined as "the physical or chemical transformation of materials of components into new products, whether the work is performed by power-driven machines or by hand, whether it is done in a factory or in the worker's home, and wether the products are sold at wholesale or retail". See Section 3 for further details on our data.

are not part of manufacturing. Therefore, an alternative way to think about deindustrialization in our framework is to assume that manufacturing is goods producing Sector 1 only. In this case, employment in manufacturing is given by $(L_{a1}+L_r)$. If $L_r \to 0$, there still is deindustrialization in terms of unskilled employment. And if $L_{a1} \to 0$, there now also is deindustrialization in terms of skilled employment. Finally, real output in manufacturing is expected to increase because of continuous capital accumulation in routine tasks, which more than compensates for the decline in manufacturing labor tasks, both routine and abstract.

2.2.3 Baumol's cost disease

Baumol's thesis states that the relative output price of Services, the least productive sector, would increase over time. To see that this is the case, relative prices can be derived from the efficient allocations discussed above. To derive an expression for the price of Services, p_s, relative to Sector 2 goods, p_2, note that utility maximization implies:

$$\frac{p_s}{p_2} = \frac{C^{(\theta-\sigma)/\sigma\theta} {C_{g2}}^{1/\theta}}{C_s^{1/\sigma}} \to \infty \tag{24}$$

Consider the different terms on the right-hand side of equation (24): (i) Given that $C \to \infty$, we have that $C^{(\theta-\sigma)/\sigma\theta} \to \infty$ under the assumption that $\sigma < \theta$; (ii) $C_{g2} \to \infty$ if $L_{a1} \to 0$ as we showed in (20) such that $C_{g2}^{1/\theta} \to \infty$; (iii) Given that $C_s \to 1$ as $L_r \to 0$, equation (24) limits to infinity predicting that the relative price of Services must rise.

Similarly, we can derive the following condition on relative goods prices:

$$\frac{p_1}{p_2} = \left[\frac{C_{g2}}{C_{g1}}\right]^{1/\theta} \to \infty \tag{25}$$

where the limit follows because $C_{g2}/C_{g1} \to \infty$. To see this, substitute equations (19) and (20) into C_{g2}/C_{g1}:

$$\frac{C_{g2}}{C_{g1}} = [1-\beta_2]/[1-\beta_1[K_1/X]^{\mu}][1-L_{a1}]^{1-\beta_2}/L_{a1}^{1-\beta_1}K_2^{\beta_2}/X^{\beta_1}$$

which limits to zero if $L_{a1} \to 0$ given that $K_1/X \to 1$, $K_2/X \to \infty$ and $0 < \beta_1 < \beta_2 < 1$. In sum, besides job polarization and employment deindustrialization, our framework also predicts Baumol's cost disease.

3 Data

To test the predictions made by the model presented above, EUKLEMS data from the March 2011 release are used for the period 1980-2005.[17] This dataset contains information about output volume and prices, value added, and labor and capital inputs for the United States and 12 European countries at the level of ISIC revision 3 classified sectors reported in Table 1. The primary sectors ("Agriculture, Hunting, Forestry and Fishing" and "Mining and Quarrying") and the sector "Private Households with Employed Persons", printed in italics in Table 1, are discarded due to limited data availability, resulting in a final sample of 28 sectors in 13 countries used in the empirical analysis below. These 13 countries are Austria, Belgium, Denmark, Finland, France, Germany, Italy, Ireland, Netherlands, Spain, Sweden, United Kingdom and United States. Finally, results will be presented with and without including the public sector ("Public Administration", "Health and Social Work" and "Education"). The reason for doing this is that output volumes and prices, value added, and labor and capital inputs in these sectors are not exclusively determined by market forces as our model assumes.

Column (1a) of Table 1 ranks sectors according to their capital intensity in 2005. This measure of capital intensity is given by a sector's ICT capital compensation as a percentage of value added averaged across countries.[18] The least ICT capital intensive sectors included in the empirical analysis below are "Real Estate Activities", "Construction", "Hotels and Restaurants", "Health and Social Work" and "Education". In line with our model, the tasks done in these sectors include an important non-routine component such as the provision of in-person services. The most ICT capital intensive sectors are "Renting of Machinery & Equipment and Other Business Activities" including computer and related activities, "Financial Intermediation" and "Post and Telecommunications". What these sectors have in common is that many of their tasks are related to information and communication activities that have been automated, which is also in line with our model. This ranking of sectors by their ICT capital intensity is

[17] See Appendix B and Timmer et al. [2007] for further details about EUKLEMS data. Michaels, Natraj and Van Reenen [2014] also use EUKLEMS data for 11 developed economies for the period 1980-2004. Their analysis shows that industries and countries that had faster growth in ICT capital also experienced faster growth in their demand for skilled and unskilled relative to medium-skilled workers. Given that skilled and unskilled workers are disproportionately employed in low-paid manual and high-paid abstract occupations, this result is consistent with job polarization within sectors. However, this paper uses EULKLEMS data not to test whether there is within-sector job polarization, but whether job polarization exists between sectors ranked by their capital intensity as our framework predicts. Moreover, Michaels, Natraj and Van Reenen [2014] use a cost-function approach to analyze their data, whereas this paper follows a more structural identification strategy by first deriving a formal model and the critical assumptions needed to predict job polarization, deindustrialization and Baumol's cost disease between sectors.

[18] EUKLEMS defines ICT capital compensation as the product of the ICT capital stock (consisting of office and computing equipment, communication equipment and software) and its user cost.

found to be stable over time.[19] Therefore, the ICT capital intensity of a sector j in country c in 2005, $CAP_{jc} \in [0,1]$, will be used in the empirical analysis below, but using 1980 or a measure averaged over time would not qualitatively change our results. Finally, column (1a) shows that the average manufacturing sector is relatively ICT capital intensive but also that some manufacturing sectors are much more ICT capital intensive than others.

Column (2a) of Table 1 lists sectoral employment shares in 2005 averaged across countries. Employment is measured as hours worked in a sector by all persons engaged (i.e. employees as well as self-employed workers). The largest sectors are "Renting of Machinery & Equipment and Other Business Activities" (12%), "Health and Social Work" (10%), "Construction" (8%) and "Retail Trade and Repair of Households Goods" (8%), "Public Administration" (7%) and "Education" (6%). Column (2a) of Table 1 also shows that the manufacturing employment share (i.e. the sum of employment shares of sectors indicated in bold) was 15% in 2005 on average across our sample of countries.

The EUKLEMS data from the March 2011 release is supplemented with data from the March 2008 release that contains information on share in total hours worked by high-skilled, middle-skilled, and low-skilled workers. High-skilled workers are generally tertiary educated, middle-skilled workers have at least completed upper-secondary education, and low-skilled workers have at most completed lower-secondary education.[20] These skill shares are only available for 10 out of 13 countries and for only 4 of these 10 countries at the same level of sector disaggregation as in the March 2011 release. These 4 countries are Belgium, Denmark, Italy and the United States. Therefore, the sample is restricted to those 4 countries whenever skill data are reported. Column (3a) in Table 1 labels high-skilled shares as "Skilled shares" and lists the sectoral employment shares of skilled workers in 2005 averaged across the 4 countries for which we have data. The low-skilled and middle-skilled are combined into a single skill group which column (4a) labels "Unskilled shares". Columns (3a) and (4a) show that skilled relative to unskilled workers are concentrated in sectors with higher ICT capital intensity. Exceptions are the high shares of skilled workers employed in "Health and Social Work" (14%) and in "Education" (16%) as these sectors are not very ICT capital intensive, and the high share of unskilled workers employed in "Renting of Machinery & Equipment and Other Business Activities" which is ICT capital intensive.

Finally, columns (5) and (6) in Table 1 uses EUKLEMS data from the March 2011 release to report the percentage increase between 1980 and 2005 in sectoral output volumes and output prices averaged across the 13 countries in our sample. In EUKLEMS, the output volume series

[19] Table B1 in Appendix B shows Spearman rank correlation coefficients of sectors ranked by their capital intensity across years by country.

[20] See Table B2 in Appendix B for more details.

are given as an index with 1995 as the base year (1995=100) and are derived from growth rates in chained volume indices reported in countries' National Accounts. EUKLEMS also obtains nominal output indices from countries' National Accounts to construct output price indices as the ratio of nominal to volume output series. In line with our model, column (5a) suggests that output has grown faster in more ICT capital intensive sectors. For example, the average growth rate in output volume across the 14 sectors with lowest ICT capital intensity out of the 28 sectors used in the empirical analysis below is 61% compared to 149% for the other 14 sectors with the highest ICT capital intensity. Also in line with our model, column (6a) suggests that the opposite is true for relative output prices: 145% for the 14 sectors with the lowest ICT capital intensity compared to 115% for the 14 sectors with the highest ICT capital intensity. To test these and other predictions of our model more formally, we now turn to the empirical analysis.

4 Empirical analysis

4.1 Job polarization

We estimate the following regression equation:

$$\triangle Y_{jct} = b_0 + b_1 \ln CAP_{jc} + b_2 \ln CAP_{jc}{}^2 + \varepsilon_{jct} \tag{26}$$

where $\triangle Y_{jct}$ is the five-year percentage point difference between years t and $t-5$ in the share of workers employed in sector j in country c, $\ln CAP_{jc}$ is the logarithm of ICT capital intensity of sector j in country c in 2005, and ε_{jct} is an error term.

Between-sector job polarization requires that a U-shaped relationship exists between a change over time in a sector's employment share and its ICT capital intensity. In terms of equation (26), this implies that $b_1 > 0$ and $b_2 > 0$ given that $-\infty < \ln CAP_{jc} < 0$ because $CAP_{jc} \in [0, 1]$ for all j and c. To see this, assume that a quadratic relationship exists such that regression estimates for b_1 and b_2, defined here as $\widehat{b}_1$ and $\widehat{b}_2$ respectively, are not zero. Taking the first-order derivative with respect to $\ln CAP_{jc}$ on the right-hand side of equation (26) then gives $\widehat{b}_1 + 2\widehat{b}_2 \ln CAP_{jc}$. Next define $\ln CAP^*_{jc}$ as the turning point where this derivative is zero or $\ln CAP^*_{jc} = -\widehat{b}_1/(2\widehat{b}_2)$. Given that $-\infty < \ln CAP^*_{jc} < 0$ for a relevant turning point within the sample range, estimates $\widehat{b}_1$ and $\widehat{b}_2$ must have the same sign. If they are both positive, $\ln CAP^*_{jc}$ is a minimum and a U-shaped relationship exists that is consistent with between sector job polarization. If they are both negative, $\ln CAP^*_{jc}$ is a maximum and an inverted U-shaped relationship would exist.

Table 2 reports regression estimates for b_1 and b_2 using all years in column (1), excluding the public sector from the analysis in column (2), using non-ICT capital intensity in column (3)[21], and by decade in columns (4)-(6). Starting with column (1a), estimates for b_1 and b_2 are both positive and significant suggesting that there exists a U-shaped relationship between changes in sectoral employment shares between 1980 and 2005 and sectors' ICT capital intensity. Turning to the bottom of column (1a) shows that the turning point, $\ln CAP^*_{jc}$, equals -4.02 with a standard error of 0.48. Taking this estimate at face value implies that on average 29% of all workers in a country in 2005 is employed in sectors with ICT capital intensities that are lower than CAP^*_{jc}. A more conservative estimate of this percentage could set the turning point equal to one standard deviation below or above $\ln CAP^*_{jc}$, i.e. $-4.02 - 0.48$ or $-4.02 + 0.48$, giving 14% and 53% respectively. In any case, non-trivial numbers of workers are employed below or above the turning points. As a robustness check, column (1b) shows that a regression estimate for b_1 when setting $b_2 = 0$ in equation (26) is not statistically significant, suggesting that a linear specification without a turning point has to be rejected as a first-order approximation to the data.

Columns (2) and (3) provide additional robustness tests. Column (2) excludes the public sectors from the analysis. The reason for doing this is that the estimates in column (1) could be biased if changes in the demand for public sector employment are not exclusively driven by market forces as our model assumes. However, column (2a) shows estimates that are very similar to those presented in column (1a). If anything, differences worth noting between columns (1) and (2) are that excluding the public sector from the analysis is shifting the turning point towards a lower ICT capital intensity and making the linear specification more upward sloping and statistically significant. What these differences reflect is that public sectors have relatively low ICT capital intensities, as is also shown in Table 1. A final robustness check is performed in column (3) by substituting a measure of non-ICT capital intensity for the measure of ICT capital intensity used in column (1). Because our model assumes that the decreasing price of digital capital is having a differential impact based on a sector's digital capital intensity, we would expect stronger evidence in support of between-sector job polarization when using measures of ICT capital compared to non-ICT capital intensity. A comparison of columns (1) and (3) shows that this is the case indeed. In particular, column (3) suggest that there exists an inverted U-shaped relationship between employment share changes and non-ICT capital intensity, although a negative linear relationship also seems to fit these data relatively well. This result is in line with Michaels et al. [2013] who also test for the sensitivity of their results by using ICT capital instead of other capital services to find that the polarization in skill

[21] EUKLEMS data reports shares of ICT an non-ICT in capital compensation that add up to one. Measures of non-ICT capital intensity are constructed by non-ICT capital compensation and expressing this difference as a fraction of value added.

demands is mainly driven by the accumulation of ICT capital.

Columns (4)-(6) of Table 2 repeat the exercise in column (1) by decade. The fact that all point estimates for b_1 and b_2 are positive suggests that there has been between-sector job polarization in all periods. However, the point estimates in columns (4a) and (5a) also suggest that between-sector job polarization was stronger in the 1980s and 1990s. Moreover, the significant point estimate in column (4b) indicates that relative employment growth in ICT capital intensive sectors was particularly strong in the 1980s. However, the point estimates for the period 2000-2005 that are reported in column (6) show that the nature of between-sector job polarization changed between 2000-2005: none of the point estimates in column (6a) is statistically significant and column (6b) suggests that the changes in employment shares were particularly large for sectors with the lowest ICT capital intensities.

To see these differences between time periods more clearly, Figure 1 shows kernel plots of average annual employment share changes by a ranking of sectors according to their ICT capital intensity in 2005 averaged across countries. The left panel shows these kernel plots for the US, whereas the right panel does the same using average employment share changes across our sample of 12 European countries. For the US, the left panel of Figure 1 shows that between-sector job polarization was present in all decades, but also that there are important differences between decades. In the 1980s the relationship clearly is U-shaped with strong growth in ICT capital intensive sectors in particular. In the 1990s there was job polarization between sectors as well, but also a slowdown in relative employment growth for those ICT capital intensive sectors that did particularly well in the 1980s. By the early 2000s a clear tilting has taken place with positive changes in employment shares for the least ICT capital intensive sectors. This tilting over time in employment share changes documented in Figure 1 corresponds to existing evidence in Acemoglu and Autor [2011], Mishel, Shierholz, and Smith [2013], Beaudry, Green and Sand [2013, 2014] and Autor [2015], although these papers use a ranking of occupations based on their mean log wage or on worker skills rather than of sectors based on the log of ICT capital intensity. Interestingly, the right panel of Figure 1 shows that a similar tilting exists across the 12 European countries in our sample.[22] If anything, in Europe the relative employment growth in ICT capital intensive sectors seems to have mattered more from the 1990s onwards, and the decline in employment shares for middling sectors as well as the increase in employment shares for the least ICT capital intensive sectors seem to have been somewhat more muted than in the US.

[22] The right-panel of Figure 1 shows a kernel plot of the percentage point changes in employment shares by sectors ranked by their cross-country average ICT capital intensity in 2005. Plotting kernel estimates using the employment share changes after pooling employment across European countries instead gives a very similar picture, see Figure C1 in Appendix C. This also suggests that differences between countries in the extent to which there is between-sector job polarization are relatively small.

What explains this tilting over time of the employment share changes in the US and Europe? Beaudry, Green and Sand [2013, 2014] argue that these changes are consistent with falling demands for abstract labor tasks as these tasks have become more codifiable over time and, therefore, more substitutable by digital capital. However, Autor [2015] offers an alternative explanation arguing that the recent slowdown in demand for high-paid workers could be due to less rather than more investment in digital capital, in large part due to the bursting of the dot-com bubble in the early 2000's. Our framework and analysis allow to shed some light on this discussion. If the nature of technological progress is changing such that the complementarity between capital tasks and abstract labor tasks is decreasing, as is argued by Beaudry, Green and Sand [2013], one would expect to find faster capital accumulation and faster output growth in more recent time periods. But if the speed of technological progress becomes slower after 2000 due to a sharp correction following a temporary dislocation of investment, as Autor [2015] argues, one would expect to see slower capital accumulation and slower output growth after 2000.[23]

Figure 2 therefore plots differences in average annual growth rates in output volumes by sector between periods 2000-2005 and 1980-2000 (grey bars) or 1995-2000 (black bars). The left panel looks at the US and the right panel gives differences in growth rates averaged across our sample of 12 European countries. Also note that both panels rank sectors from lowest to highest ICT capital intensity, identical to the ranking of sectors in Table 1, when leaving out the sectors displayed in italics. Clearly, the negative differences for almost all sectors strongly supports the hypothesis put forward in Autor [2015]. Moreover, Figure 2 shows that these negative differences are decreasing when moving down the list towards more ICT capital intensive sectors. In our framework, this result is in line with a slowdown in the speed of technological progress having a more negative impact in more ICT capital intensive sectors. Finally, the differences between the period 2000-2005 and 1995-2000 (black bars) are, by and large, more negative compared to the differences between 2000-2005 and 1980-2000 (grey bars). This is in line with the hypothesis that there was a build-up of misallocated investment during the second half of the 1990s and a sharp correction after 2000 following the bursting of the dot-com bubble.

In sum, in line with the framework presented above, we find that there is between-sector job polarization when sectors are ranked by their ICT capital intensity. That is, workers are

[23] Our model also allows for other possible explanations that are isomorphic in their predictions to Autor [2015]. For example, assume that all goods have become more complementarity in consumption after 2000. This will mute the scale effects in labor demands that follow from changes in relative output prices as discussed in our model. In particular, more inelastic demand for goods and services produced by the least ICT capital intensive sectors implies an increase in their demand for labor. But a more inelastic demand for goods and services produced by the most ICT capital intensive sectors implies a decrease in their demand for labor. That is, there is a tilting of employments share changes.

increasingly employed in the least and most ICT capital intensive sectors in the economy. Moreover, in line with existing evidence about occupational employment share changes, this section shows that there has been a tilting in the US: Whereas the 1980s were characterized by relatively strong employment growth in the most ICT capital intensive sectors, the opposite holds for the period 2000-2005 with relatively stronger employment growth in the least ICT capital intensive sectors. Although somewhat muted compared to the US, similar changes are found for Europe. To explain this tilting of employment share changes in both the US and Europe, some evidence is presented in support of the hypothesis that there was a build-up of misallocated investment during the second half of the 1990s and a sharp correction after 2000 following the bursting of the dot-com bubble.

4.2 Reallocation of skilled workers

The following two subsections repeat the analysis in Table 2 using only skilled or unskilled workers respectively. That is, equation (26) is re-estimated using as the dependent variable changes in employment shares only for skilled workers or for unskilled workers.[24]

Table 3 replicates the analysis in Table 2 using employment share changes for skilled workers only. Regression estimates for b_1 and b_2 in columns (1a) and (2a) are insignificant, whereas columns (1b) and (2b) show that regression estimates for b_1 when setting $b_2 = 0$ are positive and statistically significant. This suggests that, as a first order approximation, skilled workers tend to relocate towards more ICT capital intensive sectors, which is in line with our framework presented above. Column (3) shows similar point estimates using non-ICT capital intensity as an independent variable, although point estimates are no longer statistically significant. Finally, columns (4) to (6) show that skilled workers were moving to more ICT capital intensive sectors in all decades, although it is less strong during the period 2000-2005.

To see these differences between the 1980-2000 and after 2000 graphically, Figure 3 replicates Figure 1 but only for the group of skilled workers. The panels for both the US and 3 European countries show larger employment share changes for more ICT capital intensive sectors in all decades, except for the US in the period 2000-2005. Moreover, in the US there seems to be a tilting over time in employment share changes for skilled workers, similar to the tilting that was documented for total employment in Figure 2. Although not shown in Figure 3, the observations underlying the kernel plot indicate that this tilting does not depend on the influence of one or a few sectors. In particular, the employment share changes in each of the four most ICT capital intensive sectors decreased over time, whereas the employment share changes in each of the four least ICT capital intensive sectors increased over time and particularly so in the 2000s. Interestingly, no similar tilting for skilled workers is observed in the sample of 3 European

[24] Note that these regression include fewer countries, namely the US, Belgium, Denmark and Italy.

countries.

4.3 Reallocation of unskilled workers

Table 4 presents regression estimates of equation (26) only using the group of unskilled workers in the analysis. Although point estimates in column (1) are not statistically significant, their magnitudes are comparable to those in Table 2. This suggests that between-sector job polarization exists for unskilled workers. On the one hand, the more positive employment share changes for the least compared to middling ICT capital intensive sectors is as our model predicts. On the other hand, our model assumes away the possibility that the employment share changes for the most compared to middling ICT capital intensive sectors are larger. Column (2) shows that excluding the public sector from the analysis does not change this result and column (3b) shows that there is a marginally significant negative linear effect when using non-ICT capital intensity rather than ICT capital intensity as a regressor.

Columns (4)-(6) of Table 4 and Figure 4 examine differences between decades. In line with our framework, the percentage point changes are larger for the least compared to middling ICT capital intensive sectors in all decades. Moreover, Figure 4 shows that this difference has increased after 2000 following an increase in employment share changes for the least ICT capital intensive sectors. Although not shown in the figure, the observations underlying the kernel plot show that this is true in all five of the lowest ICT capital intensive sectors in both the US and in our sample of 3 European countries. This finding is in line with the evidence presented in Autor and Dorn [2013] that there has been an acceleration over time of rising employment shares for workers in low-paid service occupations in the US between 1980 and 2005.

Moreover, the acceleration of an increasing employment share for unskilled workers in the least ICT capital intensive sectors implies that some other sectors must have seen a decceleration of employment share changes for unskilled workers, and Figure 4 is informative about what these sectors are. In particular, it shows that there has been a decrease in the positive employment share changes for the most ICT capital intensive sectors. Although unskilled workers in more ICT capital intensive sectors are concentrated in "Renting of Machinery & Equipment and Other Business Activities" – see Table 1 – the shifting down of the kernel plot is driven by each of the five most ICT capital intensive sectors.

In sum, the results presented in the previous two subsections suggest that, as a first-order approximation, technological progress is leading to an upscaling towards more ICT capital intensive sectors for skilled workers and a downscaling towards less ICT capital intensive sectors for unskilled workers. However, there also exist differences between regions and time periods. In the US after 2000, skilled workers became less likely to be employed in the most ICT capital intensive industries and more likely to be employed in the least ICT capital intensive industries.

Interestingly, a similar tilting of employment share changes for skilled workers is not observed in our sample of 3 European countries. However, for unskilled workers tilting took place in both the US and Europe. What this suggests is that the sharp correction of ICT capital investment that took place after 2000 affected the probability of employment in ICT capital intensive sectors for both skilled and unskilled workers in the US and for unskilled workers in Europe. To the contrary, the bursting of the dot-com bubble did not affect the probability of being employed in an ICT capital intensive sector for skilled workers in Europe.

4.4 Deindustrialization

Figure 5 illustrates the process of employment deindustrialization as described by Rodrik [2015] for both the US and our sample of 12 European countries. The solid lines in the figure show the evolutions of manufacturing employment. Clearly, manufacturing employment decreased in both the US and Europe between 1980 and 2005. However, the dashed lines in the figure show the evolutions of manufacturing real output indicating an increase over time. That is, there is deindustrialization in terms of employment but not real output.

To see that employment in manufacturing has decreased over time, consider the following regression equation:

$$\triangle Y_{jct} = d_0 + d_1 MAN_j + \varepsilon_{jct} \tag{27}$$

with $\triangle Y_{jct}$ the five-year percentage point difference between years t and $t-5$ in the share of workers employed in sector j in country c, MAN_j a dummy that equals unity if sector j is a manufacturing sector, and ε_{jct} is an error term.

Panel A of Table 5 shows regression estimates of equation (27) using all workers. In line with Rodrik's [2015] deindustrialization hypothesis, regression estimates for d_1 are negative and statistically significant. For example, the manufacturing employment share decreased by an average annual (0.31/5 =) 0.062 percentage points between 1980 and 2005. Panels B and C of Table 5 repeat the analysis in Panel A but only for skilled and unskilled workers respectively. Although the point estimates for d_1 in Panel B are all negative, they are relatively small in absolute value and statistically insignificant. To the contrary, point estimates for d_1 in Panel C are all negative, much larger in absolute value and statistically significant. These results are in line with Rodrik's [2015] hypothesis that there is employment deindustrialization mainly of unskilled workers.

But the framework presented above also goes beyond Rodrik [2015]. To show this in the simplest way possible, Figure 6 repeats the kernel plot in Figure 1 but also adds the dots of the predicted percentage points changes for each manufacturing sector from regressing the employment share changes of manufacturing sectors only. In line with the evidence in Table 5 above, predicted employment share changes are negative for each manufacturing sector in both the US and Europe. However, Figure 6 also shows that these negative employment share changes are in line with predictions from our framework because most manufacturing sectors are around the middle of the ICT capital intensity ranking. Moreover, the tilting that is observed across all sectors is also observed across sectors within manufacturing only. Again, this points to the importance of ICT capital intensity to capture the employment impact of RBTC.

Rodrik [2015] argues that deindustrialization is happening in terms of falling employment but not real output in manufacturing. This is in line with the dashed line in Figure 5 showing that manufacturing real output is increasing over time in both the US and Europe. In our framework, this increase in real output despite a fall in employment is driven by the accumulation of ICT capital in manufacturing. Moreover, our framework predicts that the accumulation of ICT capital and therefore output growth is faster the more ICT capital intensive a sector is. To see this more formally, Table 6 replicates the analysis in Table 2 but using percentage growth in sectoral real output instead of changes in employment shares as the dependent variable in equation (26). As a first-order approximation to the data, our framework predicts that $b_1 > 0$ when setting $b_2 = 0$ and column (1b) of Table 6 shows that this is the case indeed. Excluding the public sector in column (2b) does not qualitatively change this result, and column (3b) suggests that it is the accumulation of ICT specific capital that matters most for output growth. Columns (4b), (5b) and (6b) show that the relationship between output growth and ICT capital intensity was relatively strong in the 1990s and weak in the 2000s. This is in line with the evidence in Figure 2 suggesting that there was a build-up of misallocated investment during the 1990s and a sharp correction after 2000 following the bursting of the dot-com bubble. Finally, quadratic specifications in columns (1a)-(6a) show a significant J-shaped rather than U-shaped relationship given that point estimates for b_1 are large relative to b_2 and that relatively few workers are employed in the declining section.[25]

In sum, Rodrik [2015] argues that the decrease in manufacturing employment, mainly through the displacement of unskilled workers, is driven by an increase in the productivity of manufacturing workers that is larger for the skilled than for the unskilled – this is the SBTC hypothesis. However, this section has shown that the more nuanced RBTC hypothesis provides a more accurate explanation. Moreover, the result that there is no deindustrialization in terms of manufacturing real output is in line with the prediction from our RBTC model that there is ICT capital accumulation in the economy including in manufacturing.

[25] A kernel plot similar to Figure 1 but using output growth on the vertical axis is given by Figure C2 in Appendix C.

4.5 Baumol's Cost Disease

Baumol's [1967] original thesis stated that the relative output price for goods and services produced by less innovative sectors would increase. In our framework, this happens because less ICT capital intensive sectors will see their relative marginal costs and therefore their relative output price increase following RBTC. The aim of this section is to show that this is also the case in our data.

Table 7 shows regression estimates for equation (26) using as the dependent variable the percentage change in the output price for goods or service sector j in country c between years t and $t-5$. In line with Baumol's cost disease, column (1) of Table 7 shows that there is a significant negative relationship between the ICT intensity of sectors and growth in output prices. Column (2) shows that excluding the public sector does not qualitatively change this result. Replacing our measure of ICT capital intensity with a measure of non-ICT capital intensity in column (3) still gives a negative point estimate, but its magnitude is much smaller in absolute value and only marginally significant. This suggests that mainly decreases in the price of ICT specific capital together with a sectors' ICT capital intensity matter for changes in relative output prices. Columns (4)-(6) replicate the analysis in column (1) by decade. Point estimates show that the negative linear relationship between a sector's ICT capital intensity and its output price growth is pervasive across time periods. Finally, Figure 7 shows separate evidence for the US and Europe suggesting that Baumol's cost disease is also pervasive across regions.[26]

In sum, this section has shown evidence in support of Baumol's cost disease because firms innovate to compete in relative output prices. In particular, more ICT capital intensive industries will see a larger decrease in marginal costs and therefore output prices following a decrease in the price of ICT capital. As such, the phenomenon of Baumol's cost disease is intrinsically related to the phenomena of deindustrialization and between-sector job polarization documented above.

5 Conclusions

Building on recent work, this paper focussed on the importance of capital accumulation in explaining the impact of recent technological progress on labor and product markets. In particular, a framework has been presented that captures the impact of Moore's Law for capital performing routine tasks on capital accumulation – leading to a routinization of tasks in the economy and therefore RBTC – but also on sectoral employment, output and output prices.

[26] Note that the slightly positive slope in the regression line for US sectors at the top of the distribution may be due to the less accurate performance known of kernel plots at the boundary of the sample range because of the use of a symmetric estimation window.

The contribution of this framework is it allows to explicitly derive critical assumptions that can jointly explain three empirical phenomena that have recently been discussed in the literature: between-sector job polarization, deindustrialization and Baumol's cost disease. That between-sector job polarization, deindustrialization and Baumol's cost disease are intrinsically related phenomena resulting from ongoing technological progress is also supported by our empirical analyses for 13 advanced economies.

However, our theory and empirical analysis also show that the impact of technological progress on labor and product markets does not result in any "natural laws" that must hold over time or between regions. We have shown that the nature and speed of technological progress, the capital intensity of production, the substitutability between capital and different labor tasks in production, and the substitutability between goods and services in consumption are all critical in predicting the phenomena of between-sector job polarization, deindustrialization and Baumol's cost disease. To explain changes over time or differences between regions in these phenomena, our framework points to differences in the nature and speed of technological progress and the mechanisms through which technological progress impacts on labor and product markets. For example, our analysis suggests that the recent tilting of employment share changes in both the US and Europe is best explained by a build-up of misallocated investment during the second half of the 1990s and a sharp correction after 2000 following the bursting of the dot-com bubble.

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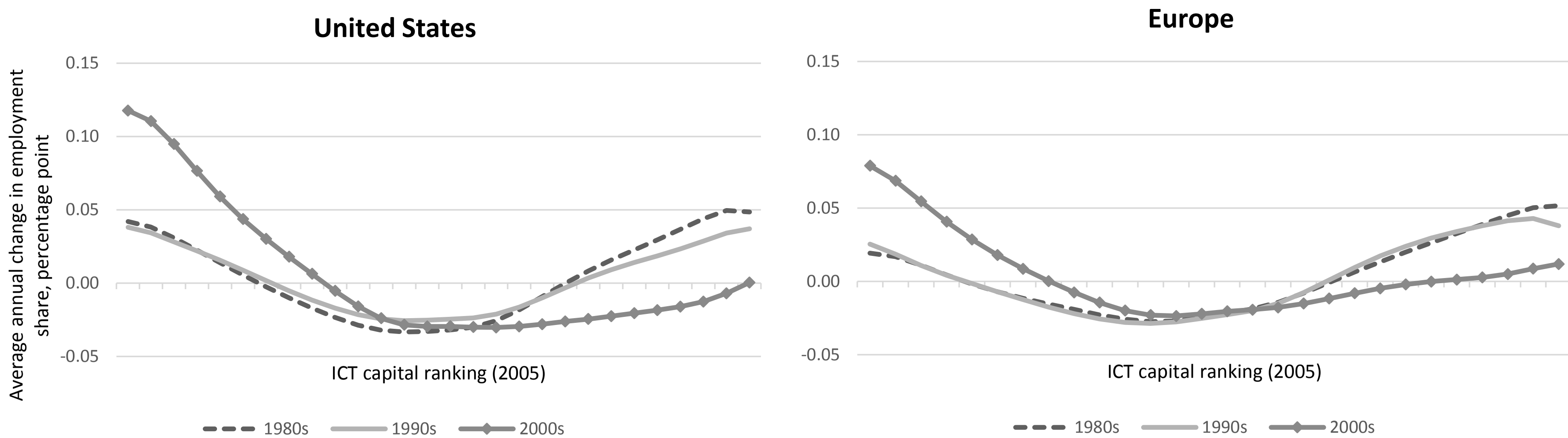
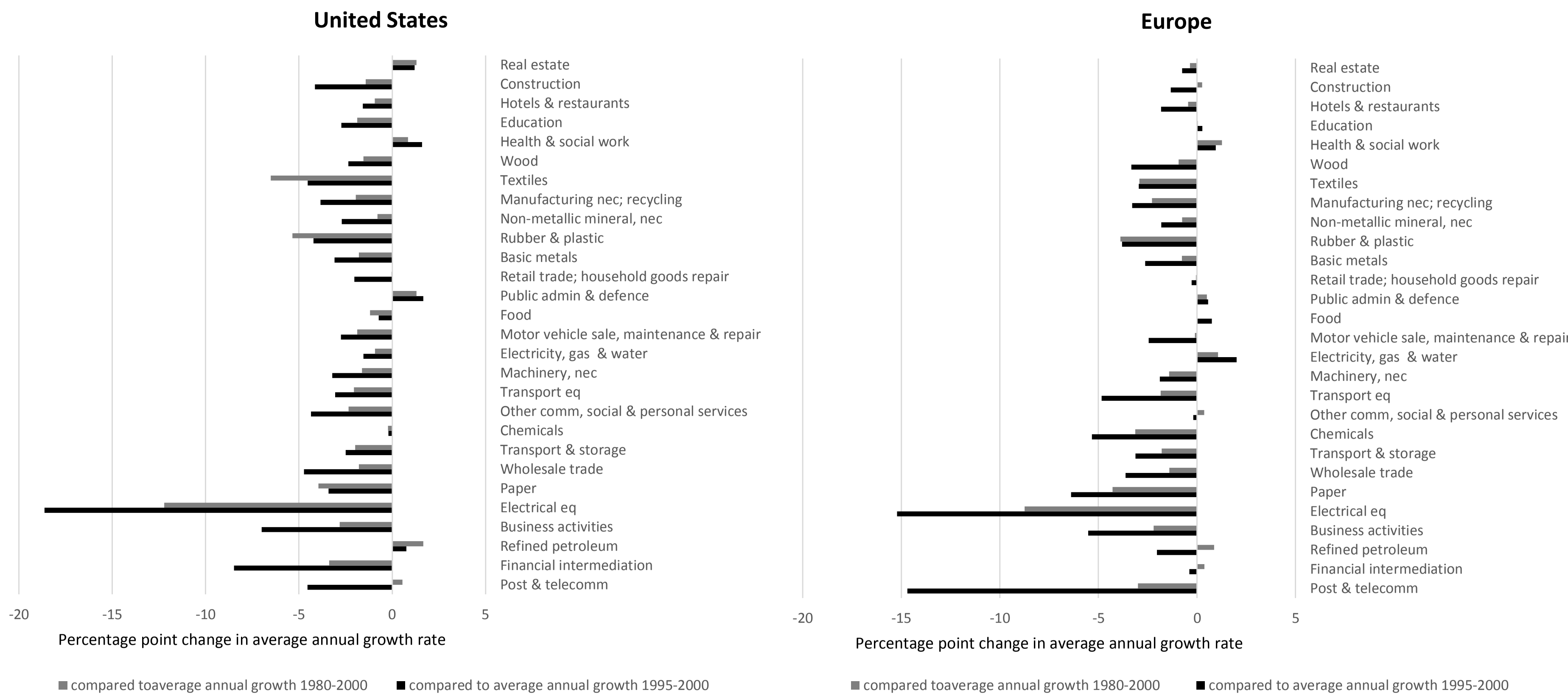
Figure 1: Kernel plot of average annual employment shares changes by sectoral capital intensity (in percentage points, 1980-2005)



Source: EUKLEMS 2011 release.

Notes: Percentage point changes in employment share by average capital intensity ranking in 2005 using a locally weighted smoothing regression (bandwidth 0.8 with 27 observations). Employment expressed in hours. European employment shares defined as the average of country-level employment shares in the 12 European countries.

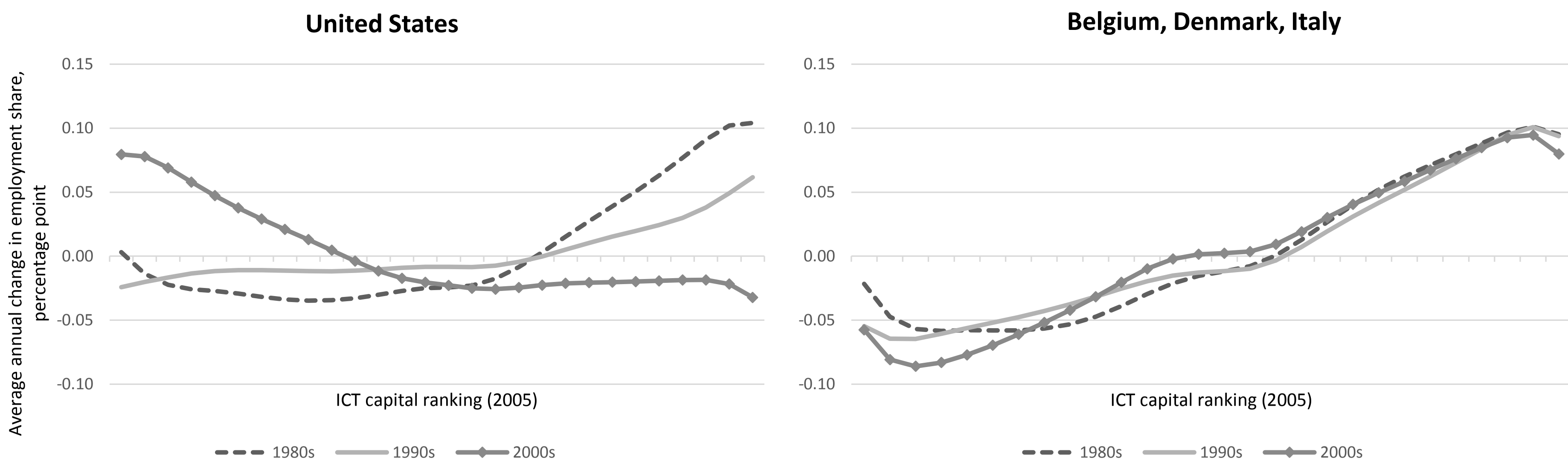
Figure 2: Changes in average annual output volume index growth by sector capital intensity (in percentage points)



Source: EUKLEMS 2011 Release

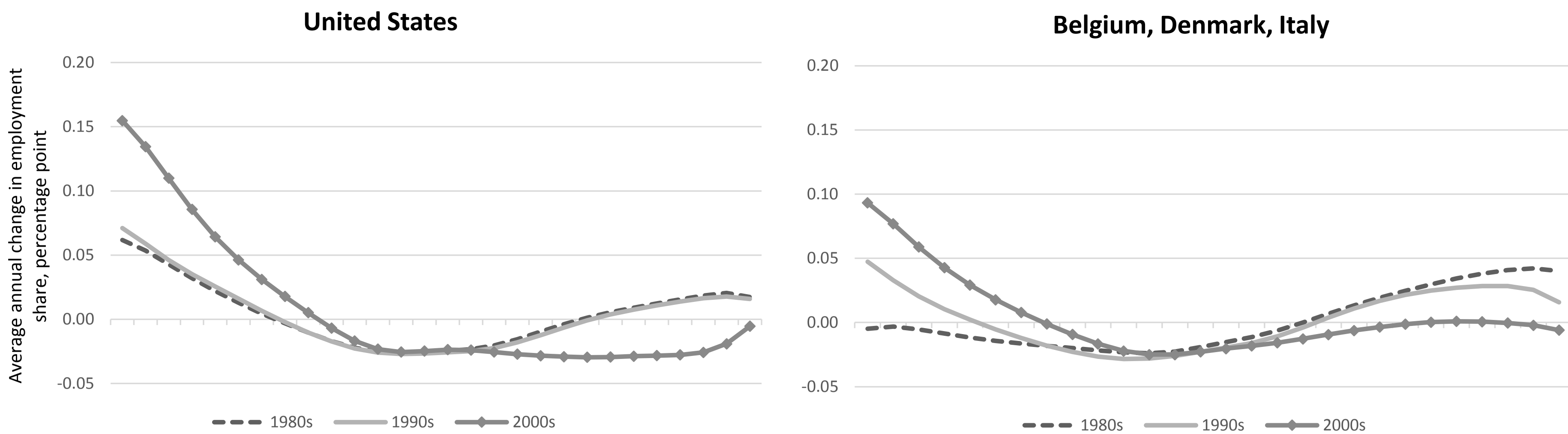
Notes: Sectors are ranked by their ICT capital intensity in 2005. Average annual growth rates in the period 2000-2005 are compared to average annual growth rates in 1995-2000 and 1980-2000. Output Volume is indexed, 1995=100. European growth rates are defined as a cross-country average of country level output volume growth in the 12 European countries.

Figure 3: **Kernel plot of average annual skilled employment share changes by sectoral capital intensity (in percentage points, 1980-2005)**



Source: EUKLEMS 2008 and 2011 release.
Notes: Percentage point changes in employment share by average capital intensity ranking in 2005 using a locally weighted smoothing regression (bandwidth 0.8 with 27 observations). Employment expressed in hours. European employment shares defined as the average of country-level employment shares in the 4 European countries.

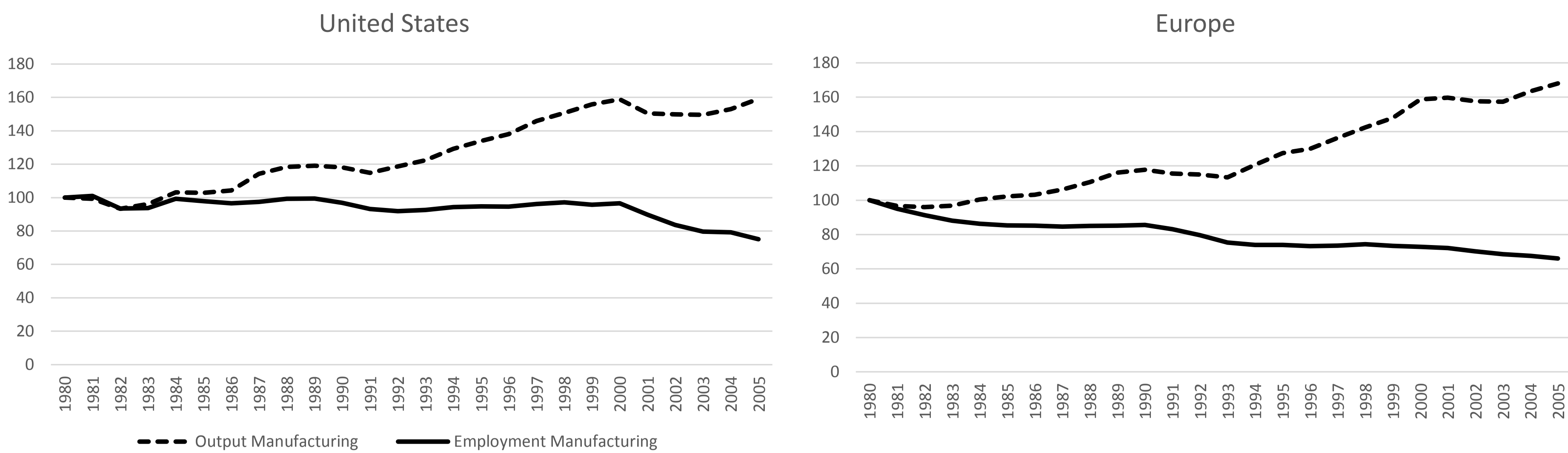
Figure 4: **Kernel plot of average annual unskilled employment share changes by sectoral capital intensity (in percentage points, 1980-2005)**



Source: EUKLEMS 2008 and 2011 release.

Notes: Percentage point changes in employment share by average capital intensity ranking in 2005 using a locally weighted smoothing regression (bandwidth 0.8 with 27 observations). Employment expressed in hours. European employment shares defined as the average of country-level employment shares in the 4 European countries.

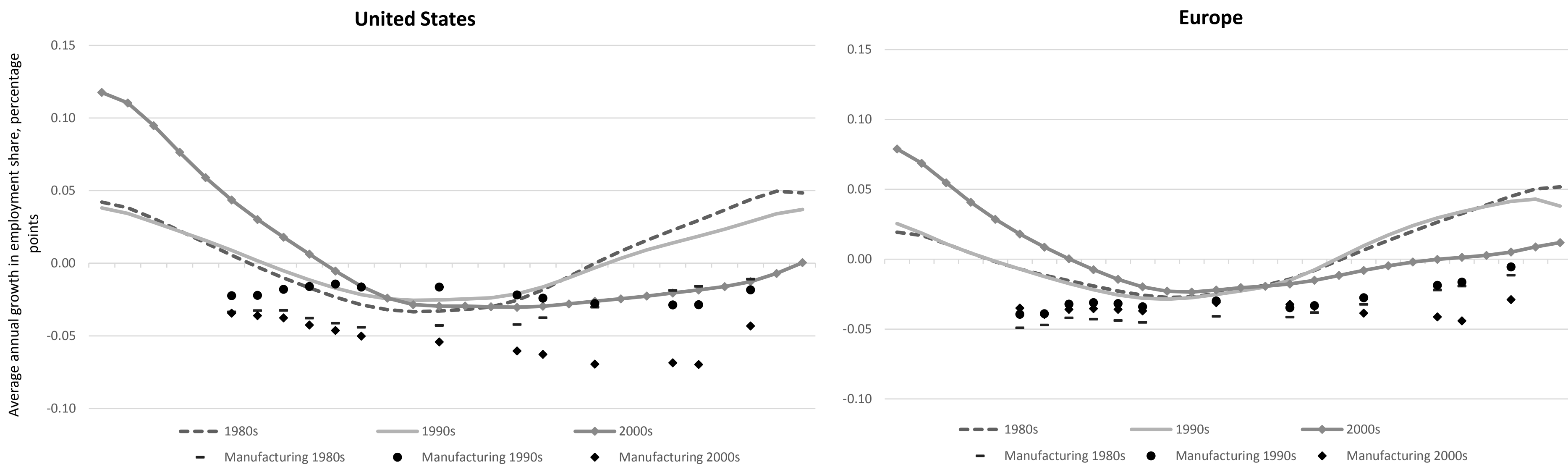
Figure 5: Index of employment and output for manufacturing sectors: US and Europe (1980=100)



Source: EUKLEMS 2011 Release.

Notes: Employment and Outpur volume is indexed at 100 in 1980. European employment is defined as a cross-country average of country-level employment in the 12 European countries.

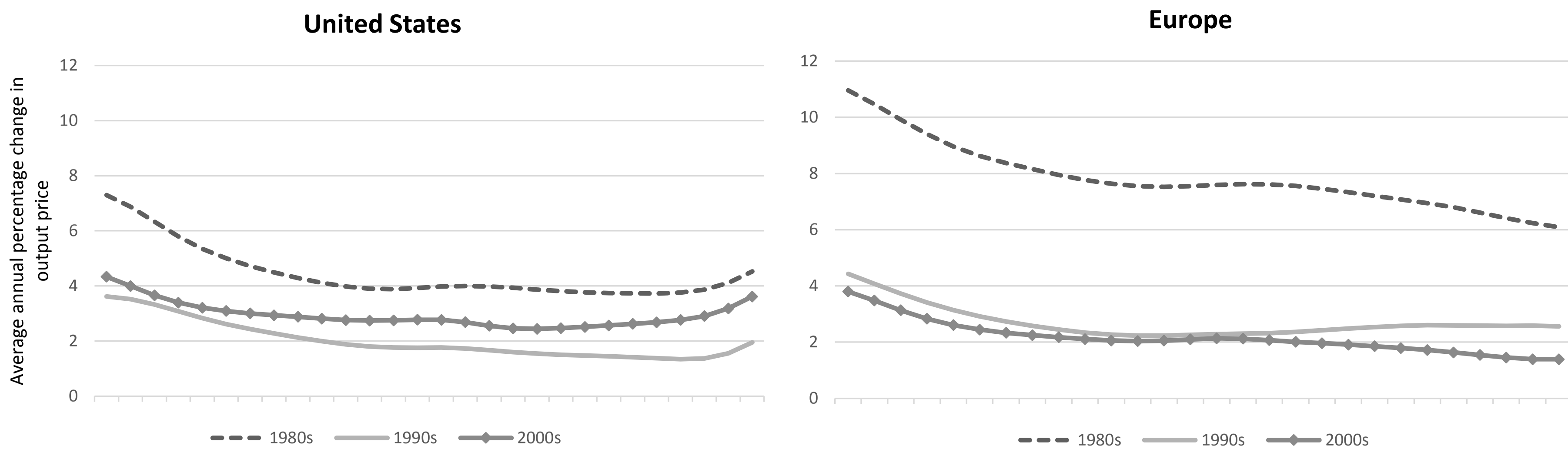
Figure 6: Kernel plot of average annual employment shares changes by sectoral capital intensity for manufacturing and all sec tors (in percentage points, 1980-2005)



Source: EUKLEMS 2011 release.

Notes: Percentage point changes in employment share by average capital intensity ranking in 2005 using a locally weighted smo othing regression (bandwidth 0.8 with 27 observations for all sectors and 13 observations for manufacturing only). Employment expressed in hours. European employment shares defined as the average of country -level employment shares in the 12 European countries.

Figure 7: **Kernel plots of average annual output price changes by sectoral capital intensity (in percentages, 1980-2005)**



Source: EU KLEMS 2011 release.

Notes: Prices are indexed. 1995=100. Percentage changes in output pricesby average capital intensity ranking in 2005 using a locally weighted smoothing regression (bandwidth 0.8 with 27 observations). European output prices defined as the average of country-level output prices in the 12 European countries.

Table 1: ICT Capital Intensity, Employment by Skill Level, Output Volumes and Prices by Sector Averaged Across Countries, 1980-2005

	(1) ICT Capital intensity		(2) Employment shares		(3) Skilled shares		(4) Unskilled shares		(5) Output volume	(6) Output price
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)		
	2005 (in %)	Percentage point change 1980-2005	2005 (in %)	Percentage point change 1980-2005	2005 (in %)	Percentage point change 1980-2005	2005 (in %)	Percentage point change 1980-2005	% change 1980-2005	% change 1980-2005
Private Households with Employed Persons	0.03	0.03	1.29	0.22	0.77	0.29	1.58	0.27	55.05	205.42
Agriculture, Hunting, Forestry and Fishing	0.63	0.34	4.34	-5.69	1.41	-0.68	4.67	-5.44	27.64	32.00
Real Estate Activities	0.84	0.11	1.16	0.42	1.61	0.26	1.03	0.34	113.76	216.69
Construction	1.40	0.88	8.09	-0.02	2.19	-0.85	9.01	0.63	40.66	175.75
Hotels and Restaurants	1.57	-0.03	4.66	1.23	1.67	0.56	5.45	1.61	68.40	210.36
Health and Social Work	1.63	0.60	10.44	3.30	13.58	-0.68	9.23	3.04	99.96	221.01
Mining and Quarrying	1.75	0.93	0.22	-0.45	0.16	-0.33	0.23	-0.45	-14.13	106.38
Education	1.75	0.78	6.07	0.90	16.08	-8.82	3.70	0.20	48.43	215.97
Wood and Wood Products	1.97	0.71	0.63	-0.29	0.35	-0.10	0.70	-0.29	61.58	96.37
Textiles, Textile, Leather and Footwear	2.08	1.37	0.80	-1.95	0.25	-0.41	1.03	-2.17	-36.81	91.04
Manufacturing Not Elsewhere Classified and Recycling	2.19	1.01	0.93	-0.39	0.47	-0.04	1.06	-0.40	60.87	104.47
Other Non-Metallic Mineral Products	2.29	0.64	0.69	-0.45	0.43	-0.19	0.78	-0.45	30.52	120.96
Rubber and Plastics	2.49	1.32	0.70	-0.08	0.44	0.03	0.76	-0.03	141.28	78.08
Basic and Fabricated Metals	2.56	1.48	2.30	-1.04	1.33	-0.41	2.55	-1.02	42.32	103.55
Retail Trade and Repair of Household Goods	2.80	1.31	7.53	-0.33	3.16	-0.30	8.66	0.12	91.17	134.72
Public Administration	2.87	1.66	6.79	-0.34	9.63	-1.22	6.40	-0.54	45.65	180.71
Food, Beverages and Tobacco	2.95	1.64	2.07	-0.99	0.79	-0.15	2.23	-0.87	39.56	82.38
Sale, Maintenance and Repair of Motor Vehicles	3.33	1.88	2.30	-0.03	0.93	0.20	2.74	0.14	95.28	145.70
Electricity, Gas and Water Supply	3.69	1.35	0.59	-0.29	0.49	-0.18	0.55	-0.29	98.59	103.99
Machinery Not Elsewhere Classified	3.70	2.00	1.72	-0.72	1.17	-0.12	1.86	-0.54	65.87	111.24
Transport Equipment	3.73	2.65	1.28	-0.68	1.07	-0.07	1.26	-0.68	106.61	114.80
Other Community, Social and Personal Services	3.83	-0.10	4.80	1.63	4.93	1.31	4.63	1.61	98.39	223.47
Chemicals and Chemical Products	4.02	2.51	0.98	-0.39	0.98	-0.18	0.97	-0.41	144.42	81.23
Transport and Storage	5.26	2.98	4.94	0.15	1.91	-0.02	5.69	0.50	114.02	125.12
Wholesale Trade and Commission Trade	5.54	2.77	4.92	0.20	2.57	0.05	5.61	0.57	123.91	114.41
Pulp, Paper, Printing and Publishing	5.77	3.42	1.46	-0.66	1.07	-0.19	1.52	-0.62	78.97	111.84
Electrical and Optical Equipment	5.96	2.87	1.79	-0.74	1.58	-0.08	1.66	-0.69	305.84	25.82
Renting of Machinery & Equipment and Other Business Activities	7.34	2.20	11.84	7.45	23.20	11.40	10.13	6.38	239.03	181.58
Coke, Refined Petroleum and Nuclear Fuel	7.48	4.81	0.08	-0.07	0.06	-0.06	0.08	-0.07	44.07	85.54
Financial Intermediation	14.47	8.46	3.03	0.27	4.49	0.61	2.65	-0.20	180.89	133.47
Post and Telecommunications	18.96	6.15	1.56	-0.18	1.22	0.37	1.60	-0.26	396.42	46.27

Source: EUKLEMS 2008 and 2011 Release.

Notes: ICT capital intensity, total employment share and price average of countries (Austria, Belgium, Denmark, Spain, Finland, France, Germany, Ireland, Italy, Netherlands, Sweden, United Kingdom, United States). ICT capital intensity is missing in 1980 for Ireland and Sweden such that the average change in column (1b) is calculated with an unbalanced panel of countries. Shares are defined at the country-year level. Skilled and unskilled shares averaged across countries with skill observations at the same sectoral level as capital intensity data is limited to the following set of countries: Belgium, Denmark, Italy and United States. Unskilled defined as low- plus middle-skill categories in EU KLEMS. ICT capital intensity is defined as the ratio of ICT capital compensation over value added at the sectoral level. Manufacturing sectors displayed in bold. Sectors that are discarded for the empirical analysis are displayed in italics.

Table 2: Changes in employment shares by sectoral capital intensity (in percentage points, 1980-2005)

	Δ Employment share (percentage point)											
	(1)		(2)		(3)		(4)		(5)		(6)	
	All years		All years, excluding public sector		All years, non ICT capital		1980s		1990s		2000s	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
ln(ICT CAP)	0.202**	0.024	0.226***	0.053**			0.241***	0.052**	0.206*	0.036	0.115	-0.056*
	(0.085)	(0.024)	(0.085)	(0.025)			(0.093)	(0.025)	(0.110)	(0.031)	(0.099)	(0.031)
[ln(ICT CAP)]²	0.025**		0.025**				0.027**		0.024		0.024	
	(0.011)		(0.011)				(0.012)		(0.015)		(0.015)	
ln(nonICT CAP)					-0.093***	-0.034						
					(0.032)	(0.022)						
[ln(nonICT CAP)]²					-0.005***							
					(0.002)							
Constant	0.380**	0.085	0.446**	0.161*	-0.123***	-0.052	0.497***	0.183*	0.410*	0.128	0.087	-0.198*
	(0.172)	(0.092)	(0.174)	(0.096)	(0.036)	(0.033)	(0.182)	(0.094)	(0.219)	(0.119)	(0.173)	(0.106)
Turning point												
point estimate	-4.017		-4.582		-9.008		-4.514		-4.298		-2.373	
	(0.480)		(0.579)		(0.444)		(0.560)		(0.780)		(0.776)	
Employment share on declining section (in %)												
at point estimate	29.24		10.24		0.08		12.55		20.38		93.21	
at point estimate - st. deviation	13.82		3.66		0.08		3.93		3.93		72.73	
at point estimate + st. deviation	53.38		29.76		0.08		31.38		55.05		98.80	
N	*1820*	*1820*	*1625*	*1625*	*1820*	*1820*	*728*	*728*	*728*	*728*	*364*	*364*

Source: EUKLEMS 2011 Release.

Notes: Standard errors clustered at the country-sector level. Employment expressed in hours worked. Δ refers to stacked 1980-1985, 1985-1990, 1990-1995, 1995-2000 and 2000-2005 changes. Shares defined at the country-year level. Point estimates and standard errors for the level of log (non)ICT capital intensity at the turning point of the dependent variable are computed by the delta method. The employment share on the declining section of the change in employment shares is a cross-country average of employment shares in 2005.

Table 3: Changes in skilled employment shares by sectoral capital intensity (in percentage points, 1980-2005)

	Δ Skilled employment share (percentage point)											
	(1) All years		(2) All years, excluding public sector		(3) All years, non ICT capital		(4) 1980s		(5) 1990s		(6) 2000s	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
ln(ICT CAP)	-0.306	0.234***	0.032	0.133**			-0.375	0.295***	-0.065	0.209***	-0.694	0.157
	(0.416)	(0.071)	(0.374)	(0.057)			(0.587)	(0.097)	(0.397)	(0.078)	(0.746)	(0.110)
[ln(ICT CAP)]²	-0.082		-0.016				-0.103		-0.042		-0.129	
	(0.065)		(0.056)				(0.095)		(0.063)		(0.120)	
ln(nonICT CAP)					-0.326	0.143						
					(0.292)	(0.114)						
[ln(nonICT CAP)]²					-0.146							
					(0.119)							
Constant	-0.039	0.795***	0.372	0.523**	-0.098	0.21	-0.028	1.001***	0.286	0.708**	-0.792	0.534
	(0.625)	(0.257)	(0.577)	(0.22)	(0.135)	(0.159)	(0.876)	(0.327)	(0.612)	(0.292)	(1.076)	(0.365)
Turning point												
point estimate	-1.857		1.012		-1.114		-1.826		-0.776		-2.694	
	(1.092)		(15.323)		(0.210)		(1.216)		(3.624)		(0.506)	
Skilled employment share on declining section (in %)												
at point estimate	92.68		100.00		92.41		92.68		100.00		73.72	
at point estimate - st. deviation	69.13		0.00		74.35		67.00		9.45		64.83	
at point estimate + st. deviation	100.00		100.00		96.99		100.00		100.00		92.54	
N	558	558	498	498	558	558	224	224	223	223	111	111

Source: EUKLEMS 2008 and 2011 Release.

Notes: Standard errors clustered at the country-sector level. Employment expressed in hours worked. Δ refers to stacked 1980-1985, 1985-1990, 1990-1995, 1995-2000 and 2000-2005 changes. Shares defined at the country-year level. Skill-data at the correct sector level only available for Belgium, Denmark, Italy and United States. Point estimates and standard errors for the level of log (non)ICT capital intensity at the turning point of the dependent variable are computed by the delta method. The employment share on the declining section of the change in employment shares is a cross-country average of employment shares in 2005.

Table 4: Changes in unskilled employment shares by sectoral capital intensity (in percentage points, 1980-2005)

	Δ Unskilled employment share (percentage point)											
	(1)		(2)		(3)		(4)		(5)		(6)	
	All years		All years, excluding public sector		All years, non ICT Capital		1980s		1990s		2000s	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
ln(ICT CAP)	0.168	0.033	0.232	0.052			0.151	0.067	0.145	0.046	0.224	-0.067
	(0.200)	(0.044)	(0.237)	(0.049)			(0.230)	(0.049)	(0.256)	(0.055)	(0.216)	(0.053)
$[\ln(\text{ICT CAP})]^2$	0.021		0.028				0.013		0.015		0.044	
	(0.028)		(0.035)				(0.033)		(0.035)		(0.035)	
ln(nonICT CAP)					0.101	-0.095*						
					(0.134)	(0.052)						
$[\ln(\text{nonICT CAP})]^2$					0.061							
					(0.049)							
Constant	0.319	0.111	0.427	0.16	-0.01	-0.139**	0.356	0.227	0.309	0.156	0.225	-0.229
	(0.366)	(0.165)	(0.405)	(0.179)	(0.069)	(0.063)	(0.403)	(0.170)	(0.472)	(0.208)	(0.340)	(0.179)
Turning point												
point estimate	-4.071		-4.100		-0.828		-5.870		-4.799		-2.540	
	(1.247)		(1.323)		(0.517)		(6.397)		(3.373)		(0.684)	
Unskilled employment share on declining section (in %)												
at point estimate	23.15		22.74		97.62		0.00		2.55		85.17	
at point estimate - st. deviation	1.51		0.00		75.94		0.00		0.00		70.84	
at point estimate + st. deviation	78.41		78.45		100.00		100.00		98.90		95.20	
N	558	558	498	498	558	558	224	224	223	223	111	111

Source: EUKLEMS 2008 and 2011 Release.

Notes: Standard errors clustered at the country-sector level. Employment expressed in hours worked. Δ refers to stacked 1980-1985, 1985-1990, 1990-1995, 1995-2000 and 2000-2005 changes. Shares defined at the country-year level. Skill-data at the correct sector level only available for Belgium, Denmark, Italy and United States. Point estimates and standard errors for the level of log (non)ICT capital intensity at the turning point of the dependent variable are computed by the delta method. The employment share on the declining section of the change in employment shares is a cross-country average of employment shares in 2005.

Table 5: Changes in employment shares by manufacturing indicator (in percentage points, 1980-2005)

PANEL A	**Δ Employment share (percentage point)**			
	All years	1980s	1990s	2000s
Manufacturing	-0.308***	-0.336***	-0.258***	-0.353***
	(0.036)	(0.040)	(0.045)	(0.044)
Constant	0.143***	0.156***	0.120***	0.164***
	(0.033)	(0.037)	(0.042)	(0.041)
Average employment share in manufacturing (%)	21.50	24.67	20.62	17.68
N	*1820*	*728*	*728*	*364*

PANEL B	**Δ Skilled employment share (percentage point)**			
	All years	1980s	1990s	2000s
Manufacturing	-0.096	-0.047	-0.111	-0.165
	(0.129)	(0.136)	(0.127)	(0.191)
Constant	0.044	0.022	0.051	0.076
	(0.128)	(0.136)	(0.127)	(0.190)
Average skilled share in manufacturing (%)	22.54	25.33	21.89	18.97
N	*558*	*224*	*223*	*111*

PANEL C	**Δ Unskilled employment share (percentage point)**			
	All years	1980s	1990s	2000s
Manufacturing	-0.289***	-0.294***	-0.243***	-0.372***
	(0.057)	(0.070)	(0.069)	(0.070)
Constant	0.134**	0.137**	0.112*	0.171***
	(0.053)	(0.063)	(0.066)	(0.065)
Average unskilled share in manufacturing (%)	10.49	11.23	10.64	9.01
N	*558*	*224*	*223*	*111*

Source: EUKLEMS 2008 and 2011 Release.

Notes: Standard errors clustered at the country-sector level. Employment expressed in hours worked. Δ refers to stacked 1980-1985, 1985-1990, 1990-1995, 1995-2000 and 2000-2005 changes. Skill-data at the correct sector level only available for Belgium, Denmark, Italy and United States. Employment shares in manufacturing are averaged within each time period and across the 12 European countries and the United States.

Table 6: Changes in output volme by sectoral capital intensity (in percentages, 1980-2005)

	Δ Output Volume (%)											
	(1) All Years		(2) All years, excluding public		(3) All Years, non ICT capital		(4) 1980s		(5) 1990s		(6) 2000s	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
ln(ICT CAP)	18.09***	4.66***	17.548***	4.822***			16.93***	3.10***	21.60***	7.12***	13.39***	2.88***
	(3.310)	(0.823)	(3.368)	(0.885)			(3.266)	(0.846)	(6.219)	(1.354)	(3.635)	(0.935)
[ln(ICT CAP)]²	1.90***		1.814***				1.96***		2.05***		1.49***	
	(0.408)		(0.414)				(0.429)		(0.751)		(0.463)	
ln(nonICT CAP)					4.812***	1.35						
					(1.306)	(1.071)						
[ln(nonICT CAP)]²					0.304***							
					(0.074)							
Turning point												
point estimate	-4.763		-4.836		-7.914		-4.327		-5.274		-5.274	
	(0.239)		(0.268)		(0.434)		(0.230)		(0.499)		(0.499)	
Employment share on declining section (in %)												
at point estimate	4.18		4.18		0.08		17.89		3.17		13.06	
at point estimate - st. deviation	3.93		3.93		0.08		10.28		0.55		4.11	
at point estimate + st. deviation	11.34		10.28		0.08		26.94		4.18		24.91	
Constant	54.37***	32.03***	53.801***	32.860***	21.850***	17.701***	48.89***	25.88***	68.03***	43.95***	37.99***	20.51***
	(6.469)	(3.009)	(6.554)	(3.149)	(2.109)	(1.853)	(5.980)	(2.922)	(12.493)	(5.182)	(6.988)	(3.478)
N	*1820*	*1820*	*1625*	*1625*	*1820*	*1820*	*728*	*728*	*728*	*728*	*364*	*364*

Source: EUKLEMS 2011 Release.

Notes: Output volume is indexed, 1995=100. Standard errors clustered at the country-sector level. Δ refers to stacked 1980-1985, 1985-1990, 1990-1995, 1995-2000 and 2000-2005 changes. Point estimates and standard errors for the level of log (non)ICT capital intensity at the turning point of the dependent variable are computed by the delta method. The employment share on the declining section of the change in output volume is a cross-country average of employment shares in 2005.

Table 7: Changes in output prices by sectoral capital intensity (in percentages, 1980-2005)

	Δ Output price (%)											
	(1)		(2)		(3)		(4)		(5)		(6)	
	All years		All years, excluding public sector		All years, non ICT capital		1980s		1990s		2000s	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
ln(ICT CAP)	-0.492	-2.532***	1.014	-2.091***			-0.712	-2.770**	3.062	-2.168***	-7.162**	-2.785***
	(2.941)	(0.647)	(2.968)	(0.668)			(4.642)	(1.083)	(3.931)	(0.731)	(2.935)	(0.776)
[ln(ICT CAP)]²	0.288		0.443				0.291		0.739		-0.619	
	(0.393)		(0.396)				(0.618)		(0.505)		(0.375)	
ln(nonICT CAP)					-1.217	-0.813*						
					(0.965)	(0.432)						
[ln(nonICT CAP)]²					-0.036							
					(0.051)							
Constant	14.48***	11.09***	17.05***	11.94***	17.64***	18.74***	26.16***	22.74***	13.19*	4.493	-6.312	0.969
	(5.495)	(2.316)	(5.546)	(2.374)	(1.150)	(0.791)	(8.720)	(3.880)	(7.549)	(2.761)	(5.793)	(2.851)
Turning point												
point estimate	0.854		-4.836		-7.914		1.222		-5.274		-5.274	
	(6.238)		(0.268)		(0.434)		(10.513)		(0.499)		(0.499)	
Employment share on declining section (in %)												
at point estimate	100.00		99.76		0.00		100.00		96.22		0.45	
at point estimate - st. deviation	3.67		55.15		0.00		0.00		62.29		0.14	
at point estimate + st. deviation	100.00		99.76		0.18		100.00		100.00		13.88	
N	*1820*	*1820*	*1625*	*1625*	*1820*	*1820*	*728*	*728*	*728*	*728*	*364*	*364*

Source: EUKLEMS 2011 Release.

Notes: Prices are indexed, 1995=100. Standard errors clustered at the country-sector level. Δ refers to stacked 1980-1985, 1985-1990, 1990-1995, 1995-2000 and 2000-2005 changes. Point estimates and standard errors for the level of log (non)ICT capital intensity at the turning point of the dependent variable are computed by the delta method. The employment share on the declining section of the change in employment shares is a cross-country average of employment shares in 2005.

Appendices

A Mathematical Appendix

A.1 Model with heterogeneity

Imagine an economy as presented above with the following changes made to the characteristics of labor supply, leaving production and consumption as described in the main text.

As before, assume that there is a continuum of skilled and of unskilled workers, each normalized to unity. An unskilled worker has a single unit of labor which can be supplied to perform manual tasks in Services or routine tasks in Sector 1. Similarly, each skilled worker has a single unit of labor which can be supplied to perform abstract tasks in Sector 1 or Sector 2. We introduce the following aspects of heterogeneity. Firstly, workers have skills, $\eta_i \in [0, \infty[$ (with $i = h$ for skilled workers and $i = l$ for unskilled workers), distributed according to the exponential density function, $f(\eta_i) = e^{-\eta_i}$.[1] Secondly, following Gibbons et al. [2005] and Cortes [2014] we assume that the productivity of skills φ_{ij}, expressed in efficiency units, differs between sectors $j = s, 1, 2$; Services, Sector 1 and Sector 2 respectively. This allows for the realistic feature that a workers earnings will not only depend on his or her skill level but also on the sector of employment.

For the unskilled workers, we follow the specification used in Autor and Dorn [2013], namely that workers are homogenous in performing manual tasks, $\varphi_{ls} = 1$, and have $\varphi_{l1} = \eta_l$ when performing routine tasks. In the case of skilled workers, productivity is specified such that every skilled workers is more productive in Sector 2. One can think of this as capital-intensive and high-technological sectors also having better, high-performance works practices that foster creativity, flexibility and cooperation amongst its workers. Therefore, $\varphi_{h1} = 1 + \eta_h$ and $\varphi_{h2} = 1 + \gamma\eta_h$, with $\gamma > 1$.[2]

The labor supplied to tasks by workers will be expressed in efficiency units which emphasizes that a worker with a certain amount of skills has a different level of productivity depending on the task that she performs. Therefore, the mass of efficiency units supplied to each task does not have a one-to-one corresponds with the mass of workers: The efficiency units supplied by unskilled workers to manual, L_m and routine, L_r tasks and by skilled workers to abstract tasks, $L_{a1}$and L_{a2}, need not lie between zero and one but rather depends on the allocation.

[1] Note that because of this, the total mass of workers of each type (skilled or unskilled) will always sum up to one.

[2] Many specifications of the form $\varphi_{ij}(\eta) = c_{ij} + \gamma_{ij}\eta_i$ are possibile in order to obtain positive sorting within a certain labor type, subject to the following restrictions which ensures that inframarginal workers strictly prefer their allocation to the alternative. For $i = h$ we must have that $c_{h1}/\gamma_{h1} > c_{h2}/\gamma_{h2}$. Similarly for $i = l$ we must have that $c_{ls}/\gamma_{ls} > c_{l1}/\gamma_{l1}$.

Note that the labor allocation is determined by sorting according to comparative advantage along the lines of a Roy-type selection model which involves a critical skill levels for each type: η_h^* and η_l^*. For example, an unskilled worker will decide whether to work in goods or service based on where his individual earnings would be highest. The earnings of a worker, ψ_{ij}, depend on the skill level, and the corresponding level of productivity expressed in efficiency units, φ_{ij}; and the wage per efficiency unit that that industry offers for the task performed, w_{tj}, where $t = m, r, a$ for manual, routine and abstract tasks respectively.

$$\psi_{ij} = \varphi_{ij} w_{tj} \tag{A.1}$$

Therefore, the allocation of labor expressed in efficiency units is determined by making a single worker with skill level η_i^* indifferent, all other workers will choose to work where their earnings are highest and sort accordingly.[3] This gives,

$$\varphi_{ls}(\eta_l^*)\ w_m = \varphi_{lr}(\eta_l^*)\ w_r \tag{A.2}$$

$$\varphi_{h1}(\eta_h^*)\ w_{a1} = \varphi_{h2}(\eta_h^*)\ w_{a2} \tag{A.3}$$

A.2 Equilibrium

An economy defined as such can be summarized by the following social planner's problem.

$$\max_{K_1, K_2, \eta_l^*, \eta_h^*} U = \left[C_s^{\frac{\sigma-1}{\sigma}} + \left(C_{g1}^{\frac{\theta-1}{\theta}} + C_{g2}^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1} \frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{A.4}$$

[3]More precisely, there is a continuum of workers with skills level η_i^* who is made indifferent by the observed relative wages.

where:

$$C_s = Y_s = L_m \tag{A.5}$$

$$C_{gj} = Y_{gj} - Y_{kj} \text{ with } Y_{kj} = p_k K_j \text{ for } j = 1, 2 \tag{A.6}$$

$$Y_{g1} = L_{a1}^{1-\beta_1} X^{\beta_1} \text{ with } X = [L_r^{\mu} + K_1^{\mu}]^{\frac{1}{\mu}} \tag{A.7}$$

$$Y_{g2} = L_{a2}^{1-\beta_2} K_2{}^{\beta_2} \tag{A.8}$$

$$L_{a2} = \int_{\eta_h^*}^{\infty} (1 + \gamma\eta_h) e^{-\eta_h} d\eta_h = (1 + \gamma + \gamma\eta_h^*)\, e^{-\eta_h^*} \tag{A.9}$$

$$L_{a1} = \int_0^{\eta_h^*} (1 + \eta_h) e^{-\eta_h} d\eta_h = 2(1 - e^{-\eta_h^*}) - \eta_h^* e^{-\eta_h^*} \tag{A.10}$$

$$L_r = \int_{\eta_l^*}^{\infty} \eta_l e^{-\eta_l} d\eta_l = (1 + \eta_l^*)\, e^{-\eta_l^*} \tag{A.11}$$

$$L_m = \int_0^{\eta_l^*} e^{-\eta_l} d\eta_l = 1 - e^{-\eta_l^*} \tag{A.12}$$

This gives us the following first-order conditions:

$$\mathbf{p}_k = \frac{\partial Y_{g1}}{\partial K_1} = L_{a1}^{1-\beta_1} \beta_1 X^{\beta_1 - \mu} K_1^{\mu - 1} \tag{A.13}$$

$$\mathbf{p}_k = \frac{\partial Y_{g2}}{\partial K_2} = L_{a2}^{1-\beta_2} \beta_2 K_1^{\beta_2 - 1} \tag{A.14}$$

$$L_r^{1-\mu} [L_m]^{-\frac{1}{\sigma}} = C^{\frac{\sigma-\theta}{\theta\sigma}} C_{g1}{}^{-\frac{1}{\theta}} \beta_1 L_{a1}^{1-\beta_1} X^{\beta_1 - \mu} \eta_l^* \tag{A.15}$$

$$L_{a1}^{-\beta_1} [L_{a2}]^{\beta_2} = \left[\frac{C_{g1}}{C_{g2}}\right]^{1/\theta} \frac{[1-\beta_2]}{[1-\beta_1]} X^{-\beta_1} K_2^{\beta_2} \frac{(1 + \gamma\eta_h^*)}{(1 + \eta_h^*)} \tag{A.16}$$

The first two equations are equal to the homogenous solution of the model. The third and fourth first-order conditions are equal to the arbitrage conditions discussed above, equations (A.2) and (A.3), namely, the marginal worker with skill level η_i^* is made indifferent between his two options.

The remainder of this section discusses asymptotes for equilibrium quantities and prices when $\mathbf{p}_k = e^{-\delta t} \to 0$ as $t \to \infty$. As in the baseline model, we continue by showing how the process of capital accumulation in the economy can under certain conditions be accompanied by the four stylized facts of job polarization, de-industrialization, Baumol's cost disease, and the tapering of the growth in the skill premium.

A.2.1 Job Polarization

The equations in this section demonstrate how the assumed heterogeneity between workers does not alter the qualitative results derived in the baseline model. As before, job polarization consists of a shift in unskilled labor away from employment in routine tasks and a shift in skilled labor away from abstract tasks in Sector 1. We discuss each of these in turn.

Given capital accumulation in both Sectors 1 and 2, equation (A.15) determines the conditions needed for $L_r \to 0$, consistent with job polarization. First consider the consumption terms in equation (A.15). Making use of equations (A.13) and (A.14) gives:

$$C_{g1} = Y_{g1} - \mathbf{p}_k K_1 = [1 - \beta_1 [K_1/X]^{\mu}] L_{a1}^{1-\beta_1} X^{\beta_1} \tag{A.17}$$

$$C_{g2} = Y_{g2} - \mathbf{p}_k K_2 = [1 - \beta_2] L_{a2}^{1-\beta_2} K_2^{\beta_2} \tag{A.18}$$

As explained in the main text, in any case we must have that $C \to \infty$ as either $C_{g1} \to \infty$ or $C_{g2} \to \infty$ or both.

Substituting equations (A.17) and (A.18) into equation (A.15) gives:

$$\begin{aligned} &[(1+\eta_l^*)e^{-\eta_l^*}]^{1-\mu}(1-e^{-\eta_l^*})^{-\frac{1}{\sigma}}\frac{1}{\eta_l^*} \\ &= C^{\frac{\sigma-\theta}{\theta\sigma}}[1-\beta_1[K_1/X]^{\mu}]^{-\frac{1}{\theta}}\beta_1 L_{a1}^{\frac{[\theta-1][1-\beta_1]}{\theta}} X^{\beta_1-\mu-\frac{1}{\theta}\beta_1} \end{aligned} \tag{A.19}$$

Low-skilled workers moving from the goods to the service sector implies that η_l^* goes to infinity. See this as the marginal worker with the critical skill level becoming more and more skilled, which will attract more workers into Services. For low-skilled workers to move to the service sector, i.e. the left-hand side of the equation to go to zero, the right-hand side must go to zero. Next, consider the terms on the right-hand side of equation (A.19) in turn. These are the same terms as described in the main text. Therefore, given $K_1 \to \infty$ and thus $X \to \infty$, a sufficient condition for the right-hand side of equation (A.19) to go to zero and thus for $L_r \to 0$ is:

$$L_r \to 0 \text{ if } \frac{1}{\sigma} > \frac{1}{\theta} > \frac{\beta_1 - \mu}{\beta_1} \tag{A.20}$$

which is the same condition given in the baseline model.

A similar derivation can be made for the reallocation of the skilled workers. Starting from the relevant first-order condition and making use of equations (A.17) and (A.18) we can rewrite the condition:

$$\begin{aligned} &[2(1-e^{-\eta_h^*}) - \eta_h^* e^{-\eta_h^*}]^{\beta_1+\frac{1}{\theta}(1-\beta_1)} \left[(1+\gamma+\gamma\eta_h^*)\, e^{-\eta_h^*}\right]^{\frac{1}{\theta}(\beta_2-1)-\beta_2} \frac{(1+\eta_h^*)}{(1+\gamma\eta_h^*)} \\ &= [1-\beta_1]\,[\beta_2-1]^{\frac{\theta-1}{\theta}}\,[1-\beta_1\,[K_1/X]^{\mu}]^{-1/\theta}\left[X^{\beta_1}/K_2^{\beta_2}\right]^{\frac{\theta-1}{\theta}} \end{aligned} \tag{A.21}$$

High-skilled workers moving from sector 1 to sector 2 is equivalent to a fall in η_h^*. In that case, the marginal worker who is made indifferent between working in Sector 1 or 2 becomes less skilled. For η_h to move to zero, i.e. the left-hand side to go to zero, the right-hand side has to go to zero. Giving that the right-hand side elements are identical to the equation in the main text, we find that skilled workers move from sector 1 to sector 2 under the same restriction, including $\theta > 1$.

In conclusion, adding heterogeneity does not qualitatively alter the outcome of job polarization as a result of capital accumulation nor the economic mechanisms behind the shift. There will, however, be quantitative changes since labor is now expressed in efficiency units. These quantitative differences and possible differences in the speed of convergence towards the limit are linked to the assumed underlying density distribution and productivity schedules.

A.2.2 Deindustrialization

Given the occurrence of capital accumulation accompanied by job polarization, deindustrialization also remains a feature of this model with heterogeneity. That is, manufacturing defined as the combination of Sector 1 and 2 experiences a decline in unskilled employment due to the reallocation of unskilled labor into services. In the limit $L_r \to 0$, $L_m \to 1$ and $L_{a1} \to 0$ and the share of employment in manufacturing,

$$[L_r + L_{a1} + L_{a2}] \ / \ [L_r + L_m + L_{a1} + L_{a2}] \to L_{a2} / [1 + L_{a2}] \text{ as } t \to \infty$$

which implies a decrease over time. There will be quantitative differences with the main results given that labor is now defined in efficiency units. As before this deindustrialization in terms of employment does not extend into a decline in the output from manufacturing due to the implementation of labor-replacing capital. We refer to the further discussion of deindustrialization in the main text.

A.2.3 Baumol's Cost Disease

Given that the allocation of labor and capital has not altered qualitatively, $L_{a1} \to 0$, $K_1/X \to 1$, $K_2/X \to \infty$ given $0 < \beta_1 < \beta_2 < 1.$, the differential rise in consumption from which we can derive the sign of growth in relative prices, has remained the same. Therefore, as in the baseline model, we can derive from the condition implied by utility maximization:

$$\frac{p_s}{p_2} = \frac{C^{(\theta-\sigma)/\sigma\theta} {C_{g2}}^{1/\theta}}{C_s^{1/\sigma}} \tag{A.22}$$

such that,

$$\frac{p_s}{p_2} \to \infty \tag{A.23}$$

as explained in the main text. Similarly,

$$\frac{p_1}{p_2} = \left[\frac{C_{g2}}{C_{g1}}\right]^{1/\theta} \to \infty$$

predicting that the relative price of Services must rise while attracting an increasing share of unskilled labor which is consistent with Baumol's cost disease.

B Data Appendix

Based on harmonized data from the National Statistics of several OECD countries, the authors Timmer et al [2007] have compiled a country-sector level dataset over a long period of time, 1970-2007 under the KLEMS data project. EUKLEMS data from the March 2011 release are used. This dataset contains information about output volume and prices, value added, and labor and capital inputs at the level of sectors classified by ISIC revision 3 which overlaps with the NACE revision 1. In order to have consistent information, data between 1980 and 2005 for 12 European Countries and the Unites States are considered at the level of sectors reported in Table 1. In the list of sectors reported in Table 1, those printed in bold are considered to be manufacturing sectors by ISIC defined as "the physical or chemical transformation of materials of components into new products, whether the work is performed by power-driven machines or by hand, whether it is done in a factory or in the worker's home, and wether the products are sold at wholesale or retail". The primary sectors ("Agriculture, Hunting, Forestry and Fishing" and "Mining and Quarrying") and the sector "Private Households with Employed Persons", printed in italics, are discarded due to limited data availability, resulting in a final sample of 28 sectors in 13 countries. These 13 countries are Austria, Belgium, Denmark, Finland, France, Germany, Italy, Ireland, Netherlands, Spain, Sweden, United Kingdom and United States.

The EUKLEMS dataset allows capital compensation to be split in ICT and non-ICT. This provides each sector with a measure of ICT capital intensity. The measure of capital intensity is given by a sector's ICT capital compensation as a percentage of value added, where the EUKLEMS defines ICT capital compensation as the product of the ICT capital stock (consisting of office and computing equipment, communication equipment and software) and its user cost. Stocks have been estimated by the authors on the basis of investment series using the perpetual inventory method with geometric depreciation profiles. Depreciation rates differ by asset and industry but they are assumed to be identical across countries [Timmer et al. 2007]. As presented in Table 1, this sectoral ICT capital intensity provides an intuitive ranking of sectors. Moreover, the ranking of sectors by their ICT capital intensity is found to be stable over time. Table B1 shows Spearman rank correlation coefficients of sectors ranked by their capital intensity across years by country. The coefficients lie between 0.75 and 0.95 indicating a strong positive correlation between the rankings of sectors within a country over time.

Employment is measured as hours worked in a sector by all persons engaged (i.e. employees as well as self-employed workers). Using the alternative of all persons employed (i.e. leaving out self-employed workers) does not greatly affect our results.

The EUKLEMS data from the March 2011 release is supplemented with data from the March 2008 release that contains information on share in total hours worked by high-skilled, middle-skilled, and low-skilled workers. While there are some differences between the definition of skills at the country level, high-skilled workers are generally tertiary educated, middle-skilled workers have at least completed upper-secondary education, and low-skilled workers have at most completed lower-secondary education. These skill shares are only available for 10 out of 13 countries and for only 4 of these 10 countries at the same level of sector disaggregation as in the March 2011 release. These 4 countries are Belgium, Denmark, Italy and the United States. Therefore, the sample is restricted to those 4 countries whenever skill data are reported. Table B2 lists the different definitions of low-, middle- and high-skilled at the country level and states their share in the total employment in 2005. Middle-skilled are the largest group in each of the countries, apart from Belgium, where it ties with the share of low-skilled. When taking together low- and middle-skilled to form the share of unskilled employment for the empirical analysis, this group forms the major share of employment, capturing between 74.4% in the United States and 94.7% in Denmark.

Finally, EUKLEMS data from the March 2011 release contains information on sectoral output volumes and output prices between 1980 and 2005 for the 13 countries in our sample. In EUKLEMS, the output volume series are given as an index with 1995 as the base year (1995=100) and are derived from growth rates in chained volume indices reported in countries' National Accounts. EU KLEMS also obtains nominal output indices from countries' National Accounts to construct output price indices as the ratio of nominal to volume output series.

Table B1: Capital intensity rank stability

	Average Spearman rank correlation coefficient
Austria	0.91
Belgium	0.89
Denmark	0.75
Spain	0.94
Finland	0.89
France	0.93
Germany	0.95
Ireland	0.76
Italy	0.87
Netherlands	0.90
Sweden	0.95
United Kingdom	0.79
United States	0.91

Source: EUKLEMS 2011 Release.
Notes: The coefficients are the averages of the pairwise (year-by-year) Spearman rank correlation coefficients of ICT capital intensity

Table B2: Definition and size of skill groups

	High-skilled	Middle-skilled	Low-skilled
Belgium	University and non-univeristy 2 cycles tertiary education (11.3%)	Higher/upper secondary education and non-university 1 cycle tertiary education (43.5%)	All people up to lower secondary education (45.3%)
Denmark	Long cycle higher education (5.3%)	Medium and short cycle higher education plus vocational education and training (56.9%)	Basic school (37.8%)
Italy	University graduates (6.7%)	Higher education below degree, intermediate vocational plus advance education, low intermediate (88%)	No formal qualifications (5.3%)
United States	College graduate and above (25.6%)	High school and some years of college (60.7%)	Less than high school and some years of high school (but not completed) (13.7%)

Source: Timmer M.P., Moergastel T., Stuivenwold E., Ypma G., O'Mahony M. and Kangasniemi M. (2007), EU KLEMS Growth and Productivity Accounts: Version 1.0 – Part I: Methodology, EU KLEMS.

Notes: The size of the skill groups are calculated as the share in total employment for the total economy in 2005

C Additional Analysis

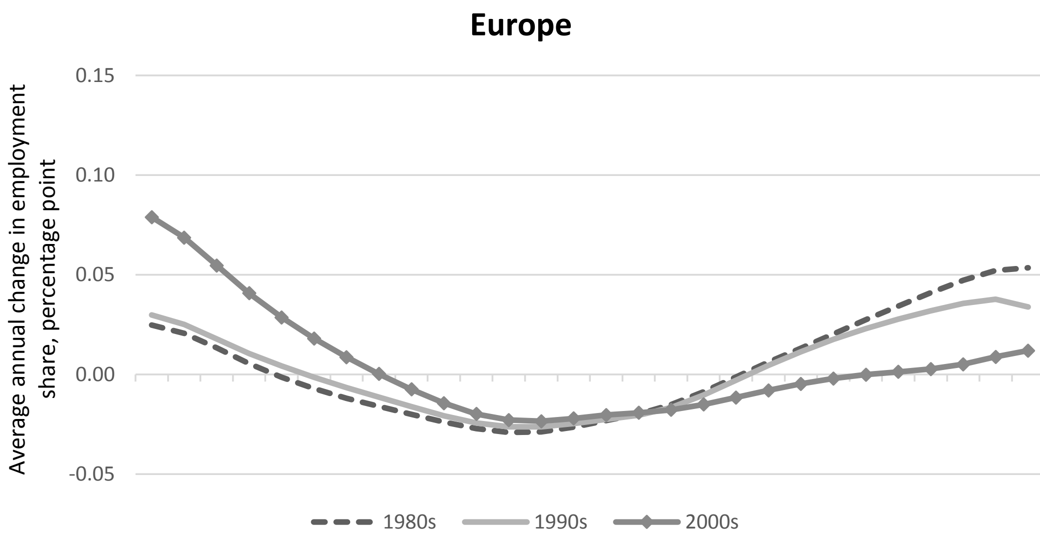
Figure C1 plots the smoothed average annual changes in sector employment shares in Europe after ranking these sectors by their ICT capital intensity. As opposed to Figure 1 where cross-country averages of the 12 European countries are used, Figure C1 plots employment shares after pooling European employment by sector. This gives a very similar picture with perhaps the only noticeable difference during 1980s. Here it seems that by pooling employment shares there is a stronger relative growth of employment in the most capital intensity sectors while the changes in shares of the least capital intensive sector lie completely below the changes in the 1990s.

On the whole, differences between European countries seem to contribute little explanatory power for job polarization between sectors taking place across the three consecutive decades.

Figure C2 plots smoothed changes in average annual growth of sectoral output volume after ranking sectors by their ICT capital intensity for the US in the left panel and European countries in the right panel. Overall, the growth in output volume is positive for all sectors across all time periods and both regions and stronger growth can be associated with more ICT capital intense sectors. However, there are differences discernible between time periods similar across the US and European countries. Namely, the relatively stronger growth in ICT capital intensive sectors was particularly present in the 1990s. During this period, the most capital intensive sectors increased their output by 8 to 10% on average *annually*, compared to less than 4% for the least capital intensive [1] During the early 2000s, the regression line falls below the level of growth in the 1980 for all but the least capital intensive sectors in both regions and resembles a slight U-shape. This reflects the evidence given in Figure 2 which is suggestive of the hypothesis put for forth by Autor [2015] of a build-up of misallocated investment in ICT during the 1990s followed by a "bursting of the bubble" around 2000.

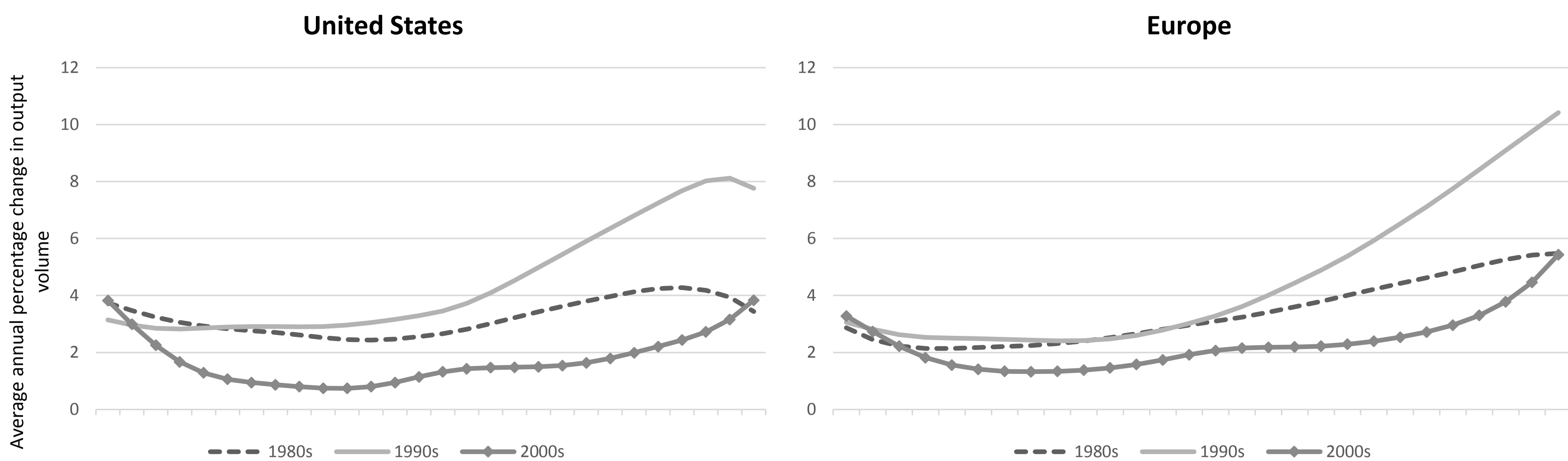
[1] The kink in the regression line for the US for the most capital intensive sectors during the 1980s and 1990s, may be due to nearness to the sample boundary. Kernel weighted regression are known to perform less accurately when nearing the boundary of the sample range because of the use of a symmetric estimation window.

Figure C1: Kernel plot of average annual pooled employment share changes by sectoral capital intensity (in percentag points, 1980-2005)



Source: EUKLEMS 2011 release.
Notes: Percentage point changes in employment share by average capital intensity in 2005 using a locally weighted smoothing regression (bandwidth 0.8 with 27 observations). Employment expressed in hours. European employment shares defined as the sum of country-level employment shares in the 12 European

Figure C2: **Kernel plots of average annual output volume changes by sectoral capital intensity (in percentages, 1980-2005)**



Source: EUKLEMS 2011 release.
Notes: Output volume is indexed, 1995=100. Percentage changes in output volume by average capital intensity ranking in 2005 using a locally weighted smoothing regression (bandwidth 0.8 with 27 observations). European output volume defined as the cross-country average of country-level output volume in the 12 European countries.