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Essays on employment, skills and wage inequality

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Marieke Vandeweyer

Daar de proefschriften in de reeks van de Faculteit Economische en Toegepaste Economische Wetenschappen het persoonlijk werk zijn van hun auteurs, zijn alleen deze laatsten daarvoor verantwoordelijk.

Doctoral Committee

Advisor
Prof. Dr. Maarten Goos (Utrecht University, KU Leuven)

Co-advisor
Prof. Dr. Jozef Konings (KU Leuven)

Committee members
Dr. Stijn Broecke (OECD)
Prof. Dr. Erik Buyst (KU Leuven)
Prof. Dr. Anna Salomons (Utrecht University)

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General Introduction

As a consequence of global megatrends, such as technological progress, globalisation and population ageing, employment and skills dynamics in developed countries have changed substantially over the past decades. With technology increasingly being able to substitute for workers doing routine, repetitive tasks, and these tasks becoming increasingly outsourceable, employment has been shifting from the middle of the skill (and wage) distribution to the top and bottom. This phenomenon is known in the labour economics literature as job polarisation, and has been extensively documented for the Unites States and Europe. The changing task structure of employment has resulted in a changing demand for skills. Whereas high-skilled workers are in high demand for their innovative capacities, low-skilled workers will increasingly be needed to complement the high-skilled (and high-wage) workers and to supply in-person services that are not easily automated. The impact of automation on the labour market has received a lot of attention in the public debate, with fears of mass unemployment as robots are taking over our jobs. Brynjolfsson and McAfee (2014) argue that technological change has been destroying jobs faster than it is creating them, and that technology is increasingly able to perform tasks that are now almost exclusively done by human labour. Estimates by Frey and Osbourne (2017) which suggested that 47% of jobs in the United States are at risk of being automated relatively soon, further fuelled the fear that in the future jobs would only be available for the happy few. However, more recent evidence has shown that this view of the labour market might be too pessimistic, with Arntz et. al (2016) showing that only 9% of jobs in OECD countries are really at risk of disappearing because of automation, but that many other jobs will be impacted through changes in content, but will not be fully automated. At the same time, Gregory et al. (2016) show that technological progress in Europe has indeed resulted in job destruction in certain parts of the labour market, but that these negative effects have been more than compensated for by the positive impact of technological progress on employment in other parts. As argued by Autor (2015), the reason that technology has not led to massive job destruction in the recent past, and is unlikely to do so in the near future, is that technology and labour are complementary, and that humans have competitive advantage in tasks that require creativity, flexibility or problem-solving skills.

While the impact of technological progress on total employment might be positive –at least in the short run-, these changes could have a considerable unequalising effect on the structure of the labour market. The process of job polarisation is inevitably linked to the issue of job quality and growing wage inequality in developed countries. Many jobs that have been created through the process of technological progress have been at the lower end of the wage distribution, and many middle-skilled workers whose job disappeared as a result of automation or outsourcing, have been forced to take lower-wage jobs. As such, not everyone has been able to benefit from the gains of these global megatrends. Moreover, Brynjolfsson and McAfee (2014) argue that digital technologies are likely to create superstar or winner-take-all markets, contributing to wealth concentration at the top one percent. Superstar firms contribute to the declining relative importance of labour as compared to capital in the

labour market (Autor et al., 2017), and, according to Piketty (2014), low labour shares are associated with higher inequality in the personal distribution of income. High levels of income inequality are detrimental for societies, as inequality has been shown to have a negative impact on economic growth (Ostry et al., 2014; Cingano, 2014), lower social cohesion and trust (Stiglitz, 2012) and fuell populist sentiments (O'Connor, 2017).

One of the key policy levers to mitigate the negative consequences of technological progress and other megatrends is skills investment. Equipping individuals with the right skills will help them access the jobs in growing segments of the labour market. Moreover, higher-skilled individuals do not only perform better in the labour market, they also have better outcomes in terms of health, civic engagement and life satisfaction (OECD, 2010, 2016). Nonetheless, skills investment alone is not enough to tackle the negative effects of technological progress on society. Policy interventions in areas, such as social protection and employment protection, can further soften the consequences for people who find themselves in low quality jobs or out of work. Job quality can, for example be improved by facilitating conductive social dialogue or by setting adequate minimum wages. At the same time, a stronger social safety net can help people who become unemployed as a consequence of structural changes, and ease their transition into growing or new economic sectors.

In the first chapter of this dissertation the phenomenon of job polarisation is analysed in detail.[1] A three-sector model is used to predict employment and output price dynamics following increased productivity of capital. The model predicts that, under critical assumptions about key structural parameters, employment will polarize across sectors, with low-skilled workers shifting to low-tech, in-person service sectors such as 'accommodation and restaurants' and high-skill workers shifting to IT-capital intensive sectors such as 'financial intermediation'. In this model technological progress will also lead to increasing prices in the low-tech sectors relative to the high-tech sectors, also known as Baumol's cost disease. These theoretical predictions are empirically tested using data from 1980-2005 for 13 developed countries. The results suggest that IT-capital intensity is indeed a driver of employment polarisation across sectors and Baumol's cost disease.

The changing demand for skills is documented for the European Union in chapter 2 by focusing on the trend in and the regional distribution of high-tech employment.[2] High-tech employment is defined as all workers in the traditional high-tech sectors plus the STEM workers outside these traditional high-tech sectors. As such the definition captures all workers involved in highly technical activities, i.e. those workers that have the strongest complementarity with productive capital. With high-tech employment growing much faster than total employment in the European Union (EU), this sector has contributed significantly to the economic performance of the EU. In spite of the strong growth of high-tech employment, large disparities remain between the European regions in terms of high-tech employment intensity. The lagging regions are mainly concentrated in Southern and Eastern Europe. The growing high-tech sector is not only beneficial for high-skilled STEM workers, but also for employment in other

[1] Chapter 1 is joint work with Maarten Goos, Emilie Rademakers and Anna Salomons.
[2] Chapter 2 is joint work with Maarten Goos and Joep Konings, and is forthcoming as
Goos, M., Konings, J. and Vandeweyer, M. (2018). Local high-tech job multipliers in Europe. *Industrial and Corporate Change.*

sectors through a significant multiplier effect. For every job created in the high-tech sector, additional jobs are created outside the sector, as a result of the complementarity between high- and low-skilled workers and the increased demand for in-person services by the high-wage workers in the high-tech sector.

Whether or not skills are important drivers of wage inequality is unclear, as there is no uniform conclusion in the literature. In chapter 3 this debate is reopened using the recent data on cognitive skills from the OECD's survey of adult skills (PIAAC).[3] The focus of the chapter is on the United States, where both wage and skills inequality is high. The importance of skills and institutions in explaining cross-country differences in wage inequality is analysed in a uniform framework that uses a reweighting method to simulate alternative wage distributions. The results of the simulations suggest that differences in skill demand and supply are an important factor in explaining differences in wage inequality. The low net-supply, defined as supply minus demand, of high-skilled workers and high net-supply of low-skilled workers in the United States relative to other OECD countries, explains around a quarter of differences in wage inequality. While skills are clearly important, the chapter also suggests that there is a big role for institutions in explaining cross-country differences. Whereas raising the minimum wage of the United States is found to have a fairly limited impact on wage inequality, the role of collective bargaining coverage is found to be more important.

The issue of high and rising income and wage inequality is not only limited to developed countries, but also affects developing countries. The minimum wage has often been used in these countries to tackle wage inequality. In the final chapter of this doctoral dissertation the impact of raising the minimum wage on employment in developing countries is analysed.[4] This chapter summarizes the growing body of literature covering the impact of minimum wages on labour market outcomes in fourteen emerging economies. The minimum wage effect can possibly differ from what has been found in the extensive literature on developed countries, as developing countries often have a large informal sector, and minimum wages are often set at very high or, on the contrary, very low levels. As the standard qualitative literature review does not provide a clear-cut answer to the question of the impact of minimum wages on employment, a complementary meta-regression analysis is added. Both the meta-analysis on the estimated elasticities and the meta-analysis on the wider sample of partial correlations suggest that the impact of minimum wages in these countries has been very limited. Slightly stronger negative effects on employment are found for vulnerable groups, such as youth and low-skilled, and there is some indication that higher minimum wages lead to more informal employment.

[3] Chapter 3 is joint work with Stijn Broecke and Glenda Quintini, and has been published as
Broecke, S., Quintini, G. and Vandeweyer, M. (2017). Explaining international differences in wage inequality: skills matter. *Economics of Education Review*, 60, 112-124.

[4] Chapter 4 is joint work with Stijn Broecke and Alessia Forti, and has been published as
Broecke, S., Forti, A. and Vandeweyer, M. (2017). The effect of minimum wages on employment in emerging economies: A survey and meta-analysis. *Oxford Development Studies*, 45/3, 366-391.

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Chapter 1

Job polarisation: Its history, an intuitive framework and some empirical evidence

Abstract

This chapter first gives an overview of the literature on job polarisation: The idea that job markets are polarizing into lovely and lousy jobs at the expense of middling jobs originates from the early 1980s. During the following decades, the phenomenon of job polarisation was documented for many advanced economies and its drivers became better understood. To summarize the intuition that economists currently have about these drivers, the chapter then provides a simple intuitive framework and some empirical evidence in support of it. The contribution of this framework is that it explicitly derives critical assumptions about key structural parameters for understanding job polarisation: the direct substitutability between differently skilled workers and new digital technologies in production, and scale-effects driven by technology-induced changes in the prices of goods and services for consumers. Finally, the importance of these channels is documented by empirical evidence from 13 advanced economies. Our analyses imply that job polarisation is not a natural law that must hold at all times and in all places, but that it critically depends on the nature of technological progress, the substitutability between differently-skilled workers and new technologies in production, and the substitutability between goods and services in consumption.

1.1 Introduction

Between the mid-1970s to mid-1980s the U.S. labour market created nearly 26 million net new jobs, more than virtually all of the other industrialized countries combined. As a result, several studies about the "The Great American Jobs Machine" emerged in the literature. However, even at the time, there were questions about the quality of jobs created, with evidence suggesting that a substantial proportion of new jobs were in low-wage employment. This controversy over the low-wage question intensified after the U.S. Joint Economic Committee (JEC) released a report in December 1986 claiming that, based on Current Population Survey (CPS) data, the share of net new employment paying low-wages had increased significantly after 1979. In particular, the JEC report indicated that between 1979 and

1984 the share of net new employment paying low wages (i.e. below half of the 1973 real median annual wage) was nearly 60%, in contrast to the 1963-1979 period when this share was less than 20%. These findings sparked an immediate debate. For example, Kosters and Ross (1987) also use CPS data but apply a different methodology to conclude that there was no rise in the share of new jobs with low-wages. In a reaction to Kosters and Ross (1987), Bluestone and Harrison (1988) again use CPS data and yet another methodology to find that, in line with the JEC report, there was an increase in the share of low-wage work. Together with an increase in the share of high-wage work at the expense of middling jobs, Bluestone and Harrison (1988) concluded that the Great American Jobs Machine of the early 1980s was faltering as a result of job polarisation.

Starting in the mid-1980s, the job-quality debate faded among economists as most labour economists came to the conclusion that the problem for unskilled workers was a declining number of jobs for them rather than an increasing number because of Skill-Biased Technological Change (SBTC) (Bound and Johnson, 1992; Katz and Murphy, 1992). The SBTC hypothesis is based on the assumption that technological progress increases the labour productivity of skilled workers by more than of unskilled workers, thereby shifting out labour demand for skilled workers by more than of unskilled workers.[5] At the same time, educational attainment rates increased, thereby shifting out the supply of skilled relative to unskilled workers. An important insight from the SBTC-framework is that skill-biased technological progress and increases in educational attainment combine to skill-upgrading of the workforce in terms of employment. Consequently, there must be a declining number of low-wage jobs in the labour market.

The success of the simple SBTC-framework came from its predictive power to explain changes in the skill-premium (i.e. the ratio of the average wage for skilled over unskilled workers) over time, driven by accelerations and decelerations in the outward shifts in supply of and demand for skilled relative to unskilled workers. For example, Goldin and Katz (2009) use U.S. data to show that the observed short-run decline of the skill-premium in the 1970s and sharp increase in the 1980s is in large part explained by an acceleration and then deceleration in the supply of skilled relative to unskilled workers, with the demand for skilled-workers relative to unskilled workers growing steadily during both decades due to SBTC. Because this simple supply-demand framework goes a substantial distance towards explaining the evolution of skill-premia in the U.S. and elsewhere, it became known as the "canonical model" to think about the impact of technological progress on labour markets for skilled and unskilled workers.[6] At its heart is the SBTC-hypothesis and the idea that there is skill-upgrading rather than employment polarisation in the labour market.

However, one can still find a number of studies from the 1990s continuing to address the major themes of the job-quality debate of the 1980s (see, for example, Costrell, 1990; Howell and Wolff, 1991; Levy

[5] There is a related hypothesis known as 'Capital-Skill Complementarity (CSC) (Griliches, 1969; Berman et al., 1994). Just like SBTC, CSC also predicts an outward shift in the demand for skilled relative to unskilled workers following technological progress. In contrast to SBTC, however, CSC assumes that this shift results from a decrease in the price of capital and the relative complementarity of skilled versus unskilled workers with capital in production. See Goos (2018) for a discussion.
[6] There is considerable debate, however, whether the canonical framework can go an equal distance toward explaining differences in the skill-premium between countries. See, for example, Blau and Kahn (1996) and Leuven et al. (2004).

and Murnane, 1992; Juhn et al., 1993; Murphy and Welch, 1993; Gittleman and Howell, 1995; Ilg, 1996; Farber, 1997; Acemoglu, 1999, 2001; Juhn, 1999; Ilg and Haugen, 2000). A common theme that emerges from these studies is that, between 1970 and 2000, there has been an increase in the number of high-paid but also low-paid jobs relative to middling jobs. In February 1997, Clinton's Council of Economic Advisors (CEA) published an influential report on the quality of new jobs. The CEA report claimed that, when one defines a job as an industry-occupation cell and ranks jobs by their median hourly wages, most of new employment growth in the U.S. in the period 1994-1996 was in jobs paying above the economy-wide median wage (U.S. Council of Economic Advisors, 1996). In a reaction to the CEA report, Wright and Dwyer (2003) used a similar methodology to conclude that the long 1990s economic boom resulted in a strong expansion in highly-paid jobs indeed. However, Wright and Dwyer (2003) also show that the job expansion of the 1990s was less strong overall than in earlier periods of expansion, and characterized by job polarisation. Moreover, Wright and Dwyer (2003) explain this pattern of job polarisation during the 1990s by a decline of middling jobs mainly in manufacturing; stronger growth of bottom-end jobs in retail trade and personal services; and very strong growth of high-end jobs in high-tech sectors. Inspired by Wright and Dwyer (2003), Goos and Manning (2007) use British data to examine employment changes in much more finely-grained occupation-industry cells for the period 1979-1999. In line with Wright and Dwyer (2003), Goos and Manning (2007) also find that there is job polarisation. Moreover, the authors show that job polarisation, rather than being related to the business cycle, has been a steady process at least since the early 1980s. Consequently, the secular phenomenon of job polarisation was documented in the economics literature by, among others, Autor et al. (2006) and Autor and Dorn (2013) for the U.S.; and Goos et al. (2009, 2014) for Europe.

To explain job polarisation, Goos and Manning (2007) refer to the task approach to labour markets, introduced by Autor et al. (2003) and further formalized by the task assignment models of Acemoglu and Autor (2011) and Acemoglu and Restrepo (2017). Technological progress in these task assignment models is not increasing labour productivity of differently-skilled workers as in SBTC, but is assumed to directly replace workers doing routine tasks that are codifiable in computer language. It also assumes that differently-skilled workers (low, medium and high) sort across different tasks (least, middling and most complex tasks) according to comparative advantage. In equilibrium, low-skilled workers are assigned to the least-complex tasks, medium-skilled workers to middling-tasks, and high-skilled workers to the most-complex tasks. The working hypothesis then is that computers have a comparative advantage in doing middling tasks because these tasks are routine intensive, such that technological progress directly displaces medium-skilled workers from middling-jobs. Consequently, some medium-skilled workers supply their labour to less-complex tasks and others to more-complex tasks, i.e. technological progress leads to job polarisation instead of skill-upgrading. Examples of low-wage non-routine manual jobs mainly done by unskilled workers are personal services such as cleaning or waiting tables in a restaurant; Routine middling jobs mainly done by medium-skilled workers are, for example, machine operators or office clerks; Examples of non-routine abstract cognitive and interactive tasks in high-paid jobs mainly done by high-skilled workers are performing surgery or managing a team. The task assignment models of Acemoglu and Autor (2011) and Acemoglu and Restrepo (2017) are increasingly considered to be the "new canonical framework" to think about the labour market impacts of recent technological progress.

To understand the channels that explain job polarisation in the new canonical framework more intuitively, first consider the reallocation of middling-paid to low-paid employment. As of yet, digital capital has had a comparative advantage in doing routine tasks concentrated in middling-occupations relative to non-routine manual tasks used intensively in low-paid work. For example, it has been more cost efficient for new machines to substitute for routine tasks done by middle-paid machine operators in manufacturing than for non-routine manual tasks done in low-paid personal services such as cleaning. Moreover, consumer demand for low-paid services is price-inelastic relative to consumer demand for manufactured goods. This is important if technological progress is leading to a cost-disadvantage for low-paid services where there is less scope for innovation relative to manufacturing, but this relative cost-disadvantage and consequent falls in relative product and therefore labour demand are quantitatively not important if demand for low-paid services is price-inelastic relative to demand for manufactured goods. A similar intuition applies to explain the reallocation of workers from middling-paid to high-paid jobs. So far, digital capital has been more efficient at automating routine tasks concentrated in middling-occupations than non-routine cognitive and interactive tasks used intensively in high-paid jobs, in which there often are strong complementarities between new technologies and skilled workers. For example, computers complement the work of computer engineers. Moreover, consumer demand for goods and services using high-paid workers intensively is generally more price-elastic, further contributing to the reallocation of employment from middling-jobs to high-paid jobs.[7]

In sum, the intuition that economists currently use to explain job polarisation critically hinges on the relative magnitudes of some key structural parameters that shape labour and product markets: 1) the task substitutability between new technologies and workers in middling jobs must be sufficiently high relative to the price-elasticity (in absolute terms) of consumer demand for goods and services using low-paid workers intensively; and 2) the price-elasticity of consumer demand for goods and services using high-paid workers intensively must be sufficiently high. The remainder of this chapter further formalizes this intuition in the simplest possible framework, and provides some empirical evidence in support of this framework. To this end, this chapter is further organized as follows. Section 1.2 presents a stylized but intuitive framework to understand the various drivers of job polarisation and the predictions we take away from it. Before testing these predictions, Section 1.3 presents our data. We make use of a broad sample of data spanning 28 sectors in the United States and 12 European countries for the period 1980 to 2005. Our data source is the EUKLEMS data project which harmonized national accounts data for several OECD countries. Section 1.4 presents our empirical results, and section 1.5 provides some robustness checks. Finally, Section 1.6 concludes by arguing that job polarisation is not a natural law that must hold at all times and all places. Instead, the process of job polarisation critically depends on the nature of technological progress, the substitutability between differently-skilled workers and new technologies in production, and the substitutability between goods and services in consumption.

[7] While technological progress has been found to be the main driver of labour market polarisation (Goos et al., 2014), Breemersch, Damijan and Konings (2017) show that the relative contribution of technological progress, import competition and offshoring differs between industries and countries.

1.2 An intuitive framework to understand job polarisation

1.2.1 Set-up

1.2.1.1 Technological progress

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

$$K_j(t) = Y_{kj}(t)e^{\delta t} \tag{1.1}$$

Where δ captures the speed of digital innovation and where Y_{kj} is output that is not consumed but reinvested in computer capital production. Competitive capital and output markets imply that marginal revenue must equal marginal cost in each sector *j*:

$$p_k(t) = p_j(t)\frac{\partial Y_{kj}(t)}{\partial K_j(t)} = p_j(t)e^{-\delta t} \tag{1.2}$$

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 $p_k(t) = p_k(t)/\, p_j(t)$, equation (1.2) can be written as:

$$p_k(t) = e^{-\delta t} \tag{1.3}$$

Equation (1.3) formally summarizes Moore's Law. In 1965, Intel co-founder 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 (Koh and Magee, 2006; Nordhaus, 2007; Nagy et al., 2013). 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 labour costs, has fallen by 60 to 75 percent annually. Equation (1.3) captures this exponential decrease over time in the relative price per efficiency unit of computer capital limiting to zero asymptotically: $p_k = e^{-\delta t} \to 0$ as $t \to \infty$.

1.2.1.2 Services

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

$$Y_s = L_m \tag{1.4}$$

with L_m workers performing manual labour tasks. The manual labour 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. These jobs mainly consist of manual tasks that do not

require much schooling or experience. 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 in a restaurant 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 hurdles to automation.

1.2.1.3 Goods producing sectors

Assume that there are two additional sectors in the 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 labour, whereas routine tasks are performed by labour and capital:

$$Y_{g1} = L_{a1}^{1-\beta_1} X^{\beta_1} \quad \text{with } X \equiv \left[L_r^{\mu} + K_1^{\mu}\right]^{\frac{1}{\mu}} \tag{1.5}$$

with L_{a1} abstract labour tasks, X total input of routine tasks consisting of L_r^{μ} routine labour tasks and K_1^{μ} capital tasks. Assuming that $0 < \mu < 1$ implies that the elasticity of substitution between routine labour and capital tasks is larger than unity, i.e. $1/[1-\mu] > 1$, and therefore also larger than the elasticity of substitution between abstract labour and routine tasks (which equals unity given the Cobb-Douglas specification in equation (1.5)). Also assume that Sector 2 produces Y_{g2} by combining abstract labour tasks and capital:

$$Y_{g2} = L_{a2}^{1-\beta_2} K_2^{\beta_2} \tag{1.6}$$

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

A difference between equations (1.5) and (1.6) is the simplifying assumption that in Sector 1 routine tasks are performed by both labour and capital whereas in Sector 2 routine tasks are performed solely by capital. Moreover, 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. 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 counsellors still perform various routine activities (e.g. filling in the standardized information of new requests for benefits).

1.2.1.4 Consumption

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

$$U = \left[C_s^{\frac{\sigma-1}{\sigma}} + C^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \text{ with } C \equiv \left[C_{g1}^{\frac{\theta-1}{\theta}} + C_{g2}^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} \tag{1.7}$$

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 consumer 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 because output prices of goods producing sectors fall given technological progress. For example, the demand for child care by parents or for hotels and catering by business travellers is unlikely to dissipate in face of falling prices for sending text messages. 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, Ngai and Pissarides (2007); Acemoglu and Guerrieri (2008); Autor and Dorn (2013); Goos et al. (2014)). Finally, since a fraction of final goods produced is allocated towards capital production, consumption equals: $C_{gj} = Y_{gj} - Y_{kj} = Y_{gj} - p_k K_j$ for j=1, 2 and $C_s = Y_s$.

1.2.1.5 Labour Supply

Assume that there is a continuum of skilled as well as of unskilled workers, each normalized to unity. Each skilled worker has a single unit of labour which can be supplied to perform abstract labour tasks in Sector 1 or 2. The fractions 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 labour which can be supplied to perform manual labour tasks in Services or routine labour tasks in Sector 1. The fractions 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.

1.2.2 Model predictions

Our framework set out above predicts job polarisation under a set of critical assumptions which we discuss here. For a more detailed exposition and formal proofs we refer the reader to Appendix 1.A.

1.2.2.1 Job Polarisation

Job polarisation 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 $L_{a1} \to 0$. We discuss each of these worker reallocations in turn.

Unskilled labour 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

$p_k \rightarrow 0$. The accumulation of capital in Sector 1 drives unskilled workers to reallocate to the Services sector under one additional (and sufficient) condition:

$$L_r \rightarrow 0 \text{ if } \frac{1}{\theta} > \frac{\beta_1 - \mu}{\beta_1} \tag{1.8}$$

The inequality in equation (1.8) is more likely to hold if μ is large relative to θ. A large μ relative to θ (and thus relative to σ, because $\theta > \sigma$) points to the following two opposing forces for unskilled employment: (i) a negative direct substitution-effect away from Sector 1, driven by the substitution in the production of routine tasks towards cheaper capital (i.e. μ is large); (ii) a positive but small scale-effect towards Sector 1 following a decrease in its output price relative to the price of Services. This scale-effect is small because the demand for Services is price-inelastic (i.e. θ and therefore σ is small). In sum, unskilled workers will reallocate from Sector 1 towards Services if the task substitutability between new technologies and unskilled workers in Sector 1 is sufficiently high relative to the price-elasticity (in absolute terms) of consumer demand for Services.

Skilled labour 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 decline in the price of capital leads to a greater adoption of routine tasks in Sector 2 than in Sector 1. In our framework, this leads to a decline in the output price of Sector 2 relative to Sector 1 (see also below). The demand for abstract labour tasks in Sector 2 relative to Sector 1 increases because the decline in the relative output price of Sector 2 leads to a positive scale-effect in Sector 2 relative to Sector 1 for skilled employment. This relative positive scale-effect for Sector 2 is large because the demand for goods is price-elastic, as given by $\theta > 1$, such that it dominates $\beta_1 < \beta_2$ or that the share of output going to abstract labour tasks is smaller in Sector 2 than in Sector 1. In sum, skilled workers reallocate from Sector 1 to Sector 2 if consumer demand for goods using skilled workers intensively is sufficiently price-elastic.

1.2.2.2 Changes in relative output prices and volumes

From the reallocation of workers discussed above we can predict changes in relative output prices and output volumes. If $L_r \rightarrow 0$ and $L_{a1} \rightarrow 0$, we have that:

$$\frac{p_s}{p_2} \rightarrow \infty \tag{1.9}$$

$$\frac{p_1}{p_2} \rightarrow \infty \tag{1.10}$$

The increase in the price of Services relative to Sector 2 and of Sector 1 relative to Sector 2 is driven by our assumption that the routine task intensity of Sector 2 is larger than Sector 1 and also larger than Services where it equals zero ($\beta_2 > \beta_1 > 0$). Following technological progress, the greater accumulation of routine tasks in Sector 2 is driving down its output price relative to Services as well as relative to Sector 1.

These predicted changes in relative output prices go hand in hand with relative changes in consumption or output volumes:

$$\frac{C_{g2}}{C_s} \to \infty \tag{1.11}$$

$$\frac{C_{g2}}{C_{g1}} \to \infty \tag{1.12}$$

In sum, our framework predicts a relative decline of output prices and a relative increase of output volumes for more routine-task intensive sectors.

1.2.3 Empirical implementation

Equations (1.5) and (1.6) together with the assumption that $\beta_2 > \beta_1$ also imply that Sector 2 is 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 labour, capital and output markets gives:

$$CAP_1 = \frac{p_k K_1}{Y_{g1}} = \frac{\partial Y_{g1}}{\partial K_1}\frac{K_1}{Y_{g1}} = \beta_1 \frac{K_1^{\mu}}{L_r^{\mu} + K_1^{\mu}} \leq \beta_1 \tag{1.13}$$

$$CAP_2 = \frac{p_k K_2}{Y_{g2}} = \frac{\partial Y_{g2}}{\partial K_2}\frac{K_2}{Y_{g2}} = \beta_2 \tag{1.14}$$

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 and use this ranking to test predictions from our framework in the empirical analysis below.

Specifically, we estimate the following regression equation:

$$\Delta Y_{jct} = b_0 + b_1 rank[CAP]_{jc} + b_2 rank[CAP]_{jc}{}^2 + \gamma_c + \eta_t + \varepsilon_{jct} \tag{1.26}$$

where ΔY_{jct} is the five-year percentage point difference between years *t* and *t-5* in the outcome variable of sector j in country c, $rank[CAP]_{jc}$ is the ranking of sectors *j* by ICT capital intensity of country c in 2005. γ_c and η_t are country and year fixed effects respectively, and ε_{jct} is an error term. By including fixed effects we rule out that our outcomes are driven by general trends or country-specific shocks.[8]

Note that the ranking of ICT capital intensity is time invariant, because the ranking of sectors by their ICT capital intensity is found to be stable over time.[9] Therefore, the ICT capital intensity of a sector *j* in

[8] Note that these fixed effects are redundant when the outcome variable is employment shares because these shares are calculated at the country-year level.

[9] Tables 1.B1 and 1.B2 in Appendix 1.B shows Spearman rank correlation coefficients of sectors ranked by their capital intensity across years by country and across countries for the year 2015.

country *c* in 2005, $CAP_{jc} \in [0, 1]$, is used in the empirical analysis below. However, using ICT capital intensity in 1980 or a measure averaged over time would not qualitatively change our results.

Our model predicts that a U-shaped relationship exists between a change over time in a sector's employment share and its ICT-capital intensity ranking. In terms of equation (1.15), this implies that $b_1 < 0$ and $b_2 > 0$. Our model also predicts monotonic changes in relative output prices and output volumes. Firstly, the conditions discussed in Section 1.2.2 showed that, over time, relative output prices decline in sectors with higher ICT-capital intensity. Secondly, this coincides with relative output volumes increasing in sectors with higher ICT-capital intensity. For our empirical equation (1.15), this implies that $b_2 = 0$ and that $b_1 < 0$ for output prices but $b_1 > 0$ for output volumes.

1.3 Data sources

To test the predictions made by the model presented above, EUKLEMS data from the March 2011 release are used for the period 1980-2005.[10] This dataset contains information about output volume and prices, value added, and labour and capital inputs for the United States and 12 European countries at the 2-digit level of ISIC (revision 3) sectors reported in Table 1.1. 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 1.1, are discarded due to limited data availability, resulting in a final sample of 28 sectors in 13 countries used in the empirical analysis below.[11] The 13 countries are Austria, Belgium, Denmark, Finland, France, Germany, Italy, Ireland, Netherlands, Spain, Sweden, United Kingdom and United States.

Column (1a) of Table 1.1 ranks sectors according to their ICT-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.[12] 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.

[10] See Timmer et al. (2007) for further details about EUKLEMS data. Unfortunately, more recent updates of the dataset do not include the breakdown of capital compensation into ICT and non-ICT which is crucial in linking our framework to the empirics as explained in section 1.2.3.

[11] Another reason not to include the agricultural sector is that its highly technological production is not captured by the accumulation of computer capital, which is the focus of this paper

[12] EUKLEMS defines ICT-capital compensation as the product of the ICT-capital stock (consisting of office, process control and computing equipment, communication equipment and software) and its user cost. Stocks are derived from investment flows in ICT-capital using the perpetual inventory model. See Table 1.B3 in the Annex 1.B for more information on the content of ICT-capital.

Table 1.1: ICT capital intensity, employment share, output volume and prices per sector, cross-country average, 1980-2005

	(1) ICT Capital intensity		(2) Employment shares		(3) Output volume	(4) Output price
	(a) 2005 (in %)	(b) Percentage point change 1980-2005	(a) 2005 (in %)	(a) Percentage point change 1980-2005	% change 1980-2005	(a) % change 1980-2005
Private Households with Employed Persons	0.03	0.03	1.29	0.22	87.73	233.85
Agriculture, Hunting, Forestry and Fishing	0.63	0.34	4.34	-5.69	29.38	42.96
Real Estate Activities	0.84	0.11	1.16	0.42	116.60	262.69
Construction	1.40	0.88	8.09	-0.02	46.41	186.92
Hotels and Restaurants	1.57	-0.03	4.66	1.23	72.44	240.29
Health and Social Work	1.63	0.60	10.44	3.30	115.32	246.19
Mining and Quarrying	1.75	0.93	0.22	-0.45	126.56	123.28
Education	1.75	0.78	6.07	0.90	58.45	246.95
Wood and Wood Products	1.97	0.71	0.63	-0.29	69.38	104.82
Textiles, Textile, Leather and Footwear	2.08	1.37	0.80	-1.95	-30.95	102.25
Manufacturing Not Elsewhere Classified and Recycling	2.19	1.01	0.93	-0.39	75.33	126.79
Other Non-Metallic Mineral Products	2.29	0.64	0.69	-0.45	42.83	138.00
Rubber and Plastics	2.49	1.32	0.70	-0.08	152.74	92.76
Basic and Fabricated Metals	2.56	1.48	2.30	-1.04	55.28	116.52
Retail Trade and Repair of Household Goods	2.80	1.31	7.53	-0.33	95.14	154.36
Public Administration	2.87	1.66	6.79	-0.34	48.50	207.74
Food, Beverages and Tobacco	2.95	1.64	2.07	-0.99	49.91	98.11
Sale, Maintenance and Repair of Motor Vehicles	3.33	1.88	2.30	-0.03	108.69	171.39
Electricity, Gas and Water Supply	3.69	1.35	0.59	-0.29	107.27	122.05
Machinery Not Elsewhere Classified	3.70	2.00	1.72	-0.72	77.47	123.51
Transport Equipment	3.73	2.65	1.28	-0.68	115.72	124.31
Other Community, Social and Personal Services	3.83	-0.10	4.80	1.63	114.38	243.39
Chemicals and Chemical Products	4.02	2.51	0.98	-0.39	246.59	91.71
Transport and Storage	5.26	2.98	4.94	0.15	115.98	144.67
Wholesale Trade and Commission Trade	5.54	2.77	4.92	0.20	130.36	141.04
Pulp, Paper, Printing and Publishing	5.77	3.42	1.46	-0.66	103.47	126.87
Electrical and Optical Equipment	5.96	2.87	1.79	-0.74	736.75	37.40
Renting of Machinery & Equipment and Other Business Activities	7.34	2.20	11.84	7.45	257.15	226.20
Coke, Refined Petroleum and Nuclear Fuel	7.48	4.81	0.08	-0.07	62.46	118.63
Financial Intermediation	14.47	8.46	3.03	0.27	195.53	167.98
Post and Telecommunications	18.96	6.15	1.56	-0.18	413.60	62.26

Source: EUKLEMS 2011 release

Notes: Cross-country averages of Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Sweden, United Kingdom and United States. ICT capital intensity is missing in 1980 for Ireland and Sweden. Employment is defined in hours worked. Shares are defined at country-year level.

Column (2a) of Table 1.1 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 (2b) of Table 1.1 gives percentage-point changes in employment shares in the period 1980-2005. In line with job polarisation, the column shows an increase in some of the least capital-intensive sectors (e.g. "Hotels and Restaurants", "Health and Social Work") and in some of the most capital-intensive sectors (e.g. "Business Activities"), at the expense of employment in middling-sectors mainly concentrated in manufacturing.

Finally, columns (3) and (4) in Table 1.1 use EUKLEMS data from the March 2011 release to report the percentage increase between 1980 and 2005 in sectoral output volumes and prices averaged across 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. 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 (3) 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 (4) 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.

1.4 Main results

1.4.1 Employment shares

Table 1.2 reports regression estimates for b_1 and b_2 from equation (1.15) with the change in employment shares as dependent variable, using all years in column (1), and by decade in columns (2)-(4). Starting with column (1a), estimates for b_1 and b_2 are respectively negative and positive and both significant suggesting that there exists a U-shaped relationship between changes in sectoral employment shares between 1980 and 2005 and sectors' ICT capital intensity. The bottom of column (1a) shows that taking the estimates to compute the turning point in the U-shaped relationship at face value implies that on average 47% of all workers in a country in 2005 are employed in sectors with ICT capital intensities below the estimated turning point. A more conservative estimate of this percentage could set the turning point one standard deviation lower or higher, giving 44% and 48% respectively. As a robustness check, column (1b) shows that a regression estimate for b_1 when setting $b_2 = 0$ in equation (1.15) 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)-(4) of Table 1.2 repeat the exercise in column (1) by decade. The fact that all point estimates for b_1 and b_2 are negative and positive respectively suggest that there has been polarisation in

all periods. However, the point estimates in columns (2a) and (3a) also suggest that it was stronger in the 1980s and 1990s. Moreover, the significant point estimate in column (2b) indicates that relative employment growth in ICT-capital intensive sectors was particularly strong in the 1980s. For the period 2000-2005, the point estimates that are reported in column (4) show that the nature of polarisation changed during this period: the point estimates in column (4a) are statistically significant, but column (4b) suggests that the changes in employment shares were particularly large for sectors with the lowest ICT capital intensities. This is als confirmed by the increased employment share on the declining section of the U-shape.

Table 1.2: Regression results: Changes in employment shares by ICT capital intensity (in percentage points, 1980-2005)

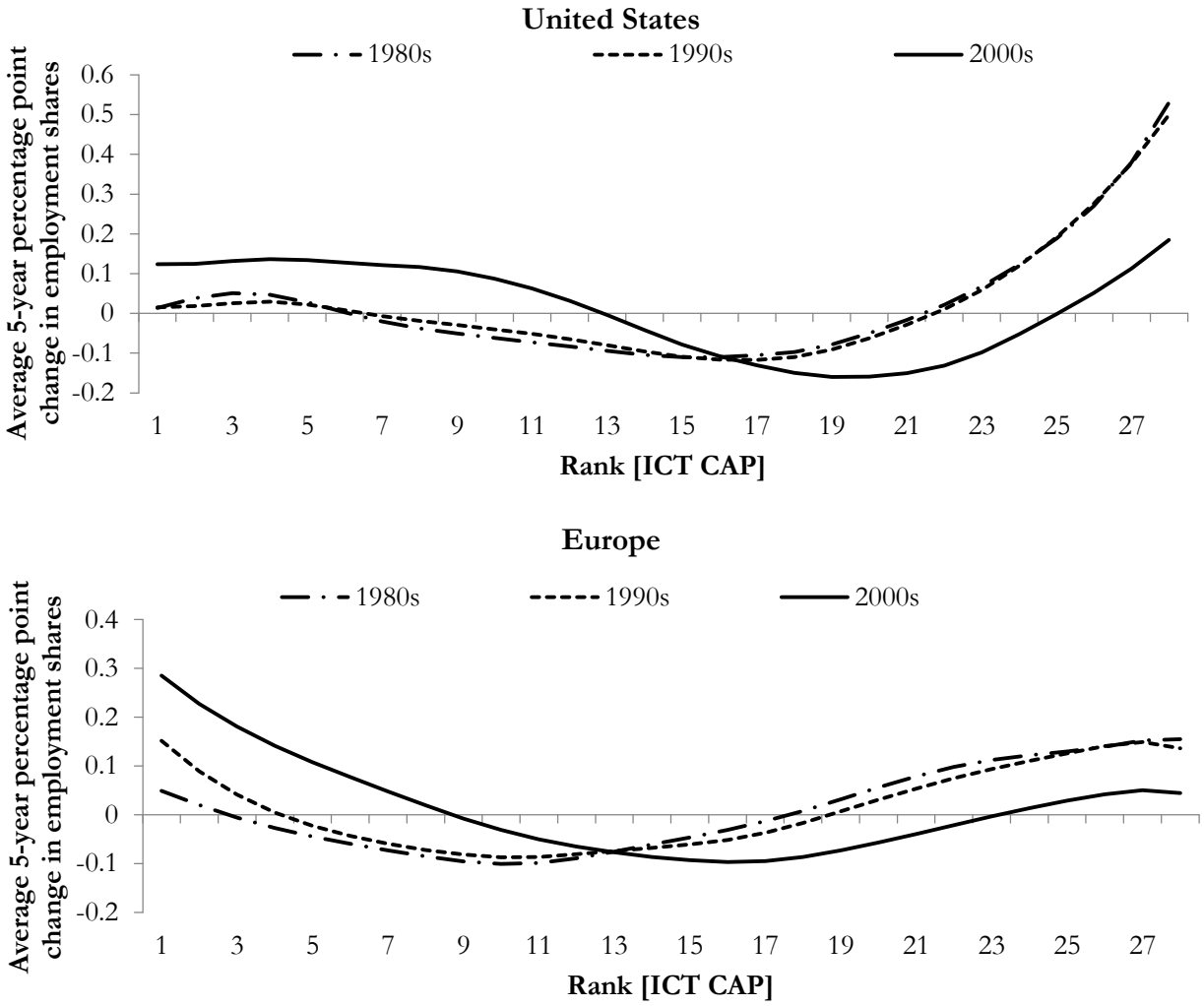
	Δ Employment share (percentage point)							
	(1)		(2)		(3)		(4)	
	All years		1980s		1990s		2000s	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
rank(CAP)	-0.032***	0.005	-0.022**	0.008***	-0.032***	0.006*	-0.052***	-0.006**
	(0.009)	(0.003)	(0.010)	(0.003)	(0.012)	(0.004)	(0.014)	(0.004)
[rank(CAP)]²	0.001***		0.001***		0.001***		0.002***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Constant	0.118***	-0.066*	0.031	-0.122***	0.104	-0.086*	0.318***	0.087
	(0.055)	(0.038)	(0.066)	(0.044)	(0.077)	(0.047)	(0.103)	(0.061)
point estimate	47.1		41.3		47.1		57.3	
point estimate - SD	43.9		34.3		41.3		53.7	
point estimate + SD	48.4		47.1		48.4		61.2	
N	*1820*	*1820*	*728*	*728*	*728*	*728*	*364*	*364*

Notes: Standard errors, in brackets, 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. Rank(CAP) is based on a cross-country average in 2005. Point estimates and standard deviations for the level of rank(CAP) 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.

To see these differences between time periods more clearly, Figure 1.1 shows kernel plots of average annual employment share changes by a ranking of sectors according to their ICT capital intensity in 2005. The top panel shows these kernel plots for the US, whereas the bottom panel does the same using average employment share changes and an ICT-capital intensity ranking across our sample of 12 European countries. Figure 1.1 shows that polarisation was present in all decades, but also that there are important differences between decades. In the 1980s and 1990s the relationship clearly is U-shaped with strong growth in ICT capital intensive sectors in particular. However, by the early 2000s a clear tilting has taken. This tilting over time in employment share changes corresponds to existing evidence for the US in Acemoglu and Autor (2011), Mishel, Shierholz, and Schmitt (2013), Beaudry, Green and Sand (2014, 2016) 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 ICT capital intensity. Interestingly,

the bottom panel of Figure 1.1 shows that a similar tilting exists across the 12 European countries in our sample.[13]

Figure 1.1: Kernel plot of average 5-year employment share changes by sectoral capital intensity (in percentage points, 1980-2005)



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 worked. European employment shares defined as the average of country-level employment shares in the 12 European countries.

In sum, consistent with the framework presented above, in sum we find that there is job polarisation when sectors are ranked by their ICT-capital intensity. That is, workers are increasingly employed in the least and most ICT capital intensive sectors in the economy and this reflects the increased (relative) demand for non-routine labour, both abstract and manual. Moreover, in line with existing evidence on

[13] The bottom panel of Figure 1.1 shows a kernel plot of the average 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. This also suggests that differences between countries in the extent to which there is job polarisation are relatively small.

occupational employment share changes, we showed that the shape of between-sector job polarisation has altered over time. After 2000, there has been a tilting of employment share change: Whereas the 1980s were characterized by relatively strong employment growth in the most ICT capital intensive sectors (especially in the US), the opposite holds after 2000 with stronger employment growth in the least ICT capital intensive sectors.

1.4.2 Changes in relative output prices and volumes

As discussed in section 1.2.3, our framework also predicts a decrease in the relative output price for sectors with higher ICT-capital intensities. This implies that the least ICT-capital intensive sectors, mostly in-person services, will see their relative price increase over time. This is in line with the well-known phenomenon called 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.[14] He refers to teaching as an example where labour itself is the output and which contained very little potential productivity growth: regardless of new inventions and gains from specialization, "there still seems to be fairly firm limits to class size" (Baumol, 1967). An alternative view, and the one that we take in this chapter, is that Baumol's cost disease does not result from unbalanced productivity growth across sectors but from differences in ICT-capital intensities between sectors (see also Acemoglu and Guerrieri (2008)). In particular, the framework presented here assumes that sectors are more ICT-capital intensive if they are more routine-task intensive. Consequently, consistent with Baumol's cost disease, more ICT-capital intensive sectors will innovate more to see their relative marginal costs and therefore their relative output price fall. Also consistent with Baumol's cost disease is that the least ICT-capital intensive sectors experience both increasing relative prices and relative employment.[15]

Table 1.3 shows regression estimates for equation (1.15) 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 the prediction from our model, columns (1a) and (1b) of Table 1.3 show that there is a significant negative relationship between the ICT-capital intensity of sectors and growth in output prices. Columns (2)-(4) show relatively small differences across decades. Figure 1.2 further illustrates the pervasiveness of these relative price changes in both the US as well as Europe.[16]

[14] 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).

[15] Young (2014) also predicts Baumol's cost disease while assuming that innovation is balanced across sectors. However, in contrast to Young (2014) it is assumed throughout this paper that preferences are homothetic.

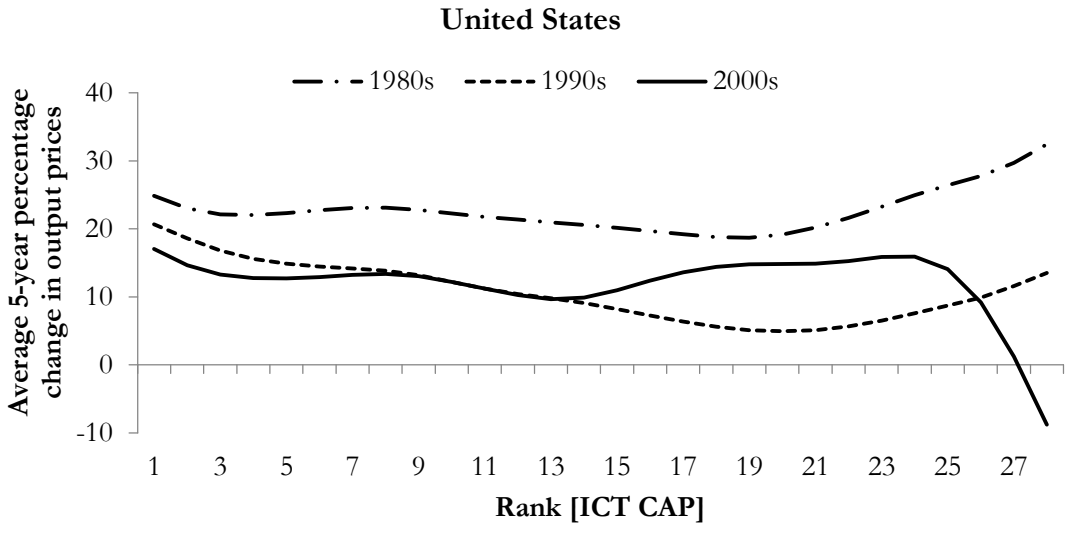
[16] The sudden changes in the slope at the top end of the ranking may be caused by the less accurate performance of kernel plots at the boundary of the sample range because of the use of a symmetric estimation window. For the most recent decade, the sector "Refined Petroleum" experienced high positive growth in the US during the 2000s, likely caused by mechanisms outside our framework, while the most capital intensive sector "Post & Telecommunications" experienced a net decline in prices.

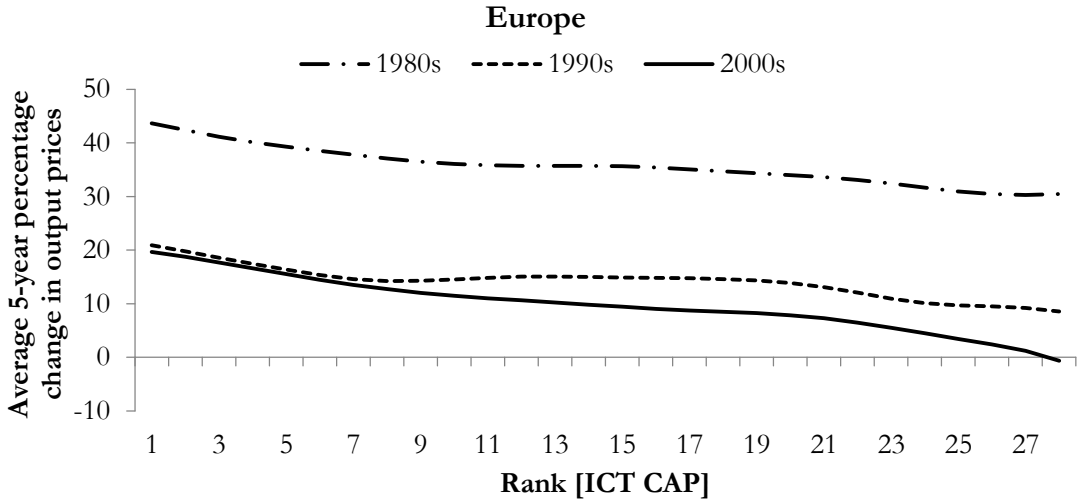
Table 1.3: Regression results: Changes in output prices by sectoral capital intensity (in percentages, 1980-2005)

	Δ Output price (%)							
	(1)		(2)		(3)		(4)	
	All years		1980s		1990s		2000s	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
rank(CAP)	-0.417	-0.375***	-0.585	-0.353**	-0.212	-0.316***	-0.490	-0.540***
	(0.404)	(0.073)	(0.420)	(0.105)	(0.822)	(0.094)	(0.425)	(0.114)
[rank(CAP)]^2	0.001		0.008		-0.004		-0.002	
	(0.013)		(0.014)		(0.27)		(0.015)	
Constant	42.482***	42.273***	37.741***	36.577***	16.589***	17.107***	12.721***	12.970***
	(3.586)	(2.581)	(3.485)	(3.038)	(4.243)	(2.272)	(2.926)	(2.393)
point estimate	100.0		100.0		100.0		100.0	
point estimate – SD	0.0		0.0		0.0		0.0	
point estimate + SD	100.0		100.0		100.0		100.0	
N	*1820*	*1820*	*728*	*728*	*728*	*728*	*364*	*364*

Notes: Prices are indexed, 1995=100. Standard errors clustered at the country-sector level. Country and time fixed effects included. Δ refers to stacked 1980-1985, 1985-1990, 1990-1995, 1995-2000 and 2000-2005 changes. Rank(CAP) is based on a cross-country average in 2005. Point estimates and standard deviations for the level of rank(CAP) 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.

Figure 1.2: Kernel plots of average 5-year output price changes by sectoral capital intensity (in percentages, 1980-2005)





Notes: Prices are indexed. 1995=100. Percentage changes in output prices by 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.

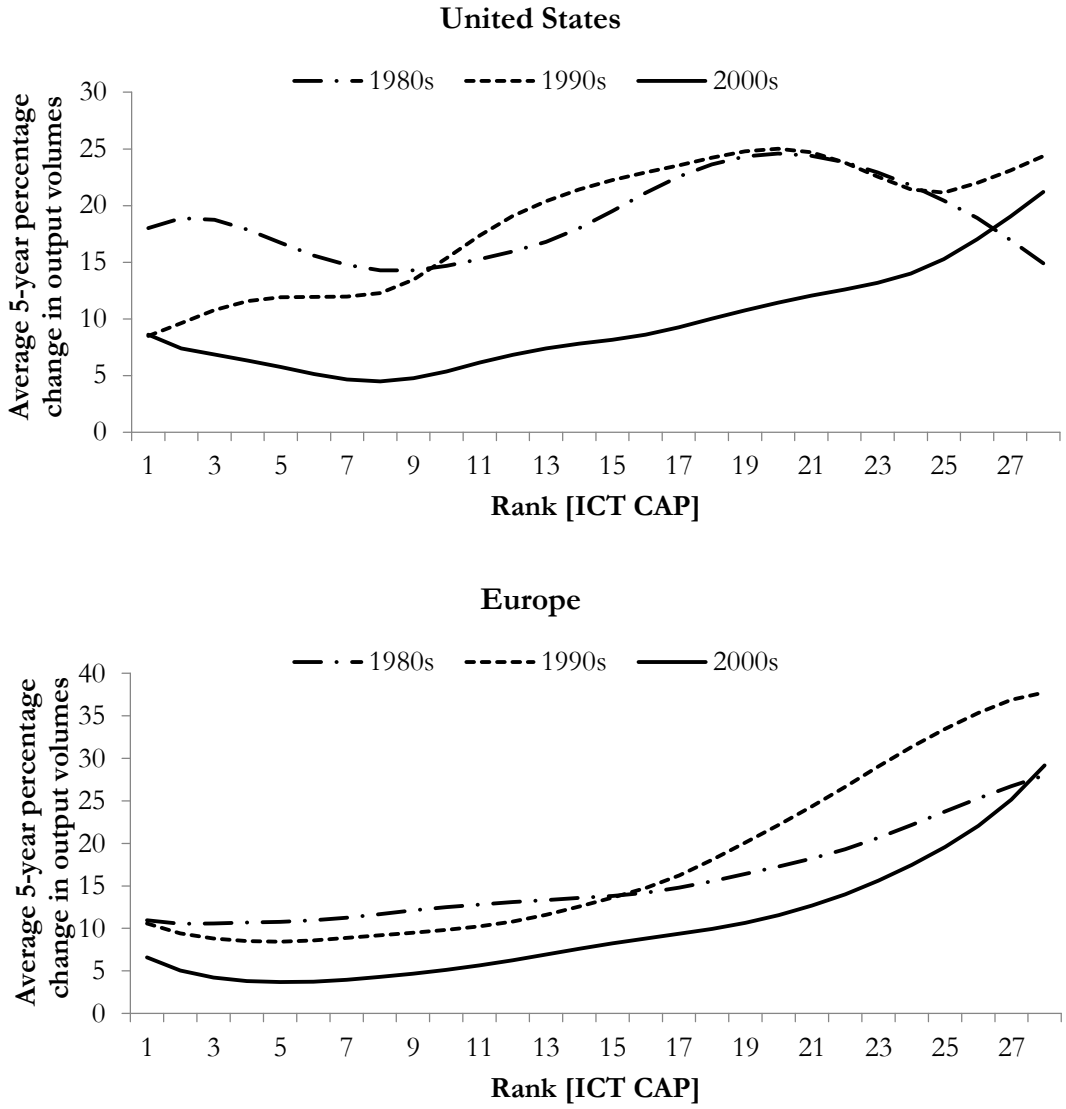
Finally, our framework also predicts that the accumulation of ICT-capital and therefore output growth is faster the more ICT-capital intensive a sector is. Table 1.4 therefore shows estimates for equation (1.15) using as the dependent variable the percentage change in the output volume, and shows this is the case indeed. Figure 1.3 further illustrates that these patterns hold in the U.S. as well as in Europe.

Table 1.4: Regression results: Changes in output volumes by sectoral capital intensity (in percentages, 1980-2005)

	Δ Output volume (%)							
	(1)		(2)		(3)		(4)	
	All years		1980s		1990s		2000s	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
rank(CAP)	-0.597	0.812***	-0.369	0.559***	-0.713	1.114***	-0.819	0.712***
	(0.424)	(0.184)	(0.427)	(0.126)	(0.708)	(0.350)	(0.531)	(0.145)
[rank(CAP)]²	0.049***		0.032**		0.063*		0.053**	
	(0.019)		(0.016)		(0.033)		(0.021)	
Constant	5.483*	-1.559	4,428	-0.215	8.125	-1.010	5.146***	-2.510
	(2.985)	(4.112)	(3.118)	(3.152)	(5.483)	(5.644)	(3.494)	(3.483)
point estimate	27.3		23.9		23.89		30.14	
point estimate – SD	13.6		3.59		9.47		23.89	
point estimate + SD	34.3		38.21		34.27		38.21	
N	*1820*	*1820*	*728*	*728*	*728*	*728*	*364*	*364*

Notes: Output volumes are indexed, 1995=100. Standard errors clustered at the country-sector level. Country and time fixed effects included. Δ refers to stacked 1980-1985, 1985-1990, 1990-1995, 1995-2000 and 2000-2005 changes. Rank(CAP) is based on a cross-country average in 2005. Point estimates and standard deviations for the level of rank(CAP) 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.

Figure 1.3: Kernel plots of average 5-year output price changes by sectoral capital intensity (in percentages, 1980-2005)



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

In sum, there are important technology-induced changes in relative output prices on product markets in line with Baumol's cost disease. These changes in relative output prices entail changes in consumption and, therefore, in output volumes. In turn, these changes in relative output volumes on product markets lead to scale-effects in labour demand on labour markets. In particular, these scale-effects mute the direct substitution-effect of technological progress leading to a reallocation of unskilled workers from sectors with middling ICT-capital intensities towards sectors with lower ICT-capital intensities, and they amplify the reallocation of skilled workers from sectors with middling ICT-capital intensities towards sectors with higher ICT-capital intensities. What our analyses therefore shows is that Baumol's

cost disease and job polarisation are phenomena that are intrinsically related by the interplay between the nature of technological progress, the direct substitutability between differently-skilled workers and new technologies in production, and the price-elasticities of product demand for different goods and services driven by the substitutability between these different goods and services in consumption.

1.5 Robustness checks

1.5.1 IV regression results

One concern in our empirical analysis is that the ranking of sectors by their ICT-capital intensity in 2005 is endogenous. To address this concern, we can use 2SLS estimators to instrument the sector ranking with the ranking in the previous period relative to the period of analysis. The second-stage estimates for our three outcome variables are shown in Table 1.5.[17,18] In the upper part of the table we report. In sum, our results remain qualitatively unaffected.

Table 1.5: Regression results: Changes in employment shares and output prices by sectoral ICT capital intensity (in percentage points, 1980-2005), IV estimates

	All years, 2SLS					
	(1)		(2)		(3)	
	Δ employment shares (% points)		Δ Output price (%)		Δ Output volume (%)	
	(a)	(b)	(a)	(b)	(a)	(b)
rank(ICAP)_t-1	-0.039***	0.004	-0.760	-0.355***	-0.878*	0.832***
	(0.013)	(0.004)	(0.523)	(0.109)	(0.462)	(0.252)
[rank(CAP)]²_t-1	0.001***		0.014		0.059***	
	(0.000)		(0.018)		(0.020)	
Constant	0.162	-0.059	25.334***	23.276***	16.292***	7.615*
	(0.113)	(0.083)	(4.043)	(2.496)	(3.534)	(4.387)
N	*1456*	*1456*	*1456*	*1456*	*1456*	*1456*

Notes: Prices and output volumes are indexed, 1995=100. Standard errors clustered at the country-sector level. Country and time fixed effects included in the price and volume regressions. Employment expressed in hours worked. Δ refers to stacked 1985-1990, 1990-1995, 1995-2000 and 2000-2005 changes. Shares defined at the country-year level. Ranking of sectors by ICT capital intensity has been instrumented with lagged values.

1.5.2 Excluding public sectors

Outcomes in public sectors are not exclusively determined by market forces, as is assumed by our framework. In addition, information about ICT-capital intensity, output prices and volumes for public goods and services is difficult to measure. Therefore, there might be substantial measurement error in them, such that including them in the analyses gives inconsistent point estimates and/or incorrect standard errors for these point estimates. Therefore, we re-estimate our empirical specification leaving out the following sectors: "Education", "Health and Social Work" and "Public administration and defence". Table 1.6 shows estimates for our three main outcome variables that are qualitatively similar to the estimates shown in previous tables.

[17] Note that we lose the first year of data, which we can only use as an instrument.

[18] The first stage results confirms the strong correlation of sector rankings across time, see Table 1.B.4 in Annex 1.B.

Table 1.6: Regression results: Changes in employment shares and output prices by sectoral capital intensity, excluding public sectors (1980-2005)

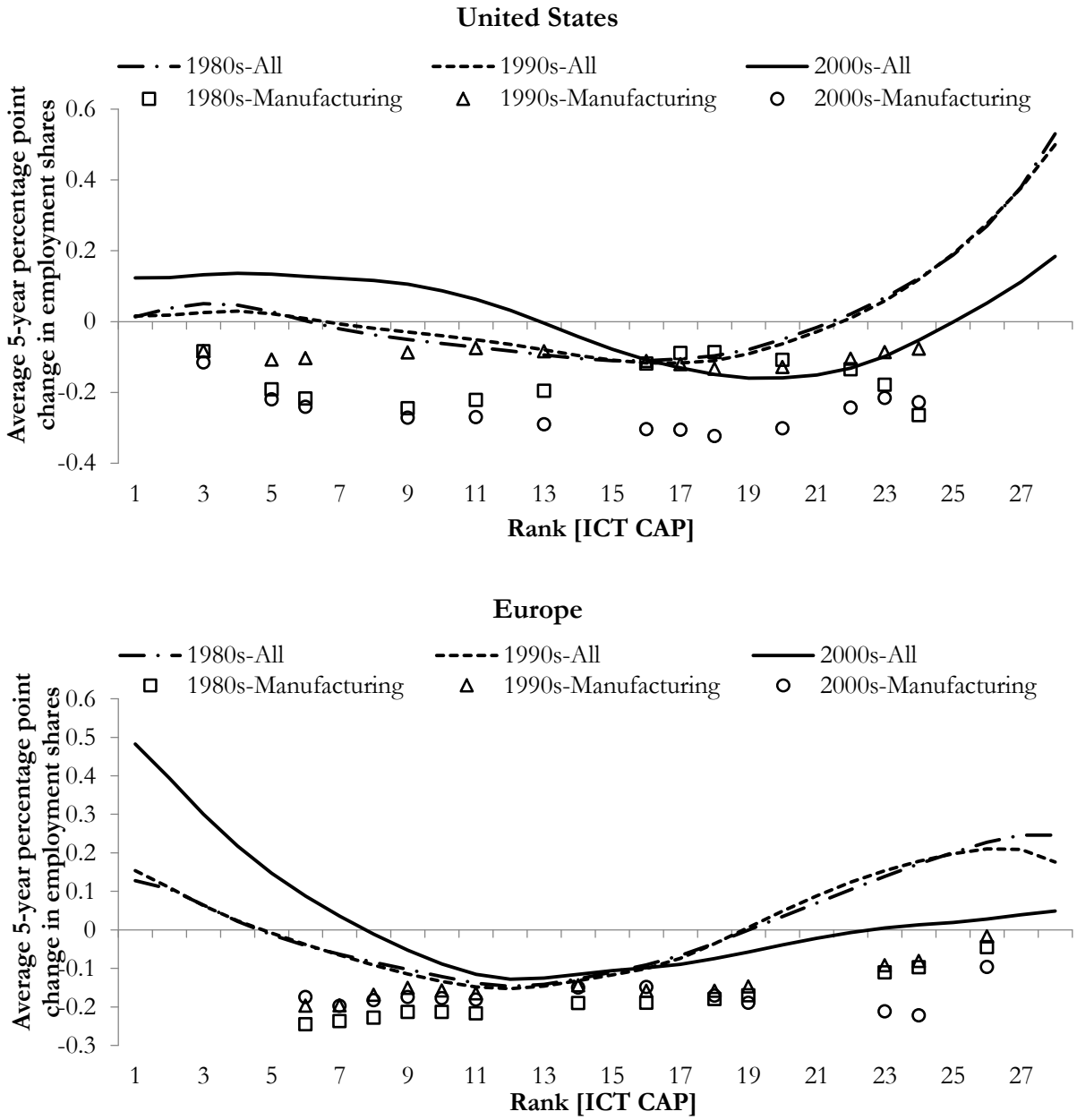
	All years, excluding public sectors					
	(1)		(2)		(3)	
	Δ employment shares (% points)		Δ Output price (%)		Δ Output price (%)	
	(a)	(b)	(a)	(b)	(a)	(b)
rank(CAP)	-0.026***	0.009***	-0.544	-0.335***	-0.414	0.847***
	(0.010)	(0.003)	(0.475)	(0.081)	(0.478)	(0.193)
[rank(CAP)]²	0.001***		0.007		0.043**	
	(0.000)		(0.016)		(0.020)	
Constant	-0.024	-0.208***	42.771***	41.664***	4.020	-2.681
	(0.092)	(0.080)	(4.258)	(1.182)	(3.402)	(4.556)
Employment share on declining section (in %)						
point estimate	43.9		100.0		19.9	
point estimate -SD	38.2		0.0		3.6	
point estimate + SD	47.1		100.0		34.3	
N	*1625*	*1625*	*1625*	*1625*	*1625*	*1625*

Notes: Prices and output volumes are indexed, 1995=100. Standard errors clustered at the country-sector level. Country and time fixed effects included in the price and volume regressions. 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 rank(CAP) 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.

1.5.3 Employment de-industrialisation

Rodrik (2015) and some related work have recently documented a process of employment deindustrialization in advanced economies: A structural employment shift away from manufacturing industries due technological progress in those (but not other) sectors and/or increasing imports of manufactured goods through international trade. If manufacturing sectors would be exclusively situated in the middle of our ICT-capital intensity ranking, this process of employment de-industrialization would be observationally equivalent to our framework in that it would also predict job polarisation. However, our data suggest that manufacturing sectors are located across a wide range in our ICT-capital intensity ranking. To see this, Figure 1.4 overlays the predicted change in the employment shares for all sectors in the economy (grey lines) with the predictions for manufacturing sectors separately (black markers). Although predominately situated in the middle, manufacturing sectors are in both the declining as well as inclining parts of the overall U-shape. What this suggests is that de-industrialization is less suited to explain economy-wide job polarisation. But Figure 1.4 also clearly shows that the process of employment de-industrialization does exist: Predicted employment share changes for manufacturing sectors are mostly negative, especially after 2000.

Figure 1.4: Smoothed average 5 year employment share changes by ICT-capital intensity for manufacturing and all sectors (in percentage points, 1980-2005)



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

1.5.4 Job Polarisation: Occupation based measures

A difference between our approach in this chapter and some (but certainly not all) of the previous literature on job polarisation is that we rank jobs by their sector's ICT-capital intensity instead of by an

occupation's task content. In particular, Autor et al. (2003) introduced an occupation-specific Routine Task Intensity index (RTI-index) that has been used extensively in the literature on occupational job polarisation. The RTI-index of Autor et al. (2003) correspond to the three tasks done by workers in our framework: Manual tasks (*M*), Routine tasks (*R*), and Abstract tasks (*A*). For each occupation, these three measures are derived from the U.S. Dictionary of Occupational Titles (DOT). The Manual task measure (M_o) corresponds to the DOT variable which captures the importance of "Eye-hand-foot coordination" in occupation *o*. The Routine task measure (R_o) is a simple average of two DOT task measures for an occupation: "Set limits, tolerances and standards" and "Finger dexterity" capturing the cognitive and manual aspect of routine tasks respectively. The Abstract task measure (A_o) is also an average of two DOT measures: "Direction control and planning" and "GED math" capturing the interactive and more analytical aspect of Abstract tasks. The RTI-index for occupation *o* is then computed by taking the log of the ratio of the Routine task measure (R_o) over the sum of Manual (M_o) and Abstract (A_o) task measures:

$$RTI_o = ln\left(\frac{R_o}{M_o + A_o}\right) \tag{1.16}$$

with positive values for RTI_o if $R_o > M_o + A_o$ and negative values otherwise.

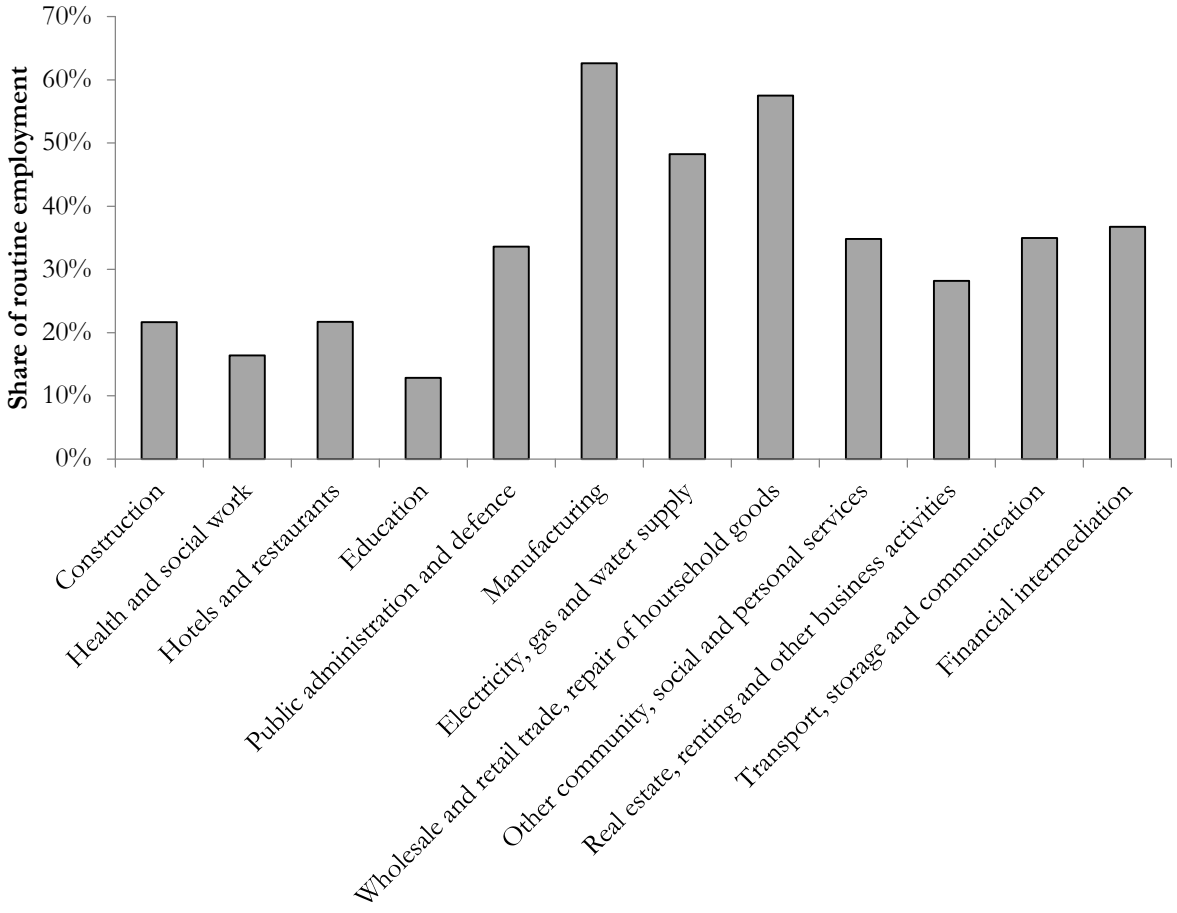
To see whether our framework and empirical results are consistent with studies defining job polarisation in terms of occupations rather than sectors, we need to convert the occupation-specific RTI_o into a sector-specific measure that can be compared to its ICT-capital intensity. To do this, we use occupation-industry employment shares from the European Union Labour Force Survey (EULFS) for the 12 European countries that are also covered by EUKLEMS. In particular, we use the EULFS to compute employment shares by 2-digit ISCO08-occupations in 1-digit NACE (rev.1)-industries.[19]

With these data, we can then compute the share of workers employed in routine occupations, i.e. occupations with RTI_o >0, for each sector at the 1-digit level. Occupational job polarisation and polarisation in our stylized framework would then be capturing the same phenomenon if the share of workers in routine occupations is lower in the least ICT-capital and most ICT-capital intensive sectors relative to middling sectors. Figure 1.5 shows that this is the case indeed: The sector with the largest share of occupational employment in routine tasks is "Manufacturing" with 63%, and second is "Wholesale and Retail" with 58%. These sectors have middling levels of ICT-capital intensity. ICT-capital intensive sectors such as "Business Services", "Transport, Storage and Communications" and "Financial Intermediation" have shares of employment in routine occupation between 28 and 37%. The smallest shares of employment in routine labour tasks can be found in the in-person sectors, around 20% or below.

[19] ISIC (rev.3) used in EUKLEMS and NACE (rev.1) used in the EU-LFS are harmonized at the 1-digit level.

Figure 1.5: Share of routine employment per sector, European countries

Sectors ranked by ICT capital intensity



Source: EUKLEMS 2011 Release; Goos, Manning and Salomons (2014); EU-LFS;

Notes: The United States is left out because of lack of data coverage in Goos et al. (2014) and EU-LFS. Sectors on the x-axis are ranked by their employment weighted average ICT capital intensity. Occupation level RTI is taken from Table 1 of Goos et al. (2014). These are aggregated to 1 digit NACE Rev. 1 sector level by taking the share of employment in 2005 with RTI>0 and averaged across European countries.

1.6 Conclusions

This chapter first gave a brief history of the literature on job polarisation: The idea that job markets are polarizing into lovely and lousy jobs at the expense of middling jobs originates from the early 1980s. During the following decades, the phenomenon of job polarisation was documented for many advanced economies, and its drivers became better understood. To summarize the intuition that economists currently use to explain job polarisation, this chapter then provided a stylized but intuitive framework. The contribution of this framework is that it explicitly derived critical assumptions about key structural parameters in labour and product markets that can predict job polarisation following technological progress: 1) the task substitutability between new technologies and workers in middling-jobs must be sufficiently high relative to the price-elasticity (in absolute terms) of consumer demand for goods and services using low-paid workers intensively; and 2) the price-elasticity of consumer demand for goods and services using high-paid workers intensively must be sufficiently high. A broad sample of

data spanning 28 sectors in the United States and 12 European countries for the period 1980 to 2005 provided some evidence in support our framework. Most importantly, this chapter made clear that job polarisation is not a natural law that must hold at all times and in all places, stressing the academic and societal relevance of an ongoing job quality debate.

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Annex 1.A Model Annex

This annex provides details the theoretical framework presented in Section 1.2, and further extends the basic model to allow for heterogeneity in skills and productivity.

1.A.1 Basic model

1.A.1.1 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:

$$\max_{K_1,K_2,L_r,L_{a1}} U = \left[C_s^{\frac{\sigma-1}{\sigma}} + C^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \text{ with } C \equiv \left[C_{g1}^{\frac{\theta-1}{\theta}} + C_{g2}^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} \tag{1.A1}$$

where:

$$C_s = Y_s = L_m = 1 - L_r \tag{1.A2}$$

$$C_{gj} = Y_{gj} - Y_{kj} \text{ with } Y_{kj} = p_k K_j \text{ for } j=1,2 \tag{1.A3}$$

$$Y_{g1} = L_{a1}^{1-\beta_1} X^{\beta_1} \quad \text{with } X \equiv \left[L_r^{\mu} + K_1^{\mu}\right]^{\frac{1}{\mu}} \tag{1.A4}$$

$$Y_{g2} = L_{a2}^{1-\beta_2} K_2^{\beta_2} \quad = \left[1 - L_{a1}\right]^{1-\beta_2} K_2^{\beta_2} \tag{1.A5}$$

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

$$p_k = \beta_1 L_{a1}^{1-\beta_1} X^{\beta_1-\mu} K_1^{\mu-1} \tag{1.A6}$$

$$p_k = \beta_2 \left[\left(1 - L_{a1}\right)/K_2\right]^{1-\beta_2} \tag{1.A7}$$

$$L_r^{1-\mu}[1 - L_r]^{-\frac{1}{\sigma}} = C^{\frac{\sigma-\theta}{\theta\sigma}} C_{g1}^{-\frac{1}{\theta}} \beta_1 L_{a1}^{1-\beta_1} X^{\beta_1-\mu} \tag{1.A8}$$

$$L_{a1}^{-\beta_1}[1 - L_{a1}]^{\beta_2} = \left[C_{g1}/C_{g2}\right]^{1/\theta}[(1-\beta_2)/(1-\beta_1)] X^{-\beta_1} K^{\beta_2} \tag{1.A9}$$

Note that equations (1.A1)-(1.A9) also give the equilibrium allocations over time for $p_k \to 0$ 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 polarisation.

1.A.1.2 Job polarisation

Job polarisation 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 $L_r \rightarrow 0$ and that $L_{a1} \rightarrow 0$ which is now shown to be the case under some additional parameter restrictions.

Unskilled labour 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: $K_1 \rightarrow \infty$ and $K_2 \rightarrow \infty$ if $p_k \rightarrow 0$. Because $K_1 \rightarrow \infty$ and L_r is bounded, *X* will essentially be determined by K_1 in the limit or $K_1/\mathrm{X} \rightarrow 1$ such that $\mathrm{X} \rightarrow \infty$: Consequently, $\mathrm{X} + K_2 \rightarrow \infty$ or the amount of routine tasks done in the economy will limit to infinity. Due to the technology embodied in (computer) capital, there is routinization through capital accumulation in the economy.[20]

Given that capital accumulates in Sectors 1 and 2, equation (1.A8) gives the conditions needed for $L_r \rightarrow 0$. To see this, first consider the consumption terms C_{g1} and C_{g2} which are both included in *C*. Making use of equations (1.A6) and (1.A7) gives:

$$C_{g1} = Y_{g1} - p_k K_1 = [1 - \beta_1 (K_1/X)^{\mu}] L_{a1}^{1-\beta_1} X^{\beta_1} \tag{1.A10}$$

$$C_{g2} = Y_{g2} - p_k K_2 = [1 - \beta_2]\left[1 - L_{a1}\right]^{1-\beta_2} \; K_2^{\beta_2} \tag{1.A11}$$

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

Substituting equation (1.A10) into equation (1.A8) gives:

$$L_r^{1-\mu}[1 - L_r]^{-\frac{1}{\sigma}} = C^{\frac{\sigma-\theta}{\theta\sigma}}[1 - \beta_1 (K_1/X)^{\mu}]^{-\frac{1}{\theta}} \beta_1 L_{a1}^{\frac{[\theta-1][1-\beta_1]}{\theta}} X^{\beta_1 - \mu - \frac{1}{\theta}\beta_1} \tag{1.A12}$$

Given that $\mu < 1$, a sufficient condition for $L_r \rightarrow 0$ on the left-hand side of equation (1.A12) is that the right-hand side of equation (1.A12) is zero asymptotically: (i) $C \rightarrow \infty$ implies that $C^{\frac{\sigma-\theta}{\theta\sigma}} \rightarrow 0$ if $\sigma < \theta$; (ii) $K_1/X \rightarrow 1$ 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 $L_{a1}^{\frac{[\theta-1][1-\beta_1]}{\theta}}$ converges to some finite number given that $\theta > 1$; (iv) Given that $\mathrm{X} \rightarrow \infty$,

[20] Moreover, given that the amount of manual and abstract tasks is bounded by L_m and L_a respectively, $\mathrm{X} + K_2 \rightarrow \infty$ implies that the share of routine tasks done in the economy converges to unity.

sufficient conditions for the right-hand side of equation (1.A12) to go to zero and therefore $L_r \rightarrow 0$ are the assumptions summarized in subsection 1.2.1 above together with:

$$L_r \rightarrow 0 \text{ if } \frac{1}{\theta} > \frac{\beta_1 - \mu}{\beta_1} \tag{1.A13}$$

Equation (1.A13) has a straightforward interpretation. For a given β_1, $L_r \rightarrow 0$ 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 labour 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 labour tasks and capital in production implies a large decrease in the demand for routine relative to manual labour 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 below), thereby increasing the demand for routine relative to manual labour 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 $L_r \rightarrow 0$. The role played by β_1 in equation (1.A13) also has a straightforward interpretation. All else equal, a smaller β_1 implies that the inequalities in equation (1.A13) 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.

Skilled labour 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. $X \rightarrow \infty$ and $K_2 \rightarrow \infty$, but also that routine tasks accumulate faster in Sector 2 than in Sector 1, i.e. $X/K_2 \rightarrow 0$.

Given that $X/K_2 \rightarrow 0$, equation (1.A9) gives the asymptotic allocation of skilled labour. Substituting equations (1.A10) and (1.A11) into equation (1.A9) gives:

$$\begin{aligned} L_{a1}^{\beta_1 + \frac{1}{\theta}(1-\beta_1)} [1 - L_{a1}]^{\frac{1}{\theta}(\beta_2 - 1) - \beta_2} \\ = [1-\beta_1][\beta_2 - 1]^{\frac{\theta-1}{\theta}} [1 - \beta_1 (K_1/X)^{\mu}]^{-1/\theta} \left[X^{\beta_1} / K_2^{\beta_2} \right]^{\frac{\theta-1}{\theta}} \end{aligned} \tag{1.A14}$$

showing that a sufficient condition for $L_{a1} \rightarrow 0$ on the left-hand side of equation (1.A14) is that its right-hand side is zero asymptotically: (i) $K_1/X \rightarrow 1$ such that $[1 - \beta_1 (K_1/X)^{\mu}]^{-1/\theta}$ converges to $[1-\beta_1]^{-1/\theta}$; (ii) $X/K_2 \rightarrow 0$ implies that $\left[X^{\beta_1} / K_2^{\beta_2} \right]^{\frac{\theta-1}{\theta}} \rightarrow 0$ given that $\beta_2 > \beta_1$ and $\theta > 1$. Consequently, the right-hand side of equation (1.A14) converges to zero such that $L_{a1} \rightarrow 0$ if the assumptions summarized in subsection 1.2.1 above hold.

The fact 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 labour 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 below), the demand for abstract labour tasks increases in 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 labour tasks in Sector 2 relative to Sector 1 dominates and $L_{a1} \to 0$. More generally, skilled workers doing abstract labour 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 labour 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 polarisation if (i)$1/[1\text{-}\mu] > 1$; (ii) $0 < \sigma < \theta < \beta_1/[\beta_1 - \mu]$; and (iii) $\theta > 1$.

1.A.1.3 Changes in relative output prices and volumes

Relative output prices and volumescan 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:

$$\frac{p_s}{p_2} = \frac{C^{(\theta-\sigma)/\sigma\theta} C_{g2}^{1/\theta}}{C_s^{1/\sigma}} \to \infty \tag{1.A15}$$

Consider the different terms on the right-hand side of equation (1A15): (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 (1.18) such that $C_{g2}^{1/\theta} \to \infty$; (iii) Given that $C_s \to 1$ as $L_r \to 0$, equation (1.A15) limits to infinity predicting that the relative price of Services must rise.

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

$$\frac{p_1}{p_2} = \left[\frac{C_{g2}}{C_{g1}}\right]^{1/\theta} \to \infty \tag{1.A16}$$

where the limit follows because $C_{g2}/C_{g1} \to \infty$. To see this, substitute equations (1.A10) and (1.A11) into C_{g2}/C_{g1}:

$$\frac{C_{g2}}{C_{g1}} = [1-\beta_2]/[1-\beta_1(K_1/X)^{\mu}][1-L_{a1}]^{1-\beta_2}/L_{a1}^{1-\beta_1} K_2^{\beta_2}/X^{\beta_1} \tag{1.A17}$$

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

Note that the predicted decline of relative output prices with the sectors use of ICT capital, goes hand in hand with an increase in the output volume as shown from $\frac{C_{g2}}{C_s} \to \infty$ and $\frac{C_{g2}}{C_{g1}} \to \infty$. In sum, besides job polarisation, our framework also predicts changes in relative output prices and volumes, consistent Baumol's cost disease. Moreover, they operate under the same critical assumptions.

1.A.2 Model with heterogeneity

1.A.2.1 Setup

Imagine an economy as presented above with the following changes made to the characteristics of labour 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 normalised to unity. An unskilled worker has a single unit of labour 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 labour which can be supplied to perform abstract tasks in Sector 1 or Sector 2. We introduce the following aspects of heterogeneity: (i) workers have skills, $\eta_i \in [0, 1[$ (with $i = h$ for skilled workers and $i = l$ for unskilled workers), distributed according to the exponential density function, $f(\eta_i) = e^{-\eta_i}$,[21] and (ii) following Gibbons et al. (2005) and Cortes (2016) 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 worker's 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 worker 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 $\gamma > 1$.[22]

The labour 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,

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

[22] Many specifications of the form $\varphi_{ij}(\eta) = c_{ij} + \gamma_{ij}\eta_i$ are possible 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 $\frac{c_{h1}}{\gamma_{h1}} > \frac{c_{h2}}{\gamma_{h2}}$. Similarly for $i = l$ we must have that $\frac{c_{ls}}{\gamma_{ls}} > \frac{c_{l12}}{\gamma_{l1}}$.

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.

Note that the labour 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.

$$\psi_{ij} = \varphi_{ij} w_{tj} \tag{1.A.18}$$

Therefore, the allocation of labour expressed in efficiency units is determined by making a single worker with skill level i indifferent, all other workers will choose to work where their earnings are highest and sort accordingly.[23] This gives,

$$\varphi_{ls}(\eta_l^*) w_m = \varphi_{lr}(\eta_l^*) w_r \tag{1.A.19}$$

$$\varphi_{h1}(\eta_h^*) w_{a1} = \varphi_{h2}(\eta_h^*) w_{a2} \tag{1.A.20}$$

1.A.2.2 Equilibrium

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

$$\max_{K_1, K_2, \eta_l^*, \eta_h^*} U = \left[C_s^{\frac{\sigma-1}{\sigma}} + C^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \text{ with } C \equiv \left[C_{g1}^{\frac{\theta-1}{\theta}} + C_{g2}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} \tag{1.A.21}$$

where:

$$C_s = Y_s = L_m \tag{1.A.22}$$

$$C_{gj} = Y_{gj} - Y_{kj} \text{ with } Y_{kj} = p_k K_j \text{ for } j=1,2 \tag{1.A.23}$$

$$Y_{g1} = L_{a1}^{1-\beta_1} X^{\beta_1} \quad \text{with } X \equiv \left[L_r^{\mu} + K_1^{\mu} \right]^{\frac{1}{\mu}} \tag{1.A.24}$$

$$Y_{g2} = L_{a2}^{1-\beta_2} K_2^{\beta_2} \tag{1.A.25}$$

$$L_{a2} = \int_{\eta_h^*}^{\infty} (1 + \gamma \eta_h) e^{-\eta_h} \, d\eta_h = (1 + \gamma + \gamma \eta_h^*) e^{-\eta_h^*} \tag{1.A.26}$$

$$L_{a1} = \int_{0}^{\eta_h^*} (1 + \eta_h) e^{-\eta_h} \, d\eta_h = 2\left(1 - e^{-\eta_h^*}\right) - \eta_h^* e^{-\eta_h^*} \tag{1.A.27}$$

$$L_r = \int_{\eta_l^*}^{\infty} \eta_l e^{-\eta_l} \, d\eta_l = (1 + \eta_l^*) e^{-\eta_l^*} \tag{1.A.28}$$

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

$$L_r = \int_0^{\eta_l^*} e^{-\eta_l} d\eta_l = \left(1 - e^{-\eta_l^*}\right) \tag{1.A.29}$$

This gives us the following first-order conditions:

$$p_k = \beta_1 L_{a1}^{1-\beta_1} X^{\beta_1-\mu} K_1^{\mu-1} \tag{1.A.30}$$

$$p_k = \beta_2 \left[L_{a2}/K_2\right]^{1-\beta_2} \tag{1.A.31}$$

$$L_r^{1-\mu}[L_m]^{-\frac{1}{\sigma}} = C^{\frac{\sigma-\theta}{\theta\sigma}} C_{g1}^{-\frac{1}{\theta}} \beta_1 L_{a1}^{1-\beta_1} X^{\beta_1-\mu} \eta_l^* \tag{1.A.32}$$

$$L_{a1}^{-\beta_1}[L_{a2}]^{\beta_2} = \left[\frac{C_{g1}}{C_{g2}}\right]^{1/\theta} \frac{(1-\beta_2)}{(1-\beta_1)} X^{-\beta_1} K^{\beta_2} \frac{(1+\gamma\eta_h^*)}{(1+\eta_h^*)} \tag{1.A.33}$$

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 (1.A.19) and (1.A.20), meaning that the marginal worker with skill level η_l^* is made indifferent between his two options.

The remainder of this section discusses asymptotes for equilibrium quantities and prices when $p_k = e^{-\delta t} \to 0$ 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 job polarisation and Baumol's cost disease.

1.A.2.3 Job Polarisation

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 polarisation consists of a shift in unskilled labour away from employment in routine tasks and a shift in skilled labour away from abstract tasks in Sector 1. We discuss each of these in turn.

Given capital accumulation in both Sectors 1 and 2, equation (1.A.32) determines the conditions needed for $L_r \to 0$., consistent with job polarisation. First consider the consumption terms in equation (1.A.15). Making use of equations (1.A.30) and (1.A.31) gives:

$$C_{g1} = Y_{g1} - p_k K_1 = [1 - \beta_1 (K_1/X)^{\mu}] L_{a1}^{1-\beta_1} X^{\beta_1} \tag{1.A.34}$$

$$C_{g2} = Y_{g2} - p_k K_2 = [1 - \beta_2]\left[L_{a2}\right]^{1-\beta_2} \quad K_2^{\beta_2} \tag{1.A.35}$$

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 (1.A.34) and (1.A.35) into equation (1.A.32) gives:

$$\left[(1+\eta_l^*)e^{-\eta_l^*}\right]^{1-\mu}\left[1-e^{-\eta_l^*}\right]^{-\frac{1}{\sigma}}\frac{1}{\eta_l^*} = C^{\frac{\sigma-\theta}{\theta\sigma}}[1-\beta_1(K_1/X)^{\mu}]^{-\frac{1}{\theta}}\beta_1 L_{a1}^{\frac{[\theta-1][1-\beta_1]}{\theta}} X^{\beta_1-\mu-\frac{1}{\theta}\beta_1} \qquad (1.A.36)$$

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 (1.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 (1.A.36) to go to zero and thus for $L_r \to 0$ is:

$$L_r \to 0 \text{ if } \frac{1}{\sigma} > \frac{1}{\theta} > \frac{\beta_1-\mu}{\beta_1} \qquad (1.A.37)$$

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 (1.A.34) and (1.A.35) we can rewrite the condition:

$$\begin{aligned}\left[2\left(1-e^{-\eta_h^*}\right)-\eta_h^* e^{-\eta_h^*}\right]^{\beta_1+\frac{1}{\theta}(1-\beta_1)}\left[(1+\gamma+\gamma\eta_h^*)e^{-\eta_h^*}\right]^{\frac{1}{\theta}(\beta_2-1)-\beta_2}\frac{(1+\eta_h^*)}{(1+\gamma\eta_h^*)} \\ = [1-\beta_1][\beta_2-1]^{\frac{\theta-1}{\theta}}[1-\beta_1(K_1/X)^{\mu}]^{-1/\theta}\left[X^{\beta_1}/K_2^{\beta_2}\right]^{\frac{\theta-1}{\theta}}\end{aligned} \qquad (1.A.38)$$

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 must 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 polarisation as a result of capital accumulation or the economic mechanisms behind the shift. There will, however, be quantitative changes since labour 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.

1.A.2.4 Changes in relative output prices and volumes

Given that the allocation of labour and capital has not altered qualitatively, $L_{a1} \to 0, \frac{K_1}{X} < 1, \frac{K_2}{X} \to \infty$ 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:

$$\frac{p_s}{p_2} = \frac{C^{(\theta-\sigma)/\sigma\theta} C_{g2}^{1/\theta}}{C_s^{1/\sigma}} \tag{1.A.39}$$

Such that,

$$\frac{p_s}{p_2} \to \infty \tag{1.A.40}$$

as explained in the basic model. Similarly,

$$\frac{p_1}{p_2} = \left[\frac{C_{g2}}{C_{g1}}\right]^{1/\theta} \to \infty \tag{1.A.41}$$

predicting that the relative price of Services must rise while attracting an increasing share of unskilled labour which is consistent with Baumol's cost disease. As in the basic model, the predicted decline of relative output prices with the sectors use of ICT capital, goes hand in hand with an increase in the output volume as shown from $\frac{C_{g2}}{C_s} \to \infty$ and $\frac{C_{g2}}{C_{g1}} \to \infty$.

Annex 1.B Data and results

Table 1.B1: ICT-capital intensity rank stability over time

	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

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

Table 1.B2: ICT-capital intensity rank stability across countries in 2005

	Average Spearman rank correlation coefficient
Austria	0.83
Belgium	0.79
Denmark	0.87
Spain	0.83
Finland	0.85
France	0.79
Germany	0.85
Ireland	0.73
Italy	0.71
Netherlands	0.78
Sweden	0.81
United Kingdom	0.65
United States	0.79

Notes: The coefficients are the spearman rank correlation coefficients between a country's ICT capital intensity sector ranking and the average sectoral ICT capital intensity ranking of all other countries in 2005.

Table 1.B3: Composition of Capital Assets

Total Tangible Assets		
	Total Construction	
	(i)	Residential Structure
	(ii)	Total non-residential investment
		Non-residential structures
		Infrastructure
	Machinery and Equipment	
	(i)	Transport equipment
	(ii)	Machinery and other equipment
		Computing equipment
		Communications equipment
		Other machinery and equipment
	(iii)	Other tangible assets
		Products of agriculture and forestry
		Other products
Total Intangible Assets		
	Software	
	Other intangible	

Source: Timmer et al. (2007)
Notes: the assets that fall under the EUKLEMS definition of "ICT" are highlighted in bold.

Table 1.B4: First stage results from IV regressions

	All years, 2SLS (first stage)		
	(1)		(2)
	Quadratic specification		Linear specification
	$rank(CAP)_{t-1}$	$[rank(CAP)]^2_{t-1}$	$rank(CAP)_{t-1}$
$rank(CAP)_{t-2}$	0.837***	1.613	0.823***
	(0.070)	(1.909)	(0.020)
$[rank(CAP)]^2_{t-2}$	-0.000	0.773***	
	(0.002)	(0.070)	
Constant	2.501***	39.032**	2.573***
	(0.615)	(16.383)	(0.518)
Observations	1456	1456	1456
F-statistic	1308.31	1423.39	1653.5
F-statistic p-value	0.000	0.000	0.000

Notes: See table 1.6

Chapter 2

Local high-tech job multipliers in Europe

Abstract

Examining employment growth in local labour markets across Europe, this paper finds that each worker in a high-skilled occupation creates up to five extra jobs in local less-skilled intensive services in the same region. However, it is also shown that there exist persistent differences in the size of this local high-tech job multiplier across regions. In particular, we find that the multiplier is larger in regions with higher immigration, an abundance of less-skilled workers, and lower gross output per capita. At the country level, we also show that this results in local high-tech job multipliers that are larger in Southern European countries than in the rest of Europe.

2.1 Introduction

For US cities, the importance of local job multipliers was first shown by Moretti (2010). He estimates that for every job created in manufacturing, there are 1.5 jobs created in construction and services in a city. This multiplier increases to 2.5 when only considering the creation of skilled jobs in manufacturing. Moreover, Moretti (2010) finds a local job multiplier of 5 for an additional job in high-tech sectors. In related work, Moretti and Wilson (2014) find an even larger high-tech job multiplier for jobs created by bio-tech companies. Finally, Moretti and Thulin (2013) use variation across 72 local labour markets in Sweden and find that each job created in manufacturing generates 0.5 jobs in sectors producing local goods and services. The local multiplier for an additional skilled job in manufacturing is 2.8, and for an additional job in high-tech manufacturing is 1.1. A simple way to explain the existence of these multipliers, it is argued, is that innovation and globalisation increase the demand for workers in high-tech and tradable sectors in a region. In turn, these workers generate other jobs outside these sectors in that region, resulting in a local job multiplier.[24]

[24] Other job multipliers not directly related to the impacts of innovation and globalisation have been examined. For example, Faggio and Overman (2014) consider the impact on UK local labour markets from creating public sector jobs. They find that public sector employment has no identifiable effect on the level of private sector employment but that it does

This paper adds to this literature in two ways. Firstly, because there currently exists little evidence about local job multipliers for Europe, this paper estimates local high-tech job multipliers using variation across 227 NUTS-2 regions in the EU-27 between 2000 and 2011.[25] Secondly, this paper uses a definition of high-tech employment that is complementary to existing measures. In line with existing measures, our definition of high-tech employment includes all workers employed in high-tech manufacturing, defined by a high ratio of R&D expenditure over value added, and all workers employed in high-tech knowledge-intensive services defined by a high fraction of tertiary educated workers. In contrast with traditional measures, our definition of high-tech employment includes all skilled workers in Science, Technology, Engineering and Math (STEM) occupations that are not employed in high-tech manufacturing or high-tech knowledge-intensive service sectors. As will become clear below, including these STEM occupations in our definition of high-tech jobs is important in understanding local high-tech job multipliers.

The remainder of this paper is organised as follows. Section 2.2 describes the data. Section 2.3 provides some summary statistics about overall and high-tech employment growth in Europe between 2000 and 2011. In Section 2.4 the local high-tech job multiplier is estimated, and Section 2.5 explores regional variations in the multiplier. Finally, Section 2.6 concludes.

2.2 Data

In line with standard measures of high-tech employment, we begin by defining high-tech employment as all workers employed in high-tech sectors listed in Panel A of Table 2.1. This follows Eurostat's definition of high-tech based on a firm's NACE code and include high-tech manufacturing (e.g. the production of robots or airplanes) as well as high-tech knowledge-intensive services (e.g. ICT consulting or the scientific research and development of new technologies). Manufacturing sectors are labelled high-tech when they have a high degree of technological intensity, i.e. R&D expenditure over value added, while the knowledge intensity of a service is based on its share of tertiary educated persons. Employment in high-tech sectors for each NUTS-2 region is available from Eurostat's Regional Science and Technology Statistics Database.[26]

In contrast to the traditional measures of high-tech employment discussed in the previous paragraph, we add to employment in these high-tech sectors all workers engaged in highly technical activities outside high-tech industries. In particular, we add to all workers employed in high-tech sectors all those in Science, Technology, Engineering, and Maths (STEM) occupations employed in industries not listed

affect the sectoral composition of the private sector. Specifically, they find that each additional public sector job creates 0.5 jobs in construction and services while crowding out 0.4 jobs in manufacturing.

[25] EU-27 refers to the European Union and its 27 member-states in 2011 and our precise definition of high-tech employment is given in Section 2.2 below. The time span is necessarily restricted to the period 2000-2011 due to several data limitations, see Annex 2.A.

[26] The NUTS classification (Nomenclature of territorial units for statistics) is used to divide the European territory into regions of different population sizes, mainly for statistical and EU Regional Policy purpose.

in Panel A of Table 2.1. These STEM occupations are listed in Panel B of Table 2.1 and follow the definition of the US Bureau of Labour Statistics in the United States.[27] For example, our definition of high-tech employment thereby also includes engineers in car manufacturing, computer programmers in retail trade, quantitative analysts in financial services, or statisticians in health-care administration. Employment in STEM occupations in panel B of Table 2.1 is obtained from the European Union Labour Force Survey (ELFS) micro data set, and merged at the NUTS-2 level with the data for the high-tech industries from Panel A of Table 2.1.[28]

Table 2.1: High-tech components

Panel A: High-tech industries (NACE rev. 1.1)
High-tech manufacturing
Pharmaceuticals, medicinal chemical and botanical products (24.4)
Office machinery and computers (30)
Radio, television and communication equipment and apparatus (32)
Medical, precision and optical instruments, watches and clocks (33)
Aircrafts and spacecrafts (35.3)
High-tech knowledge-intensive services
Post and telecommunications (64)
Computer and related activities (72)
Research and development (73)
Panel B: STEM occupations (ISCO-88)
Physical and life sciences
Physicists, chemists and related professionals (211)
Life science professionals (221)
Life science technicians and related associate professionals (321)
Computer and mathematical sciences
Mathematicians, statisticians and related professionals (212)
Computer professionals (213)
Computer associate professionals (312)
Engineering and related
Architects, engineers and related professionals (214)
Physical and engineering science technicians (311)

2.3 High-tech employment growth over time and across regions

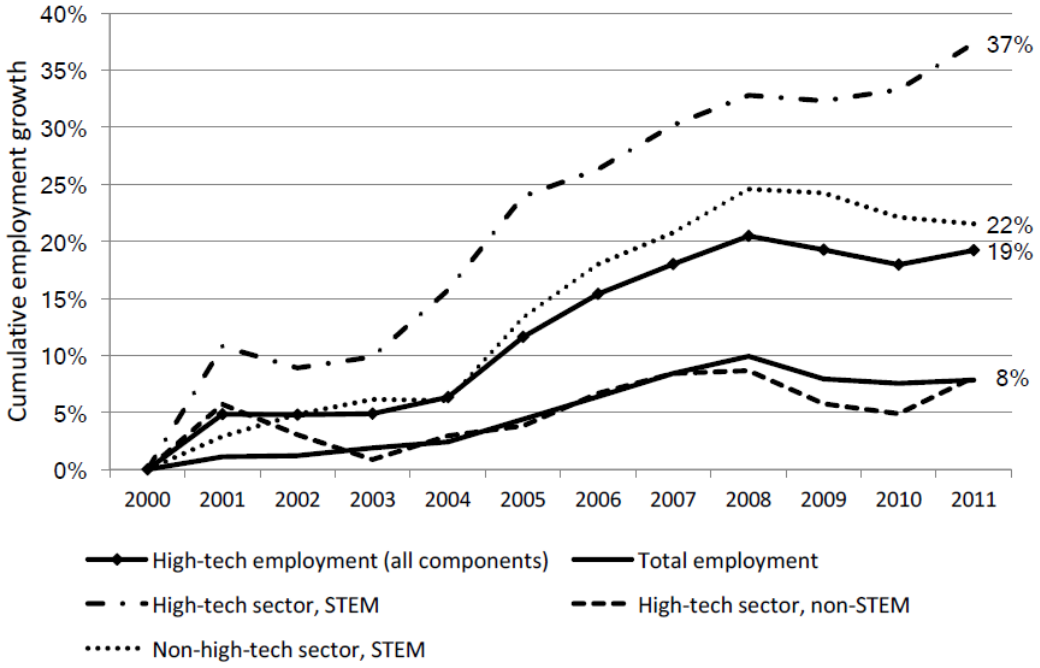
The solid lines in Figure 2.1 show the cumulative percentage growth in total and high-tech employment in the EU-27 between 2000 and 2011: 19% versus 8% respectively. The faster growth of high-tech than total employment implies that the share of high-tech in total employment increased over time from 9% in 2000 to 10% in 2011. Moreover, the dashed lines in Figure 2.1 show the importance of the different

[4] See Hecker (2005).

[28] For the UK we use the UK Labour Force Survey rather than the ELFS. Further details on the construction of the high-tech employment dataset can be found in Appendix 3.A.

components in our definition of high-tech employment. The fastest job growth can be observed for STEM workers in high-tech sectors, growing by a cumulative 37% between 2000 and 2011. Also workers in STEM occupations outside high-tech sectors grew faster than overall high-tech employment, by 22% versus 19% respectively, whereas employment of non-STEM workers in high-tech industries only increased at the pace of European-wide total employment, by 8% between 2000 and 2011. These figures clearly show the importance of the inclusion of STEM workers outside high-tech sectors, as employment in STEM occupations has been the main driver of total high-tech employment growth.

Figure 2.1: Cumulative employment growth: total vs. high-tech components (in %, EU-27, 2000-2011)

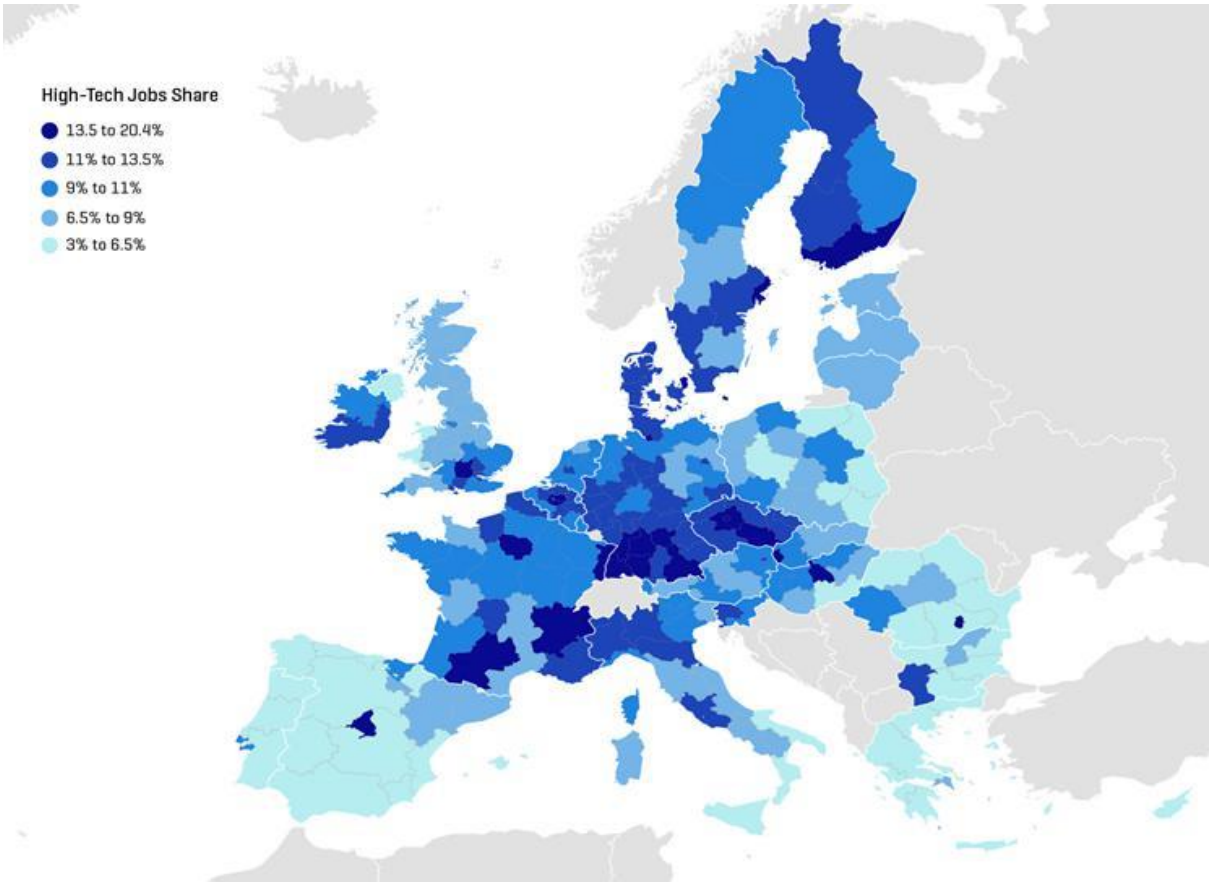


Notes: In the years before total country coverage (2000-2004) EU-27 employment in the high-tech components is calculated as the employment share of the components in the covered countries multiplied by total EU-27 employment.

The faster growth of high-tech than total employment implies that the share of high-tech in total employment increased over time from 9% in 2000 to 10% in 2011. The EU-wide high-tech employment share of 10% in 2011 masks large differences in high-tech intensity between countries and regions in Europe. To illustrate this, Figure 2.2 shows the high-tech employment shares for all EU NUTS-2 regions in 2011. While the regions in Western and Northern Europe generally have higher high-tech intensity, the share is much lower in some Southern and Eastern European regions. To illustrate this further, Table 2.2 gives the top (Panel A) and bottom (Panel B) 15 regions in terms of their high-tech employment share that are of sufficiently large size, i.e. with an employed population of at least one million in 2011. The top regions include large capital regions, such as Paris, London, Berlin and Stockholm, as well as regions with a strong sectoral specialisation, such as Midi-Pyrénées

(aerospace, ICT and agro-food) and Stuttgart (mechanical engineering). The lagging regions are mainly located in Southern Europe and Romania.

Figure 2.2: High-tech intensity per NUTS-2 region (in %, 2011)



While high-tech employment grew in the large majority of European regions, it is interesting to see in which regions high-tech growth was strongest. For example, stronger growth in regions that initially already had higher shares of high-tech employment would suggest a lack of convergence in high-tech employment across regional labour markets in Europe. To see whether this is true, Panel A of Figure 2.3 shows the evolution between 2000 and 2011 of the interquartile range of high-tech employment shares across NUTS-2 regions, the larger NUTS-1 regions, and the EU countries.[29][30] Panel A of Figure 2.3 show that the interquartile range in high-tech employment intensity between regions remained constant between 2000 and 2011, suggesting pervasive differences between regions, and between countries. To illustrate this further, Panel B of Figure 2.3 shows that the within-country interquartile

[29] The NUTS classification is used to divide the European territory into regions of different population sizes, such that each country consists of several NUTS-1 regions of similar population size and each NUT-1 region consists of several NUTS-2 regions of similar population size.

[30] The interquartile range is the difference between the 75th and 25th percentile of the high-tech employment share across regions. Using the standard deviation instead of the interquartile range gives qualitatively similar results.

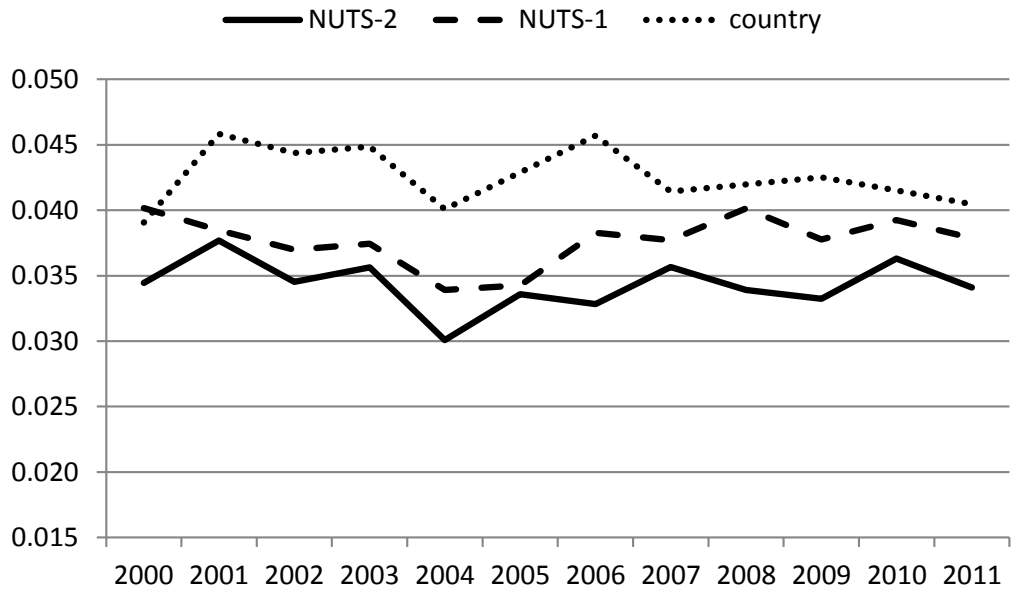
range in high-tech employment shares across NUTS-2 and NUTS-1 regions within countries remained constant over time, suggesting that also within countries regional differences remained pervasive. In sum, what Figures 2.1, 2.2 and 2.3 suggest is that European regions have been able to create high-tech jobs, but that these high-tech jobs remain highly concentrated in regionally clustered high-tech hubs.

Table 2.2: Top and bottom high-tech intensity regions (2011)

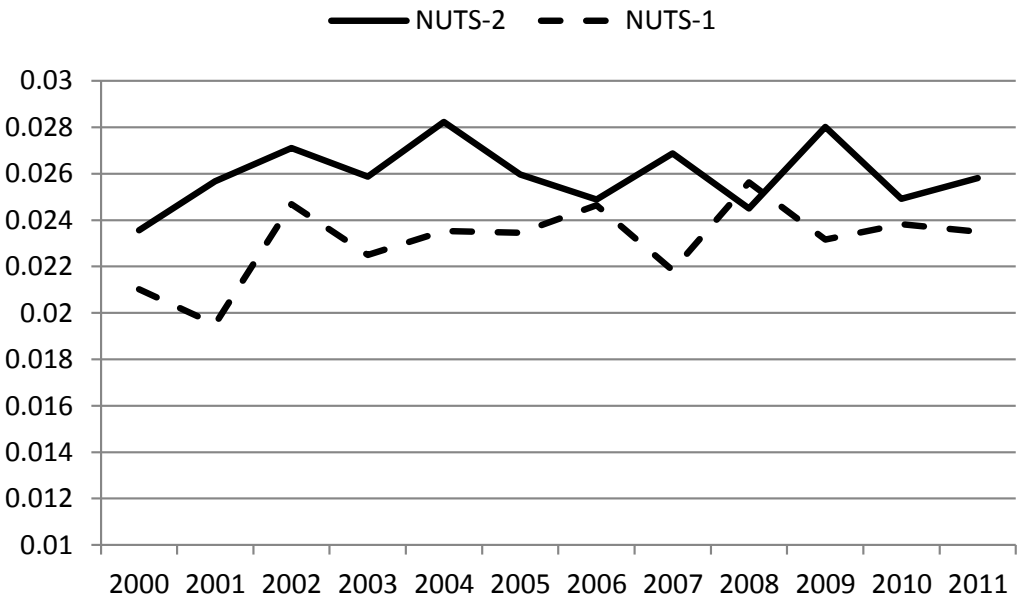
NUTS-2 region	Total employment in 2011 (in 000s)	High-tech employment share in 2011
	Panel A: Top-15	
1. Stockholm (Sweden)	1101	18.0%
2. Île de France (France)	5228	17.6%
3. Bucuresti - Ilfov (Romania)	1058	15.7%
4. Midi-Pyrénées (France)	1232	15.4%
5. Karlsruhe (Germany)	1334	15.4%
6. Etelä-Suomi (Finland)	1307	14.9%
7. Rhône-Alpes (France)	2578	14.9%
8. Oberbayern (Germany)	2241	14.4%
9. Stuttgart (Germany)	1987	14.4%
10. Közép-Magyarország (Hungary)	1243	14.3%
11. Comunidad de Madrid (Spain)	2813	14.0%
12. Freiburg (Germany)	1248	13.8%
13. Berkshire, Buckinghamshire, Oxfordshire (United Kingdom)	1306	13.6%
14. Köln (Germany)	1999	13.0%
15. Lombardia (Italy)	4263	12.4%
	Panel B: Bottom-15	
1. Centro Region (Portugal)	1103	3.6%
2. Nord-Est (Romania)	1731	4.3%
3. Norte (Portugal)	1695	4.7%
4. Sud-Est (Romania)	1106	5.2%
5. Andalucia (Spain)	2774	5.3%
6. Communidad Valencia (Spain)	1889	5.5%
7. Sud-Muntenia (Romania)	1306	5.6%
8. Galicia (Spain)	1082	5.7%
9. Sicilia (Italy)	1431	5.9%
10. Nord-Vest (Romania)	1164	5.9%
11. Puglia (Italy)	1232	6.2%
12. Wielkopolskie (Poland)	1412	6.3%
13. Sud-Vest Oltenia (Romania)	1024	6.5%
14. Lietuva (Lithuania)	1369	6.6%
15. Attiki (Greece)	1535	7.0%

Figure 2.3: Dispersion of high-tech intensity (2000-2011)

Panel A: EU-wide interquartile range



Panel B: Within-country interquartile range



Notes: Only regions or countries with twelve annual observations are included. Within-country interquartile ranges in panel B are aggregated using employment weighted averages.

2.4 The local high-tech job multiplier

The local high-tech job multiplier is given by $\gamma > 0$ in:

$$\frac{\Delta L_{j,t}}{E_{j,t-s}} = \gamma \frac{\Delta H_{j,t}}{E_{j,t-s}} \tag{2.1}$$

with $\Delta L_{j,t}$ the absolute change in employment outside high-tech in NUTS-2 region j between periods *t* and $t-s$, $\Delta H_{j,t}$ the absolute change in high-tech employment, and $E_{j,t-s}$ total employment in region *j* at time *t-s*.[31] Adding a country-time fixed effect, $F_{c,t}$, to control for country-wide shocks in employment between period *t* and $t-s$ and an error term $\varepsilon_{j,t}$, we get:

$$\frac{\Delta L_{j,t}}{E_{j,t-s}} = \gamma \frac{\Delta H_{j,t}}{E_{j,t-s}} + F_{c,t} + \varepsilon_{j,t} \tag{2.2}$$

However, the interpretation of γ in equation (2.2) is not causal if, for example, there are regional level shocks that have an impact on both high-tech as well as other employment. To address this issue, we follow Moretti (2010) in constructing two Bartik instruments. A first instrument is given by:

$$\frac{\Delta \hat{H}^1_{j,t}}{E_{j,t-s}} = \frac{H_{j,t-s}}{E_{j,t-s}} \left[\frac{\left(H_{c,t} - H_{j,t}\right) - \left(H_{c,t-s} - H_{j,t-s}\right)}{\left(H_{c,t-s} - H_{j,t-s}\right)} \right] \tag{2.3}$$

where the last term in square brackets is, by approximation, the growth rate of high-tech employment in country *c* excluding region *j*. This growth rate is multiplied by region *j*'s initial relative level of high-tech employment to get $\frac{\Delta \hat{H}^1_{j,t}}{E_{j,t-s}}$.[32]

To go even further, one could use the country level changes for each of the different components of high-tech employment outlined in Figure 2.1:

$$\frac{\Delta \hat{H}^2_{j,t}}{E_{j,t-s}} = \sum_{i \in H} \frac{H_{i,j,t-s}}{E_{j,t-s}} \left[\frac{\left(H_{i,c,t} - H_{i,j,t}\right) - \left(H_{i,c,t-s} - H_{i,j,t-s}\right)}{\left(H_{i,c,t-s} - H_{i,j,t-s}\right)} \right] \tag{2.4}$$

[31] That is, $E_{j,t-s} = H_{j,t-s} + L_{j,t-s}$. We express high- and low-tech employment relative to total employment to avoid spurious positive correlation that might arise when using absolute values - see Peri & Sparber (2011) for details.

[32] Van Dijk (2014) criticizes Moretti (2010) for overestimating the multiplier because of two reasons that we account for in our analysis. Firstly, equation (2.2) uses changes in the level of employment to directly estimate the multiplier whereas Moretti (2010) uses changes in the log of employment to estimate an elasticity instead. Moretti (2010) then multiplies this elasticity by the ratio of nonmanufacturing over manufacturing employment in the final period, $L_{c,t}/H_{c,t}$, to obtain an estimate of the multiplier. Van Dijk (2014) argues that this leads to an overestimation of the multiplier because $L_{c,t}/H_{c,t} > L_{c,t-s}/H_{c,t-s}$ given the relative decline over time in manufacturing employment. Secondly, the right-hand side of equation (2.3) subtracts employment in region *j* from total employment whereas Moretti (2010) does not exclude region *j* from total employment thereby making it more likely that the instrument is correlated with the endogenous variation in $H_{j,t}$ (especially when region *j* is relatively large in terms of employment). Van Dijk (2014) argues that these two shortcomings in Moretti (2010) lead to an overestimation of the multiplier by about 50% (e.g. a multiplier of 1 instead 1.5).

where the different components *i* are STEM occupations in high-tech sectors, STEM occupations outside high-tech sectors, and non-STEM occupations in high-tech sectors. While similar to the instrument defined in equation (2.3), the instrument in equation (2.4) also accounts for differences in the composition of high-tech employment across regions.

Table 2.3 reports the results of estimating equation (2.2) using two 5-year differences for the periods 2000-2005 and 2005-2010. The first column in Table 2.3 uses OLS to estimate equation (2.2), whereas the remaining columns show IV estimates using equations (2.3) and (2.4) as instruments for $\frac{\Delta H_{j,t}}{E_{j,t-s}}$ in equation (2.2). In particular, the second column of Table 2.3 only use equation (2.3) as an instrument, and the third column of Table 2.3 only uses equation (2.4) as an instrument. Finally, the fourth column of Table 2.3 uses both instruments in equations (2.3) and (2.4) simultaneously. For the IV estimates, first-stage coefficients are reported together with the IV first-stage F-statistic which should be sufficiently large for the first-stage to be sufficiently strong. Because the last column uses both instruments jointly, Hansen's J Chi-square statistic for IV overidentification is reported which should be sufficiently small for the instruments to be valid.

The results in Panel A of Table 2.3 show that high-tech employment growth is associated with a significant positive multiplier for non-STEM jobs in low-tech sectors, both in the OLS and the IV regressions. The IV results, our preferred specification, show that each high-tech job is linked to between 3.9 and 4.4 non-STEM jobs in low-tech sectors, depending on the chosen instrument. These results suggest that high-tech job creation in a region has a strong positive spill-over effect on other jobs in that region.

Table 2.3: Multiplier regression – Baseline results

	A. High-tech and STEM (Dependent variable: Employment growth of non-STEM occupations in low-tech industries)			
	OLS	**IV**		
Independent variable:		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth of high-tech industries and STEM occupations	1.15*	4.40*	4.08*	3.94*
	(0.24)	(1.08)	(1.04)	(1.02)
		IV first-stage coefficients		
Eq. (2.3)	-	0.70*	-	-0.36
		(0.10)		(0.43)
Eq. (2.4)	-	-	0.73*	1.08*
			(0.10)	(0.42)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	-	*46.63*	*51.70*	*28.56*
IV overidentification Chi-sq statistic	-	-	-	*3.65*

B. High-tech industry

(Dependent variable: Employment growth of non-STEM occupations in low-tech industries)

	OLS	**IV**		
		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth in high-tech industries	0.94*	4.73*	4.75*	4.88*
	(0.30)	(1.90)	(1.90)	(1.86)
		IV first-stage coefficients		
Eq. (2.3)	-	0.74*	-	-7.66
		(0.14)		(9.67)
Eq. (2.4)	-	-	0.75*	8.42
			(0.14)	(9.65)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	-	*29.30*	*29.54*	*16.88*
IV overidentification Chi-sq statistic	-	-	-	*0.79*

C. STEM occupations

(Dependent variable: Employment growth of non-STEM occupations in low-tech industries)

	OLS	**IV**		
		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth in STEM occupations	1.31*	4.32*	4.90*	5.05*
	(0.32)	(1.52)	(1.46)	(1.45)
		IV first-stage coefficients		
Eq. (2.3)	-	0.63*	-	-0.18
		(0.10)		(0.63)
Eq. (2.4)	-	-	0.65*	0.83
			(0.11)	(0.63)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	-	*35.88*	*36.66*	*18.23*
IV overidentification Chi-sq statistic	-	-	-	*5.28*

Notes: Standard errors clustered at the regional level and * indicates significance at the 1% level. All IV first-stage F-statistics are significant at 1% and none of the IV overidentification Chi-square statistics are. All regressions include country-year fixed effects.

Panels B and C of Table 2.3 repeat the analysis for the different components of our high-tech employment measure: Employment in traditional high-tech industries and employment in STEM occupations. The results in Panel B show that job creation in high-tech industries is associated with a local job multiplier of around 4.8. This definition of the high-tech job multiplier is closer in line with the definitions used in the earlier literature. In comparison to this literature, the estimates in Panel B of Table 2.3 are in the upper-range of estimates found in Moretti (2010), Moretti and Wilson (2014) and Van Dijk (2014) for the US, and Moretti and Thulin (2013) for Sweden. When focusing on the STEM-component of our definition which also includes STEM workers in low-tech sectors, Panel C shows that the STEM-multiplier has a very similar value, ranging between 4.3 and 5. As both employment in high-tech industries and employment in STEM occupations are associated with strong multiplier

effects, this confirms the importance of our complementarity definition of high-tech employment when understanding local high-tech job multipliers.

To get a better understanding of the channels through which the local multiplier operates, we repeat the analysis from Table 2.3 but using different dimensions of our employment data as dependent and independent variables. More specifically, Table 2.4 uses as the independent variable job creation in high-tech sectors, as was done in Panel B of Table 2.3. However, in contrast to Panel B of Table 2.3, Table 2.4 uses different dependent variables. Panel A of Table 2.4 uses total employment in low-tech industries, both in STEM and non-STEM occupations, whereas Panel B of Table 2.4 only uses employment growth of STEM occupations in low-tech sectors as the dependent variable. The results in Panel A show that job creation in high-tech sectors is associated with a multiplier of around 5.2 for total employment in the low-tech industry, i.e. in both STEM and non-STEM occupations. This result is similar to the estimates in Panel B of Table 2.3. However, Panel B of Table 2.4 also presents a falsification test by showing that the multiplier for STEM occupations in low-tech sectors is much less strong, with very small estimated multipliers. Taking the evidence in Panels A and B of Table 2.4 together, these results suggest that job creation in high-tech sectors entails employment growth in low-tech sectors but only in non-STEM occupations, such unskilled workers in low-tech services.

Similarly, the bottom half of Table 2.4 estimates the local job multiplier using STEM employment growth as the independent variable, as was done in Panel C of Table 2.3. However, in contrast to Panel C of Table 2.3, Table 2.4 uses different dependent variables. Panel C of Table 2.4 uses as a dependent variable employment growth in all non-STEM occupations, both in high-tech sectors as well as low-tech sectors, whereas Panel D of Table 2.4 uses employment growth of non-STEM occupations only in high-tech sectors as the dependent variable. The estimated multiplier in Panel C of Table 2.4 is similar to estimates from Panel C in Table 2.3. Moreover, the falsification exercise in Panel D of Table 2.4 shows no evidence in support of the hypothesis that this employment growth in non-STEM occupations is also happening in high-tech sectors. In sum, Tables 2.3 and 2.4 show that the local high-tech job multiplier mainly creates jobs for non-STEM unskilled workers in low-tech sectors such as local services. These results are in line with Autor and Dorn (2013) and Autor, Dorn and Hanson (2013) for the US and Goos, Manning and Salomons (2014) for Europe who have argued that innovation leads to growth in highly-skilled occupations as well as growth in local less-skilled service employment because (i) digital technologies and highly-skilled occupations are complements in local aggregate production, and (ii) innovation leads to an increase in average real income in a region, which also increases the demand for local less-skilled services that cannot easily be automated. Finally, our results suggest that regional economies are in part driven by high-tech booms (and busts), similar to literature that has examined the importance of energy boom-and-bust cycles for local labour markets - see Marchand (2012) for more details.

Table 2.4: Multiplier regressions – Different components

	A. Dependent variable: Total employment growth in low-tech industries			
	OLS	**IV**		
Independent variable:		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth in high-tech industries	0.85*	5.15*	5.16*	5.30*
	(0.32)	(2.01)	(2.01)	(1.97)
		IV first-stage coefficients		
Eq. (2.3)	-	0.74*	-	-7.66
		(0.14)		(9.67)
Eq. (2.4)	-	-	0.75*	8.42
			(0.14)	(9.65)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	-	*29.30*	*29.54*	*16.88*
IV overidentification Chi-sq statistic	-	-	-	*0.71*

	B. Dependent variable: Employment growth of STEM occupations in low-tech industries			
	OLS	**IV**		
Independent variable:		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth in high-tech industries	-0.85	0.41	0.41	0.41
	(0.61)	(0.18)	(0.18)	(0.17)
		IV first-stage coefficients		
Eq. (2.3)	-	0.74*	-	-7.66
		(0.14)		(9.67)
Eq. (2.4)	-	-	0.75*	8.42
			(0.14)	(9.65)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	-	*29.30*	*29.54*	*16.88*
IV overidentification Chi-sq statistic	-	-	-	*0.04*

	C. Dependent variable: Total employment growth in non-STEM occupations			
	OLS	**IV**		
Independent variable:		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth in STEM occupations	1.43*	4.56*	5.19*	5.36*
	(0.33)	(1.55)	(1.49)	(1.48)
		IV first-stage coefficients		
Eq. (2.3)	-	0.63*	-	-0.18
		(0.10)		(0.63)
Eq. (2.4)	-	-	0.65*	0.83
			(0.11)	(0.63)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	-	*35.88*	*36.66*	*18.23*
IV overidentification Chi-square	-	-	-	*5.98*

	D. Dependent variable: Employment growth of non-STEM occupations in high-tech industries			
	OLS	**IV**		
Independent variable:		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth in STEM occupations	0.13*	0.23	0.29*	0.31*
	(0.04)	(0.10)	(0.10)	(0.10)
		IV first-stage coefficients		
Eq. (2.3)	-	0.63*	-	-0.18
		(0.10)		(0.63)
Eq. (2.4)	-	-	0.65*	0.83
			(0.11)	(0.63)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	-	*35.88*	*36.66*	*18.23*
IV overidentification Chi-square	-	-	-	*3.89*

Notes: Standard errors clustered at the regional level and * indicates significance at the 1% level. Independent variable is employment growth in STEM occupations. All IV first-stage F-statistics are significant at 1% and none of the IV overidentification Chi-square statistics are. All regressions include country-year fixed effects.

While the results from Tables 2.3 and 2.4 show that the local high-tech job multiplier results in the creation of jobs for unskilled workers in low-tech sectors, an important prerequisite for the functioning of the multiplier mechanism is the availability of workers to fill these jobs. The increased demand for unskilled workers in low-tech sectors can be satisfied by available workers within the region, but also by attracting workers from outside the region. To see whether migration is an important channel through which the multiplier works, we can look at the link between migration and high-tech employment growth. In particular, in Panel A of Table 2.5 we regress the net migration rate in a region, which is the difference between immigration and emigration as a percentage of the local population, averaged over the periods 2000-2005 and 2005-2010 onto high-tech employment growth in that region between 2000-2005 and 2005-2010.[33] We find that there is indeed a positive relationship: Regions with strong high-tech employment growth have higher net migration rates.

An alternative approach to test for the importance of labour mobility is to see whether the local high-tech job multiplier is higher in regions with higher net migration. Therefore, Panel B of Table 2.5 repeats the analysis in Panel A of Table 2.3, but adds an interaction effect between high-tech employment growth and the net migration rate in the initial period (i.e. in 2000 for the period 2000-2005 and in 2005 for the period 2005-2010) on the right-hand-side of equation (2.2). In the first column using OLS, the positive coefficient on the interaction term (significant at the 15% level) suggests that the local high-tech job multiplier is larger in regions with more net migration: A one-standard deviation increase in the net migration rate (i.e. an increase of about 5 percentage points in our data) increases the

[33] The net migration rate covers migration of the entire population, and hence does not focus explicitly on the working age population. However, as the majority of movers are of working age, the net migration rate is considered to be a good proxy for labour mobility (Gakova and Dijkstra, 2008).

multiplier by 0.30 units.[34] The coefficients on interaction terms using IV instead of OLS are also all positive, although not statistically significant. Overall, results from Table 2.5 corroborate the idea that labour mobility is an important channel for the functioning of the local high-tech multiplier.

Table 2.5: Multiplier regressions – Migration

	A. Dependent variable: Net migration			
	OLS	**IV**		
Independent variable:		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth of (high-tech industries and STEM occupations)	0.93*	3.48*	3.19*	3.07*
	(0.18)	(0.69)	(0.67)	(0.68)
		IV first-stage coefficients		
Eq. (2.3)	-	0.71*	-	-0.32
		(0.10)		(0.44)
Eq. (2.4)	-	-	0.74*	1.04*
			(0.10)	(0.43)
Number of observations	*405*	*405*	*405*	*405*
IV first-stage F-statistic	-	*46.19*	*51.21*	*27.89*
IV overidentification Chi-sq statistic	-	-	-	*2.28*
	B. Dependent variable: Employment growth of non-STEM occupations in low-tech industries			
	OLS	**IV**		
Independent variables:		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth of (high-tech industries and STEM occupations)	0.81*	3.60*	3.35*	2.66
	(0.26)	(1.14)	(1.06)	(1.07)
Employment growth of (high-tech industries and STEM occupations) X Net migration	5.69	20.57	19.68	34.69
	(3.80)	(23.34)	(23.15)	(25.21)
Net migration	0.20*	-0.06	-0.04	-0.14
	(0.05)	(0.20)	(0.20)	(0.22)
Number of observations	*403*	*403*	*403*	*403*
IV first-stage F-statistic	-	*20.36*	*22.45*	*12.17*
IV overidentification Chi-sq statistic	-	-	-	*3.46*

Notes: Net migration is defined as the difference between immigration towards and emigration out of a region expressed as a percentage of the total population in that region. For Panel A, the 5-year average net migration rate is used for years 2000-2005 and 2005-2010. For Panel B, net migration in the initial period (i.e. in 2000 for the period 2000-2005 and in 2005 for 2005-2010) is used. Standard errors clustered at the regional level and * indicates significance at the 1% level. All F-test statistics are significant at 1% and the Chi-square tests statistics are not. All regressions include country-year fixed effects.

2.5 Regional variation in the local high-tech job multiplier

While an EU-wide estimate of the local high-tech job multiplier gives an overall sense of the impact of high-tech job creation on the demand for other jobs in a region, there could be substantial

[34] The net migration rate in the regions included in the regressions equals 2.8% on average.

heterogeneity in the size of the local high-tech job multiplier across regions. To see whether certain groups of countries have higher local high-tech job multipliers than others, Table 2.6 repeats the analysis from Panel A in Table 2.3 for four country groups separately: Northern and Western Europe (Table 2.6 Panel A), Central Europe (Table 2.6 Panel B), Southern Europe (Table 2.6 Panel C) and Eastern Europe (Table 2.6 Panel D). The results show that the multipliers in the IV specifications are only significant in Southern European countries.

Table 2.6: Multiplier regressions – country groups

	A. Region: North and West (Denmark, Finland, Ireland, Netherlands, Sweden, United Kingdom) (Dep. variable: Employment growth of non-STEM occupations in low-tech industries)			
	OLS	**IV**		
Independent variable:		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth of (high-tech industries and STEM occupations)	1.14*	-24.77	0.71	-0.10
	(0.39)	(228.09)	(2.18)	(1.33)
		IV first-stage coefficients		
Eq. (2.3)	-	-0.05	-	-1.55
		(0.40)		(0.62)
Eq. (2.4)	-	-	0.80	1.65*
			(0.31)	(0.44)
Number of observations	*113*	*113*	*113*	*113*
IV first-stage F-statistic	-	*0.01*	*6.65*	*7.09*
IV overidentification Chi-sq statistic	-	-	-	*0.13*
	B. Region: Central (Belgium, Denmark, France, Luxembourg) (Dep. variable: Employment growth of non-STEM occupations in low-tech industries)			
	OLS	**IV**		
		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth of (high-tech industries and STEM occupations)	0.93*	10.16	9.21	11.01
	(0.29)	(8.87)	(9.85)	(8.72)
		IV first-stage coefficients		
Eq. (2.3)	-	0.44	-	0.95
		(0.46)		(1.27)
Eq. (2.4)	-	-	0.36	-0.53
			(0.43)	(1.21)
Number of observations	*124*	*124*	*124*	*124*
IV first-stage F-statistic	-	*0.92*	*0.68*	*0.55*
IV overidentification Chi-sq statistic	-	-	-	*0.06*

C. Region: South

(Cyprus, Greece, Italy, Malta, Portugal, Spain)

(Dep. variable: Employment growth of non-STEM occupations in low-tech industries)

	OLS	**IV**		
Independent variable:		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth of (high-tech industries and STEM occupations)	2.42*	5.81*	5.62*	5.23*
	(0.83)	(1.60)	(1.64)	(1.73)
			IV first-stage coefficients	
Eq. (2.3)	-	0.59*	-	-1.31
		(0.11)		(1.26)
Eq. (2.4)	-	-	0.61*	1.94
			(0.11)	(1.29)
Number of observations	*84*	*84*	*84*	*84*
IV first-stage F-statistic	-	*29.21*	*30.36*	*19.90*
IV overidentification Chi-sq statistic	-	-	-	*1.50*

D. Region: East

(Austria, Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland,

Romania, Slovakia, Slovenia)

(Dep. variable: Employment growth of non-STEM occupations in low-tech industries)

	OLS	**IV**		
		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth of (high-tech industries and STEM occupations)	0.30	0.60	1.32	1.59
	(0.40)	(1.31)	(1.22)	(1.29)
			IV first-stage coefficients	
Eq. (2.3)	-	0.55	-	-0.25
		(0.36)		(0.97)
Eq. (2.4)	-	-	0.59	0.83
			(0.34)	(0.87)
Number of observations	*89*	*89*	*89*	*89*
IV first-stage F-statistic	-	*2.37*	*3.12*	*10.11*
IV overidentification Chi-sq statistic	-	-	-	*6.36*

Notes: The dependent variable is 5-year growth of employment in the non-high-tech sector. Standard errors clustered at the regional level and * indicates significance at the 1% level. None of the F-test statistics and Chi-square tests statistics are significant at the 1% level. All regressions include country-year fixed effects.

To getter a better understanding of these regional variations in the multiplier, we interact $\frac{\Delta H_{j,t}}{E_{j,t-s}}$ from equation (2.2) with regional GDP per capita (expressed relative to the EU-wide GDP per capita level). The results in Panel A of Table 2.7 show that this interaction term is significantly negative, which implies that multipliers are bigger in regions with relatively low levels of GDP per capita. One possible explanation for this finding is that high-tech employment in poorer regions is more low-skill intensive than in richer regions[35], and that regions that have low-skilled intensive high-tech industries find it easier to create or fill low-skilled jobs upon the creation of high-tech jobs. To test this further, Panel B of Table 2.7 interacts the high-tech industry multiplier with the regional share of non-STEM employment in high-tech industries. The positive interaction term (significant at the 10% level in the IV specification) confirms that regions with more low-skill intensive high-tech industries have bigger high-tech multipliers. To put the point estimates from Panel B into perspective, a one standard deviation increase in the share of non-STEM in high-tech industries (i.e. an increase of 5.8 percentage points)[36] results in a multiplier that is 6.5 units bigger (based on the estimates from the last column).

Table 2.7: Multiplier regressions – interactions

	A. Interaction of employment growth of (high-tech industries and STEM occupations) with GDP-per-capita (Dependent variable: Employment growth of non-STEM occupations in low-tech industries)			
	OLS	**IV**		
Independent variables:		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth of (high-tech industries and STEM occupations) X GDP-per-capita	-1.35* (0.43)	-4.06 (3.87)	-4.58 (2.80)	-5.75* (1.97)
Employment growth of (high-tech industries and STEM occupations)	2.60* (0.54)	8.96 (3.96)	9.32* (3.27)	10.54* (3.02)
GDP-per-capita	0.01 (0.01)	0.01 (0.04)	0.02 (0.03)	0.03 (0.02)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	-	*23.24*	*23.24*	*20.47*
IV overidentification Chi-sq statistic	-	-	-	*0.46*

[35] The data indeed show a strong negative correlation between regional GDP per capita and the share of non-STEM in total high-tech industry employment, as well as the share of non-STEM in total employment

[36] The average share of non-STEM employment in high-tech industries for the regions included in the estimations equals 70.2%.

Independent variables:	B. Interaction of employment growth in high-tech industries with share of non-STEM workers (Dependent variable: Employment growth of non-STEM occupations in low-tech industries)			
	OLS	**IV**		
		Eq. (2.3)	Eq. (2.4)	Eqs. (2.3) and (2.4)
Employment growth in high-tech industries X Share of non-STEM workers in high-tech industries	2.99 (3.88)	114.14 (69.10)	114.05 (68.44)	112.17 (61.81)
Employment growth in high-tech industries	-1.13 (2.67)	-79.18 (48.62)	-79.12 (48.16)	-77.80 (43.54)
Share of non-STEM workers in high-tech industries	0.07 (0.05)	0.17 (0.13)	0.17 (0.13)	0.17 (0.14)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	-	*5.85*	*6.05*	*3.81*
IV overidentification Chi-sq statistic	-	-	-	*0.00*

Notes: Dependent variable is employment growth of non-STEM occupations in low-tech industries. Standard errors clustered at the regional level and * indicates significance at the 1% level. All F-test statistics in Panel A are significant at 1%, the F-test statistics from Panel B and the Chi-square test statistics are not. All regressions include country-year fixed effects. GDP per capita is in initial period and in purchasing power parity.

2.6 Conclusions

This study was the first to estimate an average local high-tech job multiplier across geographically dispersed labour markets in Europe. However, this paper also documented that there exist important differences in the size of the local high-tech job multiplier that are persistent across regions. In particular, we find that the multiplier is larger in regions with higher immigration, an abundance of less-skilled workers, and lower gross output per capita. At the country level, we also show that this results in local high-tech job multipliers that are larger in Southern European countries than in the rest of Europe.

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Annex 2.A Construction of high-tech employment time series using microdata

2.A1: Construction of the employment dataset

Employment is characterized by an ISCO occupation code relating to an employee's level and field of study, and a NACE sector code relating to the employer's business activities. The definition of high-tech employment that is used throughout the main text combines employment in STEM occupations (both in high-tech and low-tech industries) and employment in non-STEM occupations in high-tech industries. Employment in high-tech industries for each NUTS-2 region is available from Eurostat's Regional Science and Technology Statistics Database that we combine with employment in STEM and non-STEM occupations aggregated from the European Union Labour Force Survey (ELFS) micro data set.

We start with ELFS data from 2000 to 2007 that contains employment by two-digit ISCO occupation and two-digit industry for all EU countries. In this dataset we can calculate the share of high-tech jobs that is done by STEM workers for each country and year:

$$\alpha_{c,t} = \frac{STEMhigh_{c,t}}{STEMhigh_{c,t} + nonSTEMhigh_{c,t}}$$

This share $\alpha_{c,t}$ is then linearly extrapolated to the years 2008-2010. Note that the STEM definition used here is broader than the STEM occupations defined in the main text since we use the two-digit rather than three-digit ISCO occupations[37], and we return to this issue below.

Multiplying high-tech employment from Eurostat with this share $\alpha_{c,t}$ gives us STEM employment in the high-tech industries for each NUTS-2 region.[38] Once we have STEM employment in the high-tech industries, we also know non-STEM employment in the high-tech industries (since we have data on total high-tech industry employment). Note that we multiply regional high-tech employment with country-level shares ($\alpha_{c,t}$), hence making the assumption that the share of STEM occupations in high-tech industry employment is the same for every region of a country.

In the most recent version of the ELFS, that has data up to 2010, we have two-digit STEM employment for every NUTS-2 region. Subtracting the just-calculated STEM employment in high-tech industries from total STEM employment taken from the ELFS, gives us STEM employment in non-high tech industries. This gives us a dataset containing high-tech employment (that is, employment in STEM occupations in high-tech and non-high tech industries as well as in non-STEM occupations in high-tech industries), where STEM is defined at the two-digit ISCO level, from 2000 to 2010 at the NUTS-2 region.

[37] The two-digit STEM occupations are: 21, 22, 31 and 32.

[38] This ELFS version only contains one-digit NACE codes and could therefore not be used for making the distinction between high-tech and non-high tech.

As two-digit STEM occupations contain some occupations that should not be classified as STEM (primarily in healthcare), we have to adjust the STEM employment data. From the most recent ELFS data we can calculate the ratio of three-digit STEM employment to two-digit STEM employment for every NUTS-2 region and every year. We can safely assume that the two-digit STEM jobs that are not in the three-digit STEM classification are concentrated in the non-high tech industries. Therefore, we subtract the difference between two-digit STEM and three-digit STEM for STEM employment in the non-high tech industries and add it to non-STEM non-high tech industry employment. This gives us a dataset containing high-tech industry employment, where STEM is defined at the more restrictive three-digit ISCO level, from 2000 to 2010 at the NUTS-2 region.

Not all necessary data are present in Eurostat's Regional Science and Technology Statistics Database and the ELFS. So, we made the following adjustments:

- As we did not have data on STEM employment in high-tech industries for Romania, Poland, Bulgaria, and Malta, for the share of STEM in high-tech industry employment we used $\alpha_{c,t}$ the average share of the new member states[39] for each year in the sample.

- The ELFS only provides two-digit ISCO employment for Bulgaria, Slovenia, and Poland. So, we made the adjustment from two-digit to three-digit STEM using the average three-digit to two-digit ratio of the new member states.

- The ratio of three-digit to two-digit STEM employment for Germany is only available from 2002 so it was linearly extrapolated to 2000 and 2001 (only at the country-level).

- The EULFS only provides one-digit ISCO employment for Malta, which makes it impossible to calculate total STEM, and therefore also STEM employment in non-high tech industries and non-STEM employment in non-high tech industries. To solve this issue, we assume that the share of total STEM employment in total employment equals the following:

$$STEMshare_{MT,t} = STEMshare_{EU,t} \frac{\alpha_{MT,t}}{\alpha_{EU,t}}$$

- Germany and Austria only provide STEM employment at the NUTS-1 level. We therefore assumed that the share of total STEM employment in total employment was the same for every NUTS-2 region of a NUTS-1 region.

[39] The new member states are Cyprus, Malta, Bulgaria, Romania, Poland, Czech Republic, Hungary, Estonia, Latvia, Lithuania, Slovenia, Slovak Republic.

- The Netherlands and Denmark only provide STEM employment at the country level. We therefore assumed that the share of total STEM employment in total employment was the same for every NUTS-2 region of a country.

- For 2011 we only have the Eurostat data on total employment and high-tech industry employment. In order to get the rest of the data, we assume that the share of total STEM employment in total employment and the share of STEM in high-tech industry employment ($\alpha_{c,t}$) are the same as in 2010.

The final dataset contains employment for our broader definition of high-tech for each NUTS-2 region in the EU for the period 2000-2011.

2.A2: Construction of United Kingdom employment data

For the United Kingdom we do not use the ELFS, but the country's own national labour force survey (UKLFS). This survey uses a different occupational classification, namely the Coding of Occupations (SOC90). We classify the following occupations as STEM:

- Natural Scientists (20)
- Engineers and technologists (21)
- Architects, town planners and surveyors (26)
- Scientific technicians (30)
- Computer analysts/programmers (32)

Although not exactly the same as the STEM occupations in the ISCO classification, these occupations are very similar to the ones defined in Table 2.1 (STEM ISCO occupations). For the industry classification, the UKLFS uses the Standard Industrial Classification of Economic Activities (SIC92). We classify the following industries as high-tech industries:

- Manufacture of office machinery and computers (30)
- Manufacture of radio, television and communication equipment and apparatus (32)
- Manufacture of medical, precision and optical instruments, watches and clocks (33)
- Post and telecommunications (64)
- Computer and related activities (72)
- Research and development (73)

Remark that both occupational and industry codes have been made consistent over time. As the UKLFS only provides two-digit industry codes, we cannot include the sectors "Manufacture of pharmaceuticals, medicinal chemicals and botanical products (24.4)" and "Manufacture of aircraft and spacecraft (35.3)". Therefore our UK high-tech employment data will slightly underestimate the true value.[40]

As our UKLFS data are only available until 2010, we use the growth rate of total employment from Eurostat in 2011 and to obtain values for our different employment categories in 2011.

The UKLFS only provides data at the NUTS-1 level (defined as combinations of government office regions), with the exception of London, which is divided into its NUTS-2 regions Inner London (UKI1) and Outer London (UKI2). The following steps were followed to impute high-tech employment at the NUTS-2 level:

- Using Eurostat total employment data, we calculate for each NUTS-2 region its share in total employment of the corresponding NUTS-1 region.[41] We apply this share to the total employment data of the EULFS to get total employment at the NUTS-2 level.

- To get total employment in high-tech industries we apply the same method to Eurostat high-tech employment data.[42]

- For STEM employment at the NUTS-2 level, we assume that the STEM share of total employment is the same for every NUTS-2 region of a NUTS-1 region.

- After applying the share of STEM in high-tech ($\alpha_{c,t}$) to total high-tech at the NUTS-2 level, we can calculate employment for all different categories.

The final dataset contains employment for our broader definition of high-tech for each NUTS-2 region in the UK for the period 2000-2011.

[40] Estimations show that the inclusion of the sectors "Manufacture of pharmaceuticals, medicinal chemicals and botanical products (24.4)" and "Manufacture of aircraft and spacecraft (35.3)" would have only increased UK high-tech employment by 0.9% in 2007. Their exclusion will hence have a negligible impact on the UK data.

[41] The total employment data differ only slightly between the European and the UK labour force.

[42] Although the high-tech employment data from the European LFS and the UK LFS show substantial differences, the distribution of high-tech employment over the NUTS-1 regions is very similar. We therefore assume that the distribution over the NUTS-2 regions will also be reliable.

Chapter 3

Explaining international differences in wage inequality: skills matter

Abstract

Several studies employing decomposition methods have argued that skills only play a minor role in explaining cross-country differences in wage inequality. In this paper, we build upon the work of Leuven, Oosterbeek and van Ophem (2004) and extend the decomposition analysis to take account of the relative demand for, and supply of, skills. Doing this confirms that skills do matter and are likely to be at least as important as labour market institutions in explaining international differences in wage inequality.

3.1 Introduction

Inequality has been rising in most OECD countries and is now at its highest level on record since the mid-1980s (OECD, 2016). This should be of great concern to policy makers because high inequality has been associated with reduced social mobility (Krueger, 2012), lower social cohesion and trust (Stiglitz, 2012), as well as a range of health and social problems (Pickett and Wilkinson, 2011) - including higher crime (Brush, 2007; Choe, 2008). In addition, recent research has suggested that inequality may even be bad for economic growth (Ostry, Berg and Tsangarides, 2014; Cingano, 2014).

While rising inequality may be partly to blame on common trends that affect all countries (such as globalisation and technological change) (Autor, Katz and Kearney, 2006; Blinder, 2009; Autor, Dorn and Hanson, 2016), there are also important differences across countries in levels of inequality - which suggests that country-specific policies and institutions may play an important role as well. Amongst the various policy levers that have been argued to impact on the income distribution, education and skills have frequently been put forward as key determinants (Autor, 2014) – alongside labour market institutions and tax-and-transfer systems (OECD, 2015).

Somewhat surprisingly, however, most research which has tried to link cross-country differences in inequality to differences in skills has concluded that the latter only play a minor role (Devroye and Freeman, 2001; Blau and Kahn, 2005; Paccagnella, 2015; Pena, 2016; Jovicic, 2016; and Machin, Salvanes and Sten Gahmberg, 2016). All these papers take a similar approach:

differences in inequality are decomposed into differences in skills endowments, on the one hand, and differences in skills prices, on the other. Invariably, differences in skills are found to account for only a small portion of cross-country differences in inequality, while a far more important role is played by skills prices (i.e. how skills are rewarded). Some of these papers then go on to argue that differences in inequality across countries must be driven primarily by labour market institutions (such as minimum wages and collective bargaining arrangements) since these have a direct impact on the return to skill.

However, skills prices are not only determined by institutions, but also by market forces – i.e. the relative scarcity of skills. If skills are in high demand but in low supply, then the reward to skill is likely to increase, and vice versa. Hence, if differences in skills prices explain a large part of cross-country differences in inequality, this could still largely be attributable to differences in skills policies rather than to differences in institutions.

The standard decomposition methods used by the above-mentioned studies fail to factor in such differences across countries in the demand for, and the supply of, skills. The only paper to have done so employed an entirely different methodology: Leuven, Oosterbeek and van Ophem (2004) used a demand and supply model in the spirit of Katz and Murphy (1992) to analyse the extent to which higher wage differentials between skills groups in the United States could be linked to differences in the relative supply of, and demand for, skilled workers. Contrary to the other papers in this literature, they found that skills did matter in explaining such wage differentials.

It is difficult, however, to compare the Leuven, Oosterbeek and van Ophem (2004) results to those obtained elsewhere in the literature because of the different methodologies employed. In this paper, we therefore propose to bridge these two strands of the literature by integrating the demand and supply framework used by Leuven, Oosterbeek and van Ophem (2004) into the standard decomposition approach used by the other papers. More specifically, we employ the full distribution accounting techniques developed by DiNardo, Fortin and Lemieux (1996) and Lemieux (2002, 2010) to decompose cross-country differences in inequality into differences in skills prices, on the one hand, and skills endowments, on the other. We then extend this decomposition analysis to consider demand and supply conditions by using the approach proposed by DiNardo, Fortin and Lemieux (1996). Finally, we also extend the model to incorporate labour market institutions (the minimum wage and collective bargaining coverage). While our approach is schematic and not intended to establish causality, it still provides useful ball park estimates of the relative importance of institutions as compared to skills in determining cross-country differences in inequality.

Using data from the first and second rounds of the Survey of Adult Skills (PIAAC) covering 29 OECD countries, our analysis confirms the findings from previous research and shows that skills prices are far more important than skills endowments in explaining cross-country differences in wage inequality. We argue that skills prices are determined both by market forces and by labour market institutions, and our analysis shows that differences in the demand for and supply of skills can explain just over a quarter of the difference in wage inequality between the United States (the base country in our analysis) and the other countries that participated in the survey.

Differences in collective bargaining coverage between the United States and the other countries also account for around a quarter of the difference in wage inequality, while minimum wages account for less than 6%.

The paper proceeds as follows. In section 3.2, we provide further detail on the Survey of Adult Skills (PIAAC). In Section 3.3 we carry out a standard decomposition of cross-country differences in wage inequality into skills endowments and skills prices, respectively. Section 3.4 then extends this decomposition exercise to factor in demand and supply conditions and Section 3.5 looks at the role of institutions. Section 3.6 summarizes the main findings, and section 3.7 offers some concluding remarks.

3.2 Data and descriptive statistics

In analysing the relationship between skills and wage inequality, Leuven, Oosterbeek and van Ophem (2004) demonstrated the importance of using direct measures of skill instead of proxies (such as years of education).[43] The OECD's adult literacy surveys, which assessed the skills of adults in a comparable manner across a number of countries, are therefore an ideal source of information to carry out such analyses. The first of these surveys, the International Adult Literacy Survey (IALS), was carried out in the 1990s in a total of 23 countries/regions across the world. This was the data used by Devroye and Freeman (2001), Leuven, Oosterbeek and van Ophem (2004) and Blau and Kahn (2005). Between 2003 and 2008, the OECD ran the Adult Literacy and Lifeskills (ALL) Survey in a total of 10 countries. To our knowledge, this survey was never used to analyse the relationship between skills and wage inequality. The latest of the OECD surveys (and the one we use in this paper) is the Survey of Adult Skills (PIAAC), the first round of which covered 24 countries/regions over the period 2008-2013. This was the data used in the analyses of Paccagnella (2015), Pena (2016), Jovicic (2016), and Machin, Salvanes and Sten Gahmberg (2016). A second round of the survey was carried out between 2012 and 2016 in a further nine countries/regions. In this paper, we use data for the 29 OECD countries/regions covered by the two rounds of PIAAC.[44]

The PIAAC surveys directly assessed the proficiency of adults (aged 16-65) in literacy, numeracy and problem solving in technology-rich environments. Computer-based assessments were used as a standard, but individuals lacking the necessary computer skills could opt for a paper-based versions of the literacy and numeracy tests instead (although they could then not sit the problem-solving test). The survey was administered in the national language of each country and was designed in such a way as to be valid cross-culturally and cross-nationally. The literacy test assessed adults' ability to understand, evaluate, use and engage with written texts, while the numeracy test looked at individuals' ability to access, use, interpret and communicate

[43] The correlation between years of education and numeracy is approximately 0.54 across the 29 countries included in this chapter.

[44] We include: Australia, Austria, Canada, Chile, the Czech Republic, Denmark, England, Estonia, Finland, Flanders (Belgium), France, Germany, Greece, Ireland, Israel, Italy, Japan, Korea, the Netherlands, New Zealand, Northern Ireland, Norway, Poland, the Slovak Republic, Slovenia, Spain, Sweden, Turkey and the United States. We leave out: Cyprus, Indonesia, Lithuania, the Russian Federation and Singapore. OECD countries will have more in common with one another than non-OECD countries. However, one of the main reasons for leaving the non-OECD countries out of the present analysis is that information on minimum wages and collective bargaining coverage is much harder to obtain.

mathematical information and ideas. The final test (problem solving in technology-rich environments) focused on the ability of adults to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others, and perform practical tasks.

In the three domains assessed, skills are reported on a 500-point scale. Table 3.1 provides some summary statistics for the three information-processing skills measured (and for the 29 OECD countries included in our analysis). In numeracy, the average score ranges from 206 points in Chile to 288 points in Japan, and the average standard deviation is 49 score points. Japan is also the highest-scoring country in literacy (296 points), while Chile is again the lowest-scoring one (with 220 points). The average standard deviation in literacy is 44 score points. To put these figures into perspective, one additional year of education translates into approximately eight more numeracy and seven more literacy points, on average.[45] One standard deviation on the literacy and the numeracy scales is therefore more or less equivalent to six years of education.

The difference between countries in the average level of problem-solving skills is lower (252 points in Chile compared to 294 points in Japan) which can be explained by the fact that individuals who lacked basic computer skills did not take the test. This also explains why proficiency in problem solving is missing for many individuals and, hence, why the sample sizes are much lower for this skill than for the others. For numeracy and literacy, the sample sizes are the same, and range from around 3,700 in Northern Ireland to 27,000 in Canada.

In addition to the cognitive assessments, the PIAAC survey contained a background questionnaire which gathered a wide range of information, including details on individuals' labour market status, contract type, wages, bonuses, education, work experience, as well as a range of demographic characteristics.

As a measure of skill, we focus on numeracy only, given that: (i) using problem solving in technology-rich environments would result in a loss of too many observations (as well as three countries[46]); and (ii) the correlation between numeracy and literacy scores is so high (0.91) that little is lost by using one rather than the other (or, indeed, both together).[47] Importantly, the key results obtained in this paper do not change when literacy is used instead of numeracy.[48]

The Survey of Adult Skills contains information only on individuals' wages, not on their incomes. While policy makers will, ultimately, be more concerned with inequality in net household income (i.e. after taxes and transfers have been taken into account), there are some strong reasons to focus the analysis on inequality in gross wages. First, wage inequality is an important component of income inequality and, as estimated by OECD (2011), greater inequality in wages and salaries has been the single most important driver of increased income inequality

[45] On average across the 29 countries included in our analysis (i.e. unweighted country average), individuals have 12.4 years of education (with a standard deviation of 2.9 years).
[46] France, Italy and Spain did not administer the problem-solving test.
[47] This correlation is high in all countries, ranging from 0.83 in Greece to 0.93 in Spain.
[48] Another reason for using numeracy scores is that they have a larger effect on wages than literacy scores (Hanushek, Schwerdt, Wiederhold and Woessman, 2015).

Table 3.1. Summary statistics cognitive skills (full sample)

	Numeracy					Literacy					Problem solving				
	N	Mean	Min	Max	SD	N	Mean	Min	Max	SD	N	Mean	Min	Max	SD
Australia	7,315	268	11	427	53	7,315	280	63	395	48	5524	289	166	391	36
Austria	5,025	275	61	410	46	5,025	269	87	410	41	3855	284	147	404	35
Canada	27,054	265	37	421	52	27,054	273	83	407	48	21441	282	109	414	42
Chile	5,192	206	38	369	57	5,192	220	13	370	50	3,342	252	58	401	46
Czech Republic	6,081	276	121	405	41	6,081	274	107	389	38	4,675	283	136	480	42
Denmark	7,286	278	86	420	48	7,286	271	58	386	45	6,098	283	95	398	40
England (UK)	5,080	262	57	403	52	5,080	273	99	388	46	4275	281	132	397	40
Estonia	7,586	273	74	412	42	7,586	276	117	393	41	5,235	278	148	406	40
Finland	5,464	282	72	443	49	5,464	288	64	411	48	4,503	289	142	399	40
Flanders (B)	4,984	280	77	414	48	4,984	275	89	403	45	4,186	281	134	419	41
France	6,907	254	58	411	54	6,907	262	92	385	47	0				
Germany	5,379	272	72	418	50	5,379	270	102	393	45	4,541	283	145	412	41
Greece	4,916	252	98	436	44	4,916	254	113	408	42	3,167	257	93	461	44
Ireland	5,963	256	25	418	51	5,963	267	106	396	44	4,092	277	153	385	37
Israel	5,344	251	28	417	60	5,344	255	45	408	52	3,598	274	127	416	49
Italy	4,589	247	91	391	47	4,589	250	98	382	42	0				
Japan	5,173	288	109	418	41	5,173	296	139	407	37	3,307	294	143	449	41
Korea	6,651	263	104	381	43	6,651	273	117	388	39	4,540	283	150	385	35
Netherlands	5,083	280	48	416	48	5,083	284	98	401	46	4,548	286	138	396	39
New Zealand	6,074	271	59	431	52	6,074	281	89	410	45	5,510	287	133	405	43
Northern Ireland (UK)	3,726	259	82	409	48	3,726	269	116	391	43	3,047	275	159	388	38
Norway	4,947	278	39	418	52	4,947	278	106	389	45	4,342	286	115	395	38
Poland	9,366	260	88	396	47	9,366	267	78	399	45	5,992	275	86	424	45
Slovak Republic	5,702	276	86	399	44	5,702	274	117	371	37	3537	281	159	424	33
Slovenia	5,293	258	54	415	52	5,293	256	94	397	45	3,995	268	128	414	45
Spain	5,971	246	82	381	49	5,971	252	79	376	47	0				
Sweden	4,469	279	52	444	52	4,469	279	24	416	48	3,963	288	135	413	42
Turkey	5,194	219	53	377	52	5,194	227	98	358	41	2,266	253	91	408	40
United States	4,898	253	71	416	55	4,898	270	120	406	47	4,103	277	125	411	41

across the OECD. The second reason for focusing on wages is that they allow us to measure more directly the prices of skills and how different returns across countries contribute to inequality.

Table 3.2 shows mean wages and numeracy skills (for wage and salary earners only) in the 29 OECD countries included in our sample, as well as their level of dispersion. Our measure of gross hourly wages includes bonuses and is expressed in purchasing power parity corrected USD. Both wage and skill dispersion are measured using the ratios of: the 90^{th} to the 10^{th} percentiles (P90/P10), the 90^{th} to the 50^{th} percentiles (P90/P50), the 50^{th} to the 10^{th} percentiles (P50/P10), as well as by the Gini index. Our sample includes all individuals aged 16 to 64 with non-missing wages, i.e. both men and women; part-time as well as full-time workers (but excluding the self-employed). Wages in Table 3.2 (and throughout this paper) are trimmed, by country, at the top and bottom percentiles.

The table confirms that skill levels are the highest in Japan, the Nordic countries, the Netherlands and Flanders, while they are the lowest in Chile, Turkey, Italy and Spain. Average skill levels are substantially lower than the average in the United States as well. Wages are highest in Norway and Denmark, and lowest in the Eastern European countries. Wage inequality as measured by the P90/P10 is highest in Turkey, Chile and Korea - followed by the United States. It is lowest in Sweden, Norway, Denmark and Finland. Most of the other wage inequality measures reported in Table 3.2 result in a similar ranking, but it is worth noting that inequality in the bottom half of the distribution is highest in Germany. The table also makes it clear that there is only a weak cross-country relationship between skills and wage inequality. While there are countries, like the United States, Canada, Germany and Italy, where both skill and wage inequality are high, and others where both skill and wage inequality are low (e.g. the Nordic countries), there are also countries that combine high skill inequality with low wage inequality (e.g. France) and some that combine low skill inequality with high wage inequality (e.g. Japan and Korea).

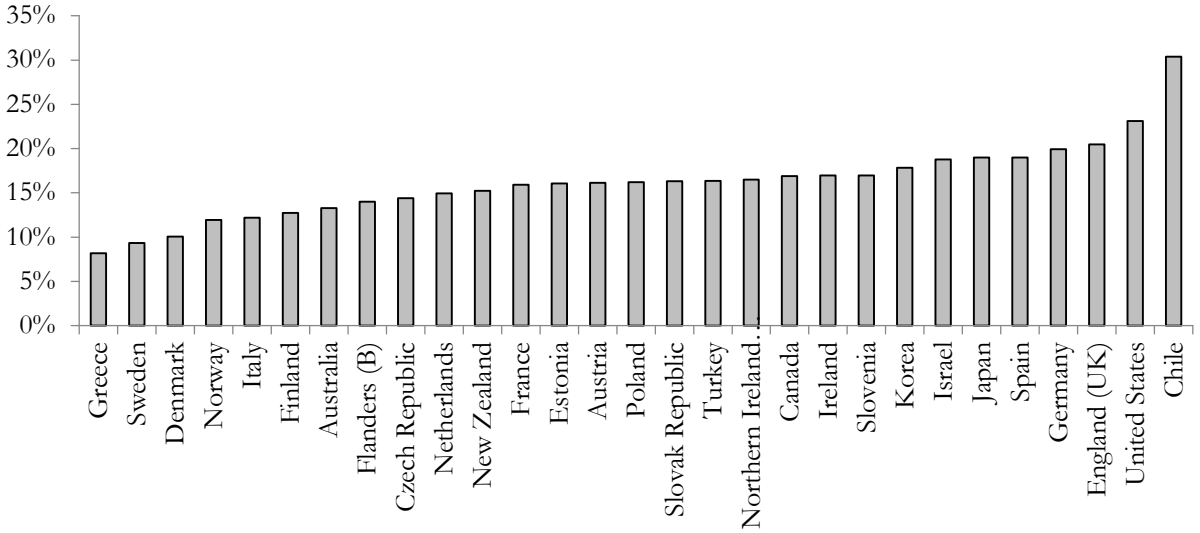
Finally, countries differ not only in terms of the skills of their workforce, but also in how these skills are rewarded in the labour market. Figure 3.1 shows that the return to skill is highest in Chile, followed by the United States. The return to skill in Chile is 3.7 times greater than in Greece, the country with the lowest return. The return to skill in the United States is nearly two times the average return across all OECD countries which participated in the PIAAC survey. Also, and critically for the analysis that follows, the return to skill in the United States is highly non-linear – i.e. rising in skill level (see Figure 3.A.1 in the Annex). In other words: the higher the skill level, the higher is the return to skill. Other countries that exhibit strongly increasing returns to skill include Canada, Israel, New Zealand, the Slovak Republic, Turkey and the United Kingdom, whereas the returns to skill are fairly constant along the skills distribution in countries like Belgium, Finland, Greece, Northern Ireland and Sweden.

Table 3.2. Summary statistics: Levels and dispersion of skills and wages (analysis sample)

		Skills					Wages				
	N	Mean	P90/P10	P90/P50	P50/P10	Gini	Mean	P90/P10	P90/P50	P50/P10	Gini
Australia	4,371	276	1.55	1.20	1.30	0.10	18.9	3.14	1.90	1.65	0.25
Austria	2,945	278	1.49	1.17	1.27	0.10	19.0	3.04	1.82	1.67	0.25
Canada	16,148	271	1.61	1.21	1.34	0.11	20.3	3.98	1.95	2.04	0.28
Chile	2,330	213	2.03	1.34	1.51	0.16	10.3	6.91	3.32	2.08	0.42
Czech Republic	2,628	279	1.43	1.16	1.24	0.09	8.9	2.84	1.67	1.70	0.24
Denmark	4,455	286	1.48	1.17	1.26	0.09	23.8	2.59	1.56	1.66	0.21
England (UK)	2,781	271	1.58	1.21	1.30	0.11	18.3	3.52	2.06	1.71	0.29
Estonia	3,968	277	1.46	1.18	1.24	0.09	9.6	4.70	2.23	2.10	0.32
Finland	3,249	291	1.46	1.18	1.25	0.09	19.1	2.58	1.73	1.49	0.21
Flanders (B)	2,739	287	1.51	1.17	1.29	0.09	21.8	2.59	1.66	1.56	0.21
France	3,697	261	1.69	1.22	1.38	0.12	15.5	2.56	1.76	1.45	0.22
Germany	3,380	277	1.55	1.19	1.30	0.10	18.6	4.19	1.90	2.21	0.29
Greece	1,238	262	1.57	1.21	1.30	0.11	10.6	3.48	2.08	1.67	0.29
Ireland	2,788	264	1.55	1.20	1.29	0.10	21.5	3.56	2.10	1.70	0.29
Israel	2,703	259	1.76	1.25	1.40	0.13	13.8	4.32	2.54	1.70	0.38
Italy	1,815	255	1.61	1.21	1.33	0.11	16.1	3.42	1.99	1.72	0.27
Japan	3,256	293	1.42	1.16	1.23	0.08	16.0	4.05	2.31	1.75	0.33
Korea	3,097	268	1.48	1.17	1.27	0.09	17.8	5.83	2.68	2.18	0.39
Netherlands	3,161	287	1.47	1.16	1.27	0.09	21.3	3.32	1.81	1.84	0.26
New Zealand	3,519	276	1.58	1.21	1.30	0.10	17.9	2.82	1.87	1.51	0.25
Northern Ireland (UK)	2,020	270	1.53	1.20	1.28	0.10	16.5	3.14	2.02	1.56	0.28
Norway	3,554	286	1.51	1.17	1.29	0.10	24.3	2.44	1.60	1.52	0.20
Poland	3,906	267	1.54	1.20	1.28	0.10	9.2	3.88	2.17	1.79	0.31
Slovak Republic	2,489	285	1.39	1.15	1.21	0.08	8.6	3.84	2.08	1.85	0.31
Slovenia	2,193	264	1.62	1.20	1.34	0.11	9.3	2.79	1.81	1.54	0.23
Spain	2,456	258	1.56	1.19	1.31	0.10	15.0	3.60	2.06	1.75	0.28
Sweden	2,890	287	1.51	1.19	1.28	0.10	18.5	2.15	1.58	1.36	0.17
Turkey	1,529	235	1.69	1.23	1.38	0.12	12.8	6.22	3.33	1.87	0.44
United States	2,797	261	1.71	1.23	1.39	0.12	21.4	4.80	2.39	2.01	0.34

Notes: Data refer to wage and salary earners only. Wages are trimmed, by country, at the top and bottom percentiles.

Figure 3.1: Returns to skill



Notes: The figure shows the coefficient on standardised numeracy scores from a regression of log hourly wages (including bonuses) for wage and salary earners on a constant and standardised numeracy scores.

3.3 The contribution of skills and skills prices to wage inequality: The standard decomposition approach and its limitations

The standard approach for analysing the contribution of skills to differences in wage inequality across countries is to decompose these differences into an endowment (skill) effect and a price effect. The particular methodology for doing these decompositions varies: Devroye and Freeman (2001) and Jovicic (2016) use a simple variance decomposition; Blau and Kahn (2005) and Pena (2016) apply the Juhn, Murphy and Pierce (1993) decomposition; while Paccagnella (2015) and Machin, Salvanes and Sten Gahmberg (2016) resort to unconditional quantile regressions (Firpo, Fortin and Lemieux, 2009).

In this paper, we use a slightly different methodology, and simulate alternative wage distributions using reweighting techniques in the spirit of DiNardo, Fortin and Lemieux (1996) and Lemieux (2002, 2010). According to Fortin, Lemieux and Firpo (2011), this reweighting approach should be the preferred method for aggregate decompositions, and we favour this approach for two reasons.[49] The first is its simplicity and transparency. The second, and perhaps more important, reason is its flexibility. Indeed, as will become clear later on in this paper, this methodology not only allows us to analyse the impact of the (full) skills distribution on wage inequality, but it can also be extended to incorporate demand and supply conditions as well as a number of labour market institutions. While these decompositions should only be interpreted in an accounting sense (and not in a causal one), they still represent a useful exercise in that they permit the relative importance of skills and labour market institutions to be compared within a single analytical framework.

[49] Unconditional quantile regressions have become a popular decomposition method. However, as argued by Fortin, Lemieux and Firpo (2011), the approximations applied by this method can be problematic in the presence of minimum wages (i.e. unsmooth wage distributions). This is another reason why we prefer to use the reweighting method in the present paper.

In this section, the reweighting technique is used to analyse the impact of skill endowments and skill prices on wage inequality, in line with the standard approach followed in the literature. In all our analysis, we have chosen the United States as our base country. There are two reasons behind this choice: (i) it is one of the countries with the highest level of wage inequality among those that participated in the PIAAC survey; and (ii) it facilitates comparisons with other studies in the literature, which have also tended to use the United States as base country.

When estimating the endowment effect, we want to know what would happen to wage inequality in the United States if it had the same skills distribution as a comparator country, *x*. To model this, we attach more/less weight to individuals in the United States whose skills are more/less common in the comparator country. This is achieved by replacing the original sample weight $\omega_{i,US}$ for each individual *i* in the United States with a counterfactual weight $\omega'_{i,US} = \omega_{i,US}\Psi_{S,x}$, where $\Psi_{S,x}$ represents the reweighting factor. In practice, we obtain the reweighting factor by first dividing the samples for both countries into *S* bins of 5 skills points each,[50] and then computing the ratio of the shares θ of total employment in each country in each of these skills bins – i.e. $\Psi_{S,x} = \frac{\theta_{S,x}}{\theta_{S,US}}$. Holding skills prices constant, this reweighting exercise results in an alternative wage distribution for the United States. Standard wage dispersion and inequality measures can then be computed and compared to those estimated on the original wage distribution, and the difference between these wage inequality measures is attributed to the effect of skills.

To estimate the price effect, we want to know what would happen to wage inequality in the United States if the skills of its workforce were rewarded in the same way as in a comparator country *x*, holding the distribution of skills constant. To model this, we base our approach on Lemieux (2002, 2010) and we start, once again, by dividing the samples for the two countries into *S* bins of 5 skills points each. We then estimate the mean of log wages of skill group *S* in the United States ($y_{S,US}$) and in the comparator country ($y_{S,x}$), and the difference between these two average wages is added to each individual's original wage to estimate his/her new counterfactual wage $y'_{i,US}$:

$$y'_{i,US} = y_{i,US} + (y_{S,x} - y_{S,US}) \tag{3.1}$$

Figure 3.2 provides an idea of what these two wage simulations look like in practice and shows the reweighted wage distributions for the United States obtained by applying: (i) the Dutch skills distribution and (ii) Dutch skills prices. The choice of the Netherlands as comparator country in this figure is somewhat arbitrary, but reflects the fact that this is a country that combines high skill levels with low inequality in both skills and wages – i.e. a very different skills distribution form the United States. In panel A, which applies the Dutch skills distribution to the United States, the United States wage distribution shifts somewhat to the right, but its height lowers and its dispersion increases (i.e. it becomes more unequal – a counterintuitive result to which we shall

[50] Bigger intervals are created at the top and bottom of the skill distribution to guarantee a non-zero number of observations. The size of the smallest bins ranges from 5 observations in the Czech Republic to 241 in Canada (and 31 observations on average across countries).

return below). In panel B, which applies the Dutch return to skill, the United States distribution becomes narrower (i.e. less unequal).

Table 3.3 repeats this exercise for all the other countries in the PIAAC data and shows what proportion of the difference in wage inequality between the United States and each country can be attributed to differences in skills endowments and skills prices, respectively. Consistent with the previous literature, differences in the return to skill appear to explain a much larger proportion of the difference in wage inequality between the United States and other countries than differences in skill endowments. Nearly 30% (23%) of differences in the P90/P10 wage ratio (Gini index) is due to differences in skills prices with the United States (excluding Estonia, a clear outlier).[51] [52] [53]

By contrast, in most cases, the P90/P10 wage ratio (and the Gini) would increase (rather than decrease) if the United States adopted the skills distribution of the comparator country – a result driven primarily by increases in the P50/P10 wage ratio. This counterintuitive result (also obtained by Paccagnella, 2015 and Pena, 2016) is the result of: (i) relatively low skills levels in the United States and (ii) significantly higher marginal returns to skill in the top half of the wage distribution in the United States (see Figure 3.A.1 in the Annex). Increasing the skills of the workforce in the United States would therefore mechanically lead to an increase in wage inequality at the bottom of the wage distribution, as the wages of those at the P50 would increase faster than those at the P10.[54] This result is clearly unrealistic and highlights a key limitation of using decomposition methods for analysing the contribution of skills to international differences in wage inequality. In reality, of course, one would expect an increase in overall skill levels to lead to a fall in the price of skill. Yet the standard decomposition methods, by taking a comparative static approach to what is essentially a dynamic phenomenon, are therefore unable to account for differences in net supply and demand conditions. This was part of Leuven, Oosterbeek and van

[51] We have also estimated our models separately for men and for women (results available upon request). While in nearly all countries both the endowment and price effects were larger for men than for women, the differences were small on average. This suggests that our overall conclusions apply to both men and women, and that little is lost by keeping both genders aggregated in the analysis.

[52] Following the previous literature, we use numeracy scores as a measure of skill. While such scores are more comparable internationally than educational attainment, the latter may embody some additional skills not captured by numeracy. To test whether the exclusion of education has a major impact on our results, we carried out a robustness test using a two-stage reweighting process for the endowment analysis. In a first step we implement the reweighting exercise using just skills (as described in the paper). In a second step we apply the same methodology using education groups. In other words, we correct the weights obtained in step 1 to reflect the size of the education groups in the comparator country. We use three education groups: tertiary, upper secondary, and everything below. To include education in the price analysis, we start by estimating the returns to skill and education in each country. Our regression includes skills, education, and an interaction term between these two. We then calculate the counterfactual wage based on the predicted values from these regressions (instead of using average wages per skill group as in the baseline methodology). The results of this analysis (available upon request) are very similar to those obtained in the paper and the overall conclusions are not affected.

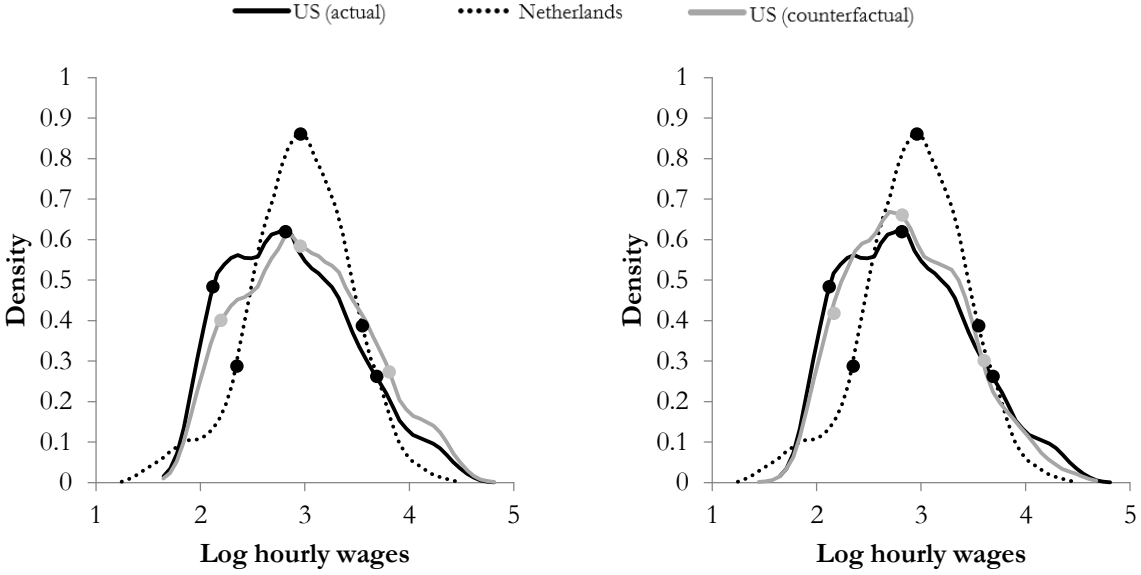
[53] The composition of the skill cells may differ across countries with respect to years of schooling, gender, and experience. This raises the possibility that what looks like a price effect might be due to composition. To test whether the estimated price effect is picking up compositional differences between countries, we repeated the analysis on numeracy scores "corrected" for gender and age (based on a regression of numeracy skills on gender, age and age squared). This correction only modestly affected the results from the endowment and price analysis, without changing the main conclusions. Similarly, using composition-corrected skills only modestly changes the results for the skills-education analysis discussed in footnote 52. All these results are available upon request.

[54] Note that this would not happen in the top half of the wage distribution, since the wages of those at the P50 and the P90 would increase at about the same rate.

Ophem's (2004) critique of Blau and Kahn (2005). In the remainder of this paper, we seek to address this limitation of the standard approach. More specifically, we extend the decomposition method used in this section to explicitly factor in demand and supply conditions.

Figure 3.2: The United States wage distribution before and after applying the skill distribution and prices of the Netherlands

A. US before and after Netherlands skills **B.** US before and after Netherlands skills prices distribution



Notes: Epanechnikov kernel density plots (evaluated at 50 points). Dots on each curve indicate, from left to right, the 10th, 50th and 90th percentile, respectively.

3.4 Factoring in the demand for and supply of skills

Leuven, Oosterbeek and van Ophem (2004) argued that one of the weaknesses of the analysis by Blau and Kahn (2005) (a weakness which also applies to the most recent papers by Paccagnella, 2015; Pena, 2016; and Machin, Salvanes and Sten Gahmberg, 2016), is that they fail to account for differences across countries in the relative demand for, and supply of, skills. Indeed, the higher price effects found by these authors will, to some extent, reflect differences in such market conditions. Leuven, Oosterbeek and van Ophem (2004) address this issue by adapting a methodology developed by Katz and Murphy (1992) to relate differences in wages between skill groups to changes in the demand for, and supply of, those skills. Their results show that about one third of the variation in relative wages between skill groups across countries can be explained by differences in the net supply of skill groups. However, because they: (i) use a different methodology; and (ii) look at relative wages between skills groups (rather than measures of wage inequality), it is difficult to compare their results to what has been obtained elsewhere in the literature. For these reasons, we propose a way of incorporating relative demand and supply conditions in the reweighting framework used so far, based on a similar exercise performed by DiNardo, Fortin and Lemieux (1996) for analysing changes in wage inequality in the United States over time.

Table 3.3: Proportion (%) of the difference in wage inequality with the United States explained by skills endowments and skills prices

	Skills endowments				Skill prices			
	P90/P10	P90/P50	P50/P10	Gini	P90/P10	P90/P50	P50/P10	Gini
Australia	-10.9	-0.5	-21.0	-0.7	35.8	37.0	29.2	26.4
Austria	-8.6	8.3	-31.3	1.3	25.0	24.5	21.0	19.7
Canada	-21.5	-2.6	201.7	-1.1	58.3	31.9	-275.8	34.5
Chile	-44.7	-10.0	-434.6	-24.1	24.9	13.4	146.6	35.5
Czech Republic	-3.5	9.0	-28.1	4.1	16.9	20.0	6.1	14.7
Denmark	-9.8	5.2	-37.5	-0.5	30.2	25.5	32.1	21.0
England (UK)	-12.6	-3.8	-18.8	-0.2	17.9	16.6	17.0	17.8
Estonia	-74.4	35.6	78.0	20.0	363.9	64.1	-59.7	62.5
Finland	-17.7	0.4	-32.4	-0.8	28.4	32.4	17.7	19.2
Flanders (B)	-11.5	3.9	-29.6	-1.0	27.5	27.4	21.0	19.2
France	1.9	2.7	0.7	1.2	26.4	28.1	19.3	20.3
Germany	-29.1	3.6	45.0	-1.2	57.7	22.3	-28.6	26.8
Greece	10.3	14.0	6.3	10.4	46.6	72.0	23.4	49.2
Ireland	9.5	16.2	3.2	8.2	29.8	43.2	16.4	27.1
Israel	-11.4	24.6	2.4	5.8	57.7	-37.4	23.2	-23.7
Italy	13.7	12.4	13.1	11.8	37.9	42.4	28.2	30.0
Japan	-43.2	48.5	-66.8	5.3	43.9	126.9	21.7	76.9
Korea	-12.3	-29.7	11.5	-17.1	-31.8	-40.4	-24.4	-24.0
Netherlands	-17.0	5.8	-79.4	-0.2	36.1	30.3	47.6	27.3
New Zealand	-9.8	-0.4	-16.0	-1.1	28.6	32.6	20.3	24.1
Northern Ireland (UK)	-2.0	10.1	-10.1	5.6	24.2	34.6	14.0	29.1
Norway	-11.0	2.9	-26.6	-1.7	26.1	24.2	21.7	18.9
Poland	7.4	19.0	-2.9	13.1	42.0	54.1	29.6	42.8
Slovak Republic	-9.3	30.5	-77.2	10.6	27.1	29.4	20.6	32.7
Slovenia	3.3	3.7	2.0	2.3	22.0	22.3	17.2	17.0
Spain	17.5	19.7	13.1	15.9	22.2	23.3	18.6	15.7
Sweden	-11.1	1.7	-20.8	-1.1	28.5	30.5	18.7	18.8
Turkey	-47.3	-19.1	98.7	-18.6	-1.7	0.0	7.3	2.6
Unweighted average	-12.7	7.6	-16.3	1.6	41.1	29.7	8.9	24.4

Notes: The table shows the proportion of the difference in wage inequality between the United States and country x that can be explained by skills and skills prices, respectively. For example, 35.8% of the difference in the P90-P10 wage ratios between the United States and Australia can be explained by different returns to skill in Australia. Negative figures indicate that the difference between the United States and the comparator country would increase (rather than decrease) if the comparator country's skills distribution or skills prices were adopted.

The basic intuition behind our approach is to see what would happen to wages for skill group S in the United States, should the supply and demand conditions for that skill group reflect those prevalent in the comparator country x. To implement this in practice, we divide the sample into S skill groups of 10 points each.[55] For each skill group in the United States, we then derive supply and demand indices relative to those prevalent for the same skill group in country x. The supply index $\Delta S_{S,x}^{US}$ is defined as the share $\varepsilon_{S,US}$ of skill group S in the working age population in

[55] The size of the skill intervals is set at 10, rather than at 5 as in the previous analyses, to guarantee a sufficient number of observations per skill-industry group.

the United States, relative to the share $\varepsilon_{S,x}$ occupied by that skill group in the comparator country, *x*:

$$\Delta S_{S,x}^{US} = \ln\left(\frac{\varepsilon_{S,US}}{\varepsilon_{S,x}}\right) \tag{3.2}$$

In building the demand index, $\Delta D_{S,x}^{US}$, we follow the approach proposed by Blau and Kahn (1996) and Leuven, Oosterbeek and van Ophem (2004) and measure the degree to which the occupation-industry structure[56] *O* in the United States favours skill group *S* in comparison to country *x*. Specifically:

$$\Delta D_{S,x}^{US} = \ln\left[1 + \sum_{o} \frac{\theta_{S,o,US}}{\varepsilon_{S,US}}\left(\theta_{o,US} - \theta_{o,x}\right)\right] \tag{3.3}$$

Where $\theta_{o,US}$ and $\theta_{o,x}$ are the total shares of employment in occupation-industry cell *O* in the United States and country *x*, respectively; $\theta_{S,o,US}$ is skill group *S*'s share of employment in occupation-industry cell *O* in the United States; and $\varepsilon_{S,US}$ is the share of skill group *S* in the working age population of the United States. The demand index therefore represents the average difference in the employment shares of each occupation/industry between the United States and the comparator country – weighted by the skill intensity of each industry/occupation relative to the overall skill intensity in the United States. If employment in the United States were strongly concentrated in industry/occupation cells that employ a large share of skilled workers compared to country x, the demand index would be high (and vice versa).

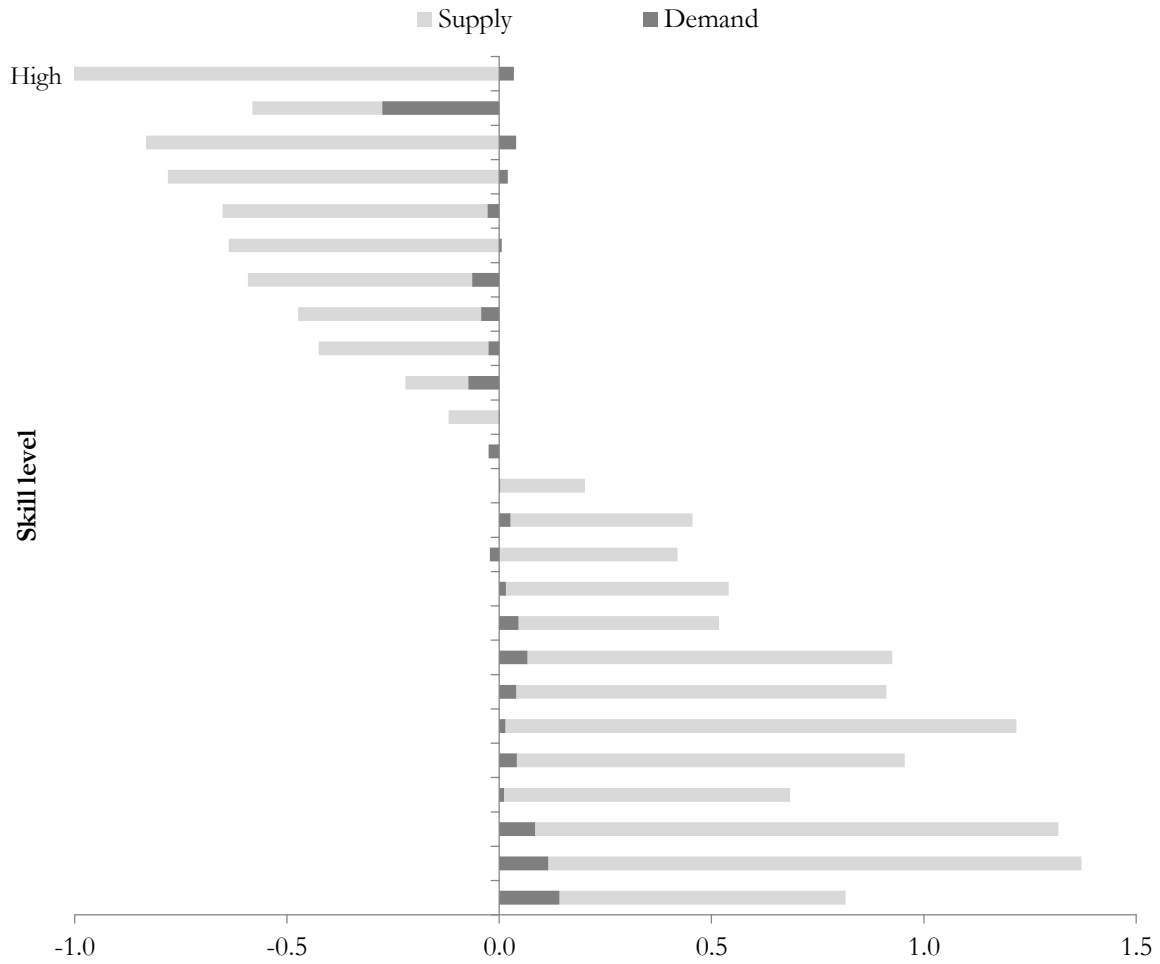
Figure 3.3 illustrates what these supply and demand indices look like when the United States is compared to the Netherlands. As the figure shows, the United States has a relatively high supply of low-skilled workers in comparison to the Netherlands, while the opposite is true for high-skilled workers. The demand index shows that the demand for high-skilled workers in the United States is slightly lower than in the Netherlands, while the demand for low-skilled workers is comparatively higher.

Table 3.4 shows what the demand for, and supply of, skills in the United States look like compared to all the other countries in the sample. As the negative values in the first column indicate, the demand for low-skilled workers is lower in the United States than in most other countries – with the exception of Canada, Denmark, Flanders, Israel, the Netherlands and New Zealand, where the demand for low-skilled workers is even lower. By contrast, the supply of low-skilled workers in the United States is one of the highest amongst the countries included in the sample, with the exception of Chile, Italy, Spain and Turkey. This picture is inverted when looking at high-skilled workers, for which there is relatively high demand in the United States, but low supply. Only in Canada, Denmark, Flanders, France, Israel, the Netherlands and New Zealand is the demand for high-skilled workers greater. The supply of high-skilled workers, however, is higher in 22 out of the 28 other countries. Overall, the differences in the supply of

[56] We use the same occupation-industry classification as Blau & Kahn (1996) and Leuven et al. (2004), i.e. three occupation groups (managers and professionals; clerical and sales workers; craft workers, operatives, laborers and service workers) and six industry groups (agriculture; mining, manufacturing and construction; transportation, communication and public utilities; trade; finance, insurance, real estate and services; government).

skills between the United States and the other countries are much larger than the differences in demand.

Figure 3.3: The supply of and demand for skills in the United States versus the Netherlands



Notes: The figure shows, for each level of skill, the difference in the supply and demand indices between the United States and the Netherlands. For example, for the most skilled group of workers (top bars), the supply line is negative (indicating that the United States has a lower supply of skilled workers than the Netherlands), while the demand line is marginally positive (indicating that the United States has a higher demand for the most skilled workers).

In the next step, we use these indices to estimate what part of the (log) wage differential $\Delta\hat{y}_{Sx}^{US}$ between the United States and the comparator country can be attributed to differences in the supply of and demand for skill:

$$\Delta\hat{y}_{Sx}^{US} = \beta_S \Delta S_{Sx}^{US} + \beta_D \Delta D_{Sx}^{US} \tag{3.4}$$

Where the parameters β_S and β_D are estimated by regressing Δy_{Sx}^{US} (the log of the ratio of wages of skill group *S* in the United States over those in country *x*) on a constant, α, the indices of demand and supply for skill group *S* in the United States relative to those in country *x*, as well as country fixed effects, ρ_x:

$$\Delta y_{Sx}^{US} = \alpha + \beta_S \Delta S_{Sx}^{US} + \beta_D \Delta D_{Sx}^{US} + \rho_x + \varepsilon_{Sx}^{US} \tag{3.5}$$

In practice, this regression is run on 28 country x 25 skill group (i.e. 700) observations. As expected, β_S is negative (i.e. an increase in the relative supply of skilled workers in the United States would lead to a fall in their wages relative to the comparator country) and β_D positive (i.e. an increase in the relative demand for skilled workers in the United States would increase the wages of skilled workers in the United States relative to those in the comparator country).

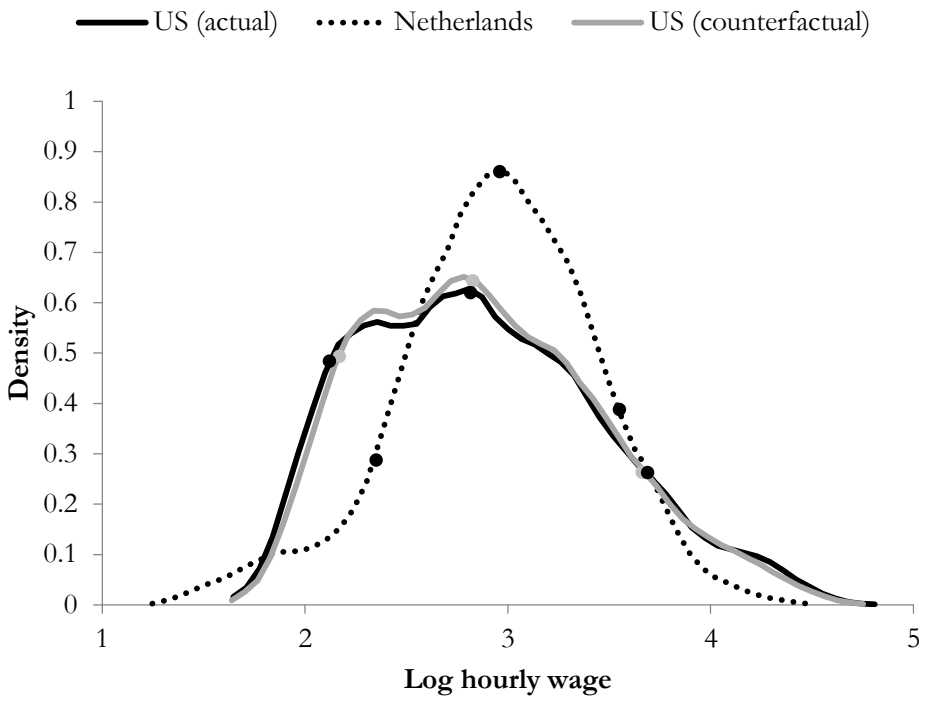
Table 3.4: The demand for and supply of skills relative to the United States

	Low-skilled*		High-skilled*	
	Demand	Supply	Demand	Supply
Australia	-0.018	0.461	0.025	-0.270
Austria	-0.044	0.785	0.045	-0.386
Canada	0.032	0.293	-0.048	-0.242
Chile	-0.160	-0.532	0.179	1.294
Czech Republic	-0.103	0.948	0.102	-0.364
Denmark	0.014	0.849	-0.017	-0.436
England (UK)	-0.046	0.197	0.062	-0.134
Estonia	-0.053	0.785	0.052	-0.312
Finland	-0.014	0.997	0.012	-0.483
Flanders (B)	0.011	0.771	-0.022	-0.482
France	-0.017	0.061	-0.021	-0.038
Germany	-0.060	0.489	0.071	-0.332
Greece	-0.114	0.044	0.108	0.315
Ireland	-0.043	0.223	0.056	0.033
Israel	0.060	0.010	-0.089	-0.023
Italy	-0.167	-0.079	0.164	0.310
Japan	-0.055	1.406	0.074	-0.600
Korea	-0.086	0.478	0.099	-0.079
Netherlands	0.044	0.834	-0.040	-0.497
New Zealand	0.017	0.432	-0.011	-0.296
Northern Ireland (UK)	-0.070	0.159	0.093	-0.022
Norway	-0.020	0.787	0.013	-0.459
Poland	-0.076	0.244	0.078	-0.043
Slovak Republic	-0.064	0.795	0.061	-0.427
Slovenia	-0.037	0.190	0.022	-0.079
Spain	-0.086	-0.038	0.103	0.349
Sweden	-0.003	0.808	0.011	-0.445
Turkey	-0.138	-0.476	0.151	1.284

* Low (high)-level skills are defined as the bottom (top) ten skills intervals (out of a total of 25).

In the next and final step, the predicted wage differential ($\Delta\hat{y}_{Sx}^{US}$) obtained from equation (3.4) is subtracted from the original wage of each individual in skill group *S* in the United States, to give the counterfactual wage of that individual if demand and supply conditions of the comparator country prevailed in the United States. Figure 3.4 shows that applying the supply and demand conditions of the Netherlands to the United States (i.e. increasing the net supply of skill in the United States) would result in a reduction in wage inequality in the United States.

Figure 3.4: The United States wage distribution before and after adjusting for Dutch supply and demand for skill



Notes: Epanechnikov kernel density plots (evaluated at 50 points). Dots on each curve indicate, from left to right, the 10th, 50th and 90th percentile, respectively.

Table 3.5 repeats this exercise for every comparator country included in the sample, and summarises the extent to which differences in wage inequality with the United States can be attributed to different demand and supply conditions. Looking at the Gini coefficient, on average 18.6% of the difference in wage inequality between the United States and other countries can be explained by differences in the demand for, and supply of, skills (12.2% excluding Japan and Estonia again two strong outliers). Interestingly (and in line with results we obtained using a different methodology in Broecke, Quintini and Vandeweyer, 2016), the importance of market forces appears to be greater at the top of the distribution (where it explains 23.2% of the difference in wage inequality with other countries) than at the bottom of the wage distribution (where it explains 6.0% of the difference). Broecke, Quintini and Vandeweyer (2016) speculate that this might be because the wages of workers in the bottom of the distribution are determined less by market forces and more by labour market institutions, like the minimum wage and other wage-setting arrangements – while the opposite is likely to be true for workers at the top of the wage distribution. [57,58]

[57] Blau and Kahn (1996) also found stronger price effects at the bottom, which they interpreted as evidence of the impact of wage floors.

[58] We have also tried to decompose the difference in wage inequality into the portions attributable to demand and supply, respectively – however no clear pattern emerged from this analysis.

Table 3.5: Proportion (%) of the difference in wage inequality with the United States explained by demand and supply conditions

	P90/P10	P90/P50	P50/P10	Gini
Australia	20.4	15.5	22.6	11.7
Austria	24.2	19.6	26.2	16.5
Canada	9.5	-2.5	-132.1	4.1
Chile	-0.5	-1.3	6.9	1.9
Czech Republic	26.4	19.5	34.1	19.4
Denmark	15.8	9.1	24.7	8.6
England (UK)	26.1	30.0	19.7	19.6
Estonia	461.0	67.1	-95.4	65.3
Finland	20.3	20.0	16.0	11.7
Flanders (B)	14.2	9.8	16.6	9.2
France	-1.3	-4.9	2.5	0.0
Germany	68.0	22.0	-43.1	30.5
Greece	17.3	9.4	21.4	14.2
Ireland	15.5	9.0	19.0	10.3
Israel	-47.5	50.1	-10.6	18.3
Italy	21.3	16.6	23.9	15.0
Japan	85.8	227.5	49.8	138.1
Korea	-30.8	-22.1	-48.3	-19.6
Netherlands	23.2	14.9	43.3	12.7
New Zealand	11.9	8.3	12.7	7.1
Northern Ireland (UK)	22.6	28.8	15.6	18.3
Norway	18.7	16.0	17.1	10.6
Poland	33.3	31.2	33.0	29.1
Slovak Republic	47.2	35.6	63.2	43.6
Slovenia	6.6	2.8	8.9	5.2
Spain	8.4	-2.1	18.2	4.8
Sweden	15.8	14.4	12.6	8.2
Turkey	10.6	6.2	-9.8	6.2
Unweighted average	33.7	23.2	6.0	18.6

Notes: The table shows the proportion of the difference in wage inequality between the United States and country x that can be explained by differences in supply and demand conditions. For example, 20.4% of the difference in the P90-P10 wage ratios between the United States and Australia can be explained by differences in the demand for, and the supply of, skilled workers in Australia. Negative figures indicate that the difference between the United States and the comparator country would increase (rather than decrease) if the comparator country's demand and supply conditions were adopted.

3.5 The role of institutions

When we decomposed differences in wage inequality with the United States into a skill endowment and a skill price effect, we argued that the latter reflected a mixture of two factors: (i) different demand and supply conditions (which were analysed in the previous section); and (ii) differences in labour market institutions that affect the way skills are rewarded. In what follows, we apply the same wage simulation techniques used so far to analyse the role of minimum wages and collective bargaining coverage in explaining differences in wage inequality between the United States and other countries. The choice of institutions reflects the fact that both of these

have been found to have had a significant impact on wage inequality in the United States.[59] It is important to point out, however, that the simulations that follow should by no means be interpreted as demonstrating the causal impact of these institutions on wage inequality. They are merely intended as an accounting exercise to put the demand and supply results obtained in the previous section into perspective.

Table 3.6 shows how the minimum-to-average wage ratio[60] and the collective bargaining coverage rate[61] in the United States compared to those in the other countries included in our sample (measured at the time of the PIAAC data collection). While not all countries have a statutory minimum wage, at 27.2%, the United States had the lowest minimum-to-average wage ratio amongst the countries that did. Minimum wages are particularly high in New Zealand, Slovenia and France, where they were set at around 50% of the average wage. At 13.1%, the United States also had one of the lowest collective bargaining (CB) coverage rates in the sample (only Chile and Korea had lower CB coverage rates). The average CB coverage rate across the countries included in our sample was 51.2%, and it exceeded 90% in five countries (Sweden, France, Slovenia, Flanders and Austria).

In what follows, we estimate the extent to which differences in wage inequality between the United States and the other countries are related to differences in minimum wages and collective bargaining coverage rates. To do this, we simulate alternative wage distributions as before. In the case of minimum wages, the approach is relatively straightforward: we impose the relative minimum wage of the comparator country onto the United States wage distribution so that any worker earning less than the new minimum wage simply moves up to this new level. In doing so, we abstract away from: (i) non-coverage and non-compliance (both in the United States and in the comparator country[62]); (ii) possible spill-over effects on wages above the minimum; and (iii) dis-employment effects from increasing the minimum wage (although, as a robustness check, we

[59] On the impact of the minimum wage, see: DiNardo, Fortin and Lemieux, 1996; DiNardo and Lemieux, 1997; Lee, 1999; Autor, Manning and Smith 2015. On the impact of declining union power, see: Blau and Kahn, 1996; Fortin and Lemieux, 1997; Card, 2001; Card, Lemieux and Riddell, 2004; DiNardo, Fortin and Lemieux, 1996; Firpo, Fortin and Lemieux, 2011; Western and Rosenfeld, 2011.

[60] The minimum-to-average wage ratio was chosen instead of the minimum-to-median purely for modelling reasons. Indeed, the United States has the lowest minimum-to-average wage ratio of the countries included in the sample, but the same is not true of the minimum-to-median. Given that it would be much more difficult (and less interesting) to simulate what would happen if the minimum wage decreased in the United States, the minimum-to-average wage ratio is a more obvious choice than the minimum-to-median.

[61] In many countries, collective bargaining agreements can be extended to non-union members, so that collective bargaining coverage exceeds union membership. For this reason, we prefer a measure of collective bargaining coverage to a measure of union membership. In the United States, collective agreements are not extended, and so the two measures are synonymous. Following Visser (2013), workers covered by a collective bargaining agreement in the United States include: (i) union members and (ii) workers who report no union affiliation but whose jobs are covered by a union or an employee association contract.

[62] The degree of non-coverage and non-compliance is low in most countries, with on average 4.5% of wage-earners across the sample reporting a wage below the minimum wage (ranging from 0% in the United States to 23.5% in Chile). Our results will nevertheless reflect both: (i) the effect of increasing the minimum wage; and (ii) the effect of moving to full compliance/coverage. To see what difference non-compliance and non-coverage make to our results, we re-ran the models after first assuming full compliance/coverage in each country (i.e. the wage of every individual reporting a wage below the national minimum wage was replaced with the national minimum wage). The effect of increasing the minimum wage was then calculated in comparison to this "full compliance and coverage" baseline scenario. While there is no impact on inequality measuring interdecile wage ratios, the average contribution of the minimum wage to explaining differences in the Gini coefficient drops from 5.5% to 4.6%.

tested how sensitive our results were to the assumption of no dis-employment effects and concluded that they were not).[63]

Table 3.6: Minimum wages and collective bargaining coverage rates

	Minimum-to-average wage (%)	Bargaining coverage rate (%)
Australia	44.0	45
Austria	..	99
Canada	39.6	28.8
Chile	42.8	6
Czech Republic	30.6	40.9
Denmark	..	85
England/N. Ireland (UK)	38.8	31.2
Estonia	31.6	25
Finland	..	89.5
Flanders (B)	43.4	96
France	49.8	92
Germany	..	61.1
Greece	29.8	65
Ireland	43.7	42.2
Israel	41.2	56
Italy	..	85
Japan	33.3	16
Korea	34.5	10
Lithuania	38.5	12
Netherlands	41.6	84.3
New Zealand	51.0	17
Norway	..	74
Poland	38.5	28.9
Slovak Republic	35.8	35
Slovenia	50.5	92
Spain	34.4	73.2
Sweden	..	91
Turkey	39.0	13.3
United States	27.2	13.1

Source: OECD (2015), "Earnings: Minimum wages relative to median wages", OECD Employment and Labour Market Statistics (database). DOI: http://dx.doi.org/10.1787/data-00313-en.

Notes: Minimum wages refer to 2012. Minimum wages refer to the adult national minimum wage or, in the absence of a national minimum wage, to the weighted average of regional minimum wages. In the case of the United States, average wages are obtained by the OECD from the U.S. Bureau of Labour Statistics, Employment and Earnings, and refer to the average hourly earnings of production and non-supervisory workers. ICTWSS (Visser ,2013) for collective bargaining coverage (latest year available). Current Population Survey (2011) for US collective bargaining coverage rate. Following Visser (2013), workers covered by a collective agreement in the United States include: (i) union members and (ii) workers who report no union affiliation but whose jobs are covered by a union or an employee association contract.

63. To do this, we first calculate the distance d (in percentage terms) between individual i's wage and the new imposed minimum wage. The probability p of becoming unemployed for that individual is then computed as $p = e*d$, where e is the elasticity of employment with respect to the minimum wage. The total employment loss u is then estimated as $u = \sum p * \frac{\omega i}{\sum \omega i}$, where ω_i is the weight attached to observation i and $\frac{\omega i}{\sum \omega i}$ therefore represents the share of observation i in the sample. With an employment elasticity of e=0.2, we find that employment losses are small (0.2% on average) and are therefore unlikely to affect our wage inequality results significantly. Indeed, assuming that employment losses are concentrated amongst those workers with the lowest wages, the contribution of the minimum wage to explaining higher wage inequality in the United States (as measured by the Gini index) falls from 5.49% to 5.45%.

PIAAC does not hold information on collective bargaining (CB) coverage. To get around this problem, we proceed in three steps. First, we use external data sources to estimate the probability of each individual in the United States PIAAC data being covered by a collective agreement or an employee association contract. Second, we use these estimated probabilities to assign CB coverage status (zero or one) to each individual in the United States PIAAC data: only those individuals with the highest predicted probabilities are assigned CB coverage status of one (subject to a number of constraints, further discussed below). Third, we use this CB coverage variable to reweight the United States data to simulate the degree of CB coverage in the other PIAAC countries. This last step then allows us to estimate the contribution of CB coverage to higher wage inequality in the United States.

To be more precise: in step one, we use data from the 2011 Current Population Survey (CPS) to estimate the likelihood of CB coverage. We do this using a linear probability model with gender, age, industry, occupation and working time regime (part-time/full-time) as explanatory variables. The coefficients obtained from this regression are subsequently used to predict the probability of CB coverage for each individual in the United States PIAAC data.

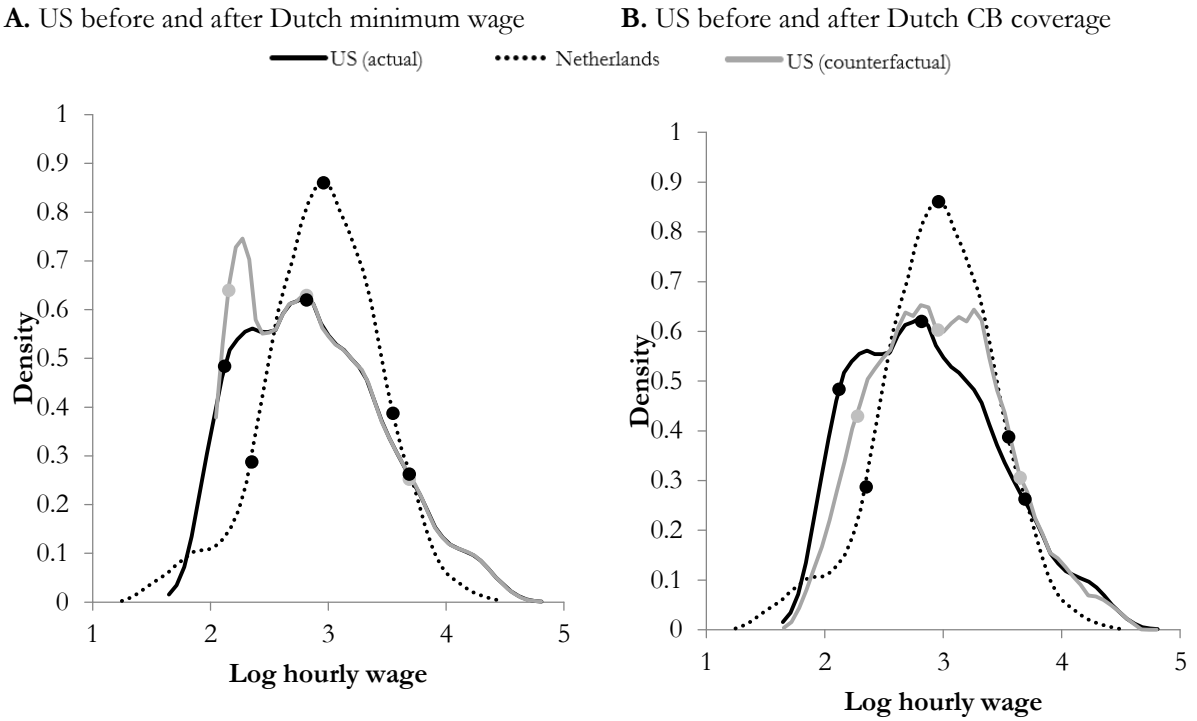
In step two, we rank all observations in the United States PIAAC data in descending order of (predicted) probability of CB coverage,[64] and set CB coverage status equal to one for those observations with the highest probabilities. The only constraint we impose is that the overall CB coverage for each characteristic (gender, age, industry, occupation and working time regime) cannot exceed the equivalent value in the CPS data. For example, if occupation *O* in the CPS data has a CB coverage rate of 60%, we only allow 60% of individuals in occupation *O* in the PIAAC data to have coverage status equal to one.[65]

In step three, we use the CB coverage variable thus derived to reweight the United States data until we obtain CB coverage rates similar to those in each of the other PIAAC countries. This is achieved simply by multiplying the survey weights of each observation that has CB coverage by the ratio of the CB coverage rate in the comparator country to CB coverage rate in the United States, $\frac{UC_x}{UC_{US}}$ and the survey weights of all other observations by $\frac{1-UC_x}{1-UC_{US}}$.
For illustrative purposes, Figure 3.5 shows what would happen to the wage distribution in the United States if the latter: (i) adopted the Dutch minimum-to-average wage ratio; and (ii) had a similar CB coverage rate as in the Netherlands. By construction, the minimum wage only affects the bottom of the wage distribution, while CB coverage rates significantly alter the entire wage distribution, leading to an important fall in wage inequality in the United States.

[64] Observations with the same collective bargaining coverage probability are ranked in descending order of age. Observations with the same collective bargaining coverage probability and age are further ranked in descending order of firm size.
[65] Using this procedure, we obtain an average collective bargaining coverage rate of 12.4% in the United States, close to the actual collective bargaining coverage rate of 13.1%. We also find that workers covered by a collective agreement are primarily concentrated at the top of the wage distribution. Further analysis suggests that this is driven by the wage premium attached to being covered by a collective agreement. When we simulate non-CB wages for workers covered by an agreement, we find that covered workers shift towards the upper-middle end of the new (simulated) wage distribution. This finding is consistent with earlier findings from Card (2001) and Card, Lemieux and Riddell (2004), who showed that union membership among males was concentrated in the (upper)-middle of the wage distribution, and female union membership rates in the (upper-)middle and top. Mayer (2004) also found that union membership is highest among workers with advanced college degrees.

The full results from the institutional simulations are presented in Table 3.7. In most cases, the minimum wage in the United States cannot explain any of the difference in wage inequality with the other countries and, on average, it accounts for less than 6% of the cross-country differences in the Gini coefficient. That being said, there are a handful of countries where higher minimum wages account for a substantial part of the difference in wage inequality with the United States (Slovenia, New Zealand, France, Australia, Ireland, the Netherlands and Flanders).

Figure 3.5: The United States wage distribution before and after applying the Dutch minimum wage and collective bargaining coverage rate



Notes: Epanechnikov kernel density plots (evaluated at 50 points). Dots on each curve indicate, from left to right, the 10th, 50th and 90th percentile, respectively.

Compared to minimum wages, differences in collective bargaining coverage between the United States and the other countries account for a much larger share of the differences in wage inequality – particularly in the top half of the wage distribution. The overall contribution of differences in collective bargaining coverage to differences in wage inequality (as measured by the Gini coefficient) is 45.3% (27.5% excluding France, a clear outlier). The role of collective bargaining also seems to be more important in explaining differences in top half than bottom half wage inequality.

Table 3.7: Proportion (%) of the difference in wage inequality with the United States explained by the minimum wage and collective bargaining coverage

	Minimum Wage				Collective Bargaining Coverage			
	P90/P10	P90/P50	P50/P10	Gini	P90/P10	P90/P50	P50/P10	Gini
Australia	24.1	0.0	47.4	11.4	47.7	41.4	6.7	26.3
Austria					88.6	75.2	15.8	56.5
Canada	8.1	0.0	-87.5	7.5	24.2	19.2	5.1	19.8
Chile	-13.1	0.0	-153.1	-11.0	7.4	6.7	0.7	2.2
Czech Republic	0.0	0.0	0.0	0.1	22.9	19.6	3.4	13.9
Denmark					73.5	66.9	7.6	44.1
England (UK)	2.2	0.0	4.0	6.8	27.1	15.6	11.7	17.4
Estonia	0.0	0.0	0.0	1.0	6.2	5.3	0.9	6.4
Finland					79.6	63.6	18.6	44.7
Flanders (B)	15.4	0.0	32.0	7.0	94.9	76.7	21.2	58.2
France	40.8	0.0	68.8	18.1	900.8	719.2	210.6	524.0
Germany					56.5	65.8	-10.3	40.1
Greece	0.0	0.0	0.0	0.1	79.0	86.3	-8.2	49.9
Ireland	29.9	0.0	49.8	17.9	41.7	33.1	9.1	23.5
Israel	27.8	0.0	18.3	-16.6	-161.5	-165.9	4.8	-106.8
Italy					164.7	150.0	17.1	98.8
Japan	0.0	0.0	0.0	3.2	4.8	0.0	4.8	1.3
Korea	0.0	0.0	0.0	-1.7	-4.6	-5.3	0.7	-1.7
Netherlands	11.6	0.0	42.4	8.0	71.4	63.4	9.3	42.4
New Zealand	50.8	0.0	84.2	26.4	10.0	1.5	8.5	3.8
Northern Ireland (UK)	1.7	0.0	2.7	5.9	20.6	11.8	8.9	13.2
Norway					60.5	70.3	-11.2	42.8
Poland	2.1	0.0	3.6	8.9	17.1	11.4	5.8	11.8
Slovak Republic	0.0	0.0	0.0	3.7	16.1	11.7	4.5	9.6
Slovenia	48.1	0.0	87.0	20.9	193.7	154.6	45.3	112.7
Spain	0.0	0.0	0.0	1.3	78.3	92.7	-16.4	55.7
Sweden					96.7	77.2	22.6	55.5
Turkey	-2.6	0.0	10.8	-3.9	25.4	0.0	25.4	1.3
Unweighted average	11.8	0.0	10.0	5.5	76.5	63.1	15.1	45.3

Notes: The table shows the proportion of the difference in wage inequality between the United States and country x that can be explained by minimum wages and collective bargaining coverage rates, respectively. For example, 24.1% of the difference in the P90-P10 wage ratios between the United States and Australia can be explained by a different collective bargaining coverage rate in Australia. Negative figures indicate that the difference between the United States and the comparator country would increase (rather than decrease) if the comparator country's minimum wage or collective bargaining coverage rate were adopted

3.6 Summary of results

Table 3.8 provides a summary overview of the results obtained in this paper. More specifically, it shows the average percentage difference in wage inequality between the United States and the other countries which can be attributed to differences in: skills endowments, skills prices, demand and supply conditions, the minimum wage, and collective bargaining coverage, respectively. Because France was a significant outlier in the collective bargaining analysis, the summary table also shows the results with France excluded from the average. To sum up: skills

prices explain a greater share of differences in inequality than skills endowments, but so do differences in the demand for, and supply of, skills; the minimum wage only explains a small share of differences in wage inequality, while differences in collective bargaining coverage play a far more important role.

Table 3.8: Summary of results

	P90/P10	P90/P50	P50/P10	Gini
Skill Endowments	-12.7	7.6	-16.3	1.6
Skill Prices	41.1	29.7	8.9	24.4
Demand and Supply	33.7	23.2	6.0	18.6
Minimum Wage	11.8	0	10	5.5
Collective Bargaining	76.5	63.1	15.1	45.3
Collective Bargaining (excluding France)	46.0	38.8	7.9	27.5

Notes: The table shows the average percentage difference in wage inequality between the United States and the other countries which can be attributed to differences in: skills endowments, skills prices, demand and supply conditions, the minimum wage, and collective bargaining coverage. These summary results are taken from tables 3.3, 3.5 and 3.7, respectively.

3.7 Conclusion

In this paper, we have revisited the role that skills play in explaining differences in wage inequality between the United States and other OECD countries and, contrary to most previous research, we concluded that this role is important. Specifically, and following Leuven, Oosterbeek and van Ophem (2004), we showed that differences in the demand for, and supply of, skills play a critical role in explaining international differences in wage inequality. Moreover, we provided some tentative evidence on the relative importance of skills and labour market institutions, and concluded that the former are likely to be at least as important as the latter in explaining cross-country differences in wage inequality. Any policy package aimed at reducing wage inequality would therefore be comprehensive only if it contained: (i) measures aimed at aligning the supply of skills with demand, as well as (ii) labour market institutions that have a more direct impact on the way skills are rewarded in the labour market (such as minimum wages and collective bargaining).

As closing remarks, two important points deserve to be raised. The first of these is that, while the present paper has separately estimated the importance of labour market institutions and skills on wage inequality, the two are, of course, highly dependent on one another. On the one hand, institutions can determine the demand for skills: for example, if minimum wages (including bargained wages) and non-wage costs are high, employers are likely to offshore part of their activity where this is possible or, alternatively, invest in labour-saving technologies. Similarly, if high income taxes reduce the wage premium to be gained from investing in skills, then individuals may be deterred from making human capital investments (or move abroad in pursuit of higher returns). Vice versa, if the demand for skills is high, then this will stimulate investment in skills (or attract workers from abroad). The second point to be made is that institutions are, of course, highly endogenous: societies that are more homogenous are likely to choose institutions that reflect this – which may, in turn, have an impact on the relative supply of skills groups. This interdependence and endogeneity imply that it may not be possible to change just one institution and obtain the desired effect on wage inequality. Alternatively, it could mean that policy

interventions have multiplier effects beyond the results hoped for. These are important points to bear in mind for policy makers concerned with reducing inequality.

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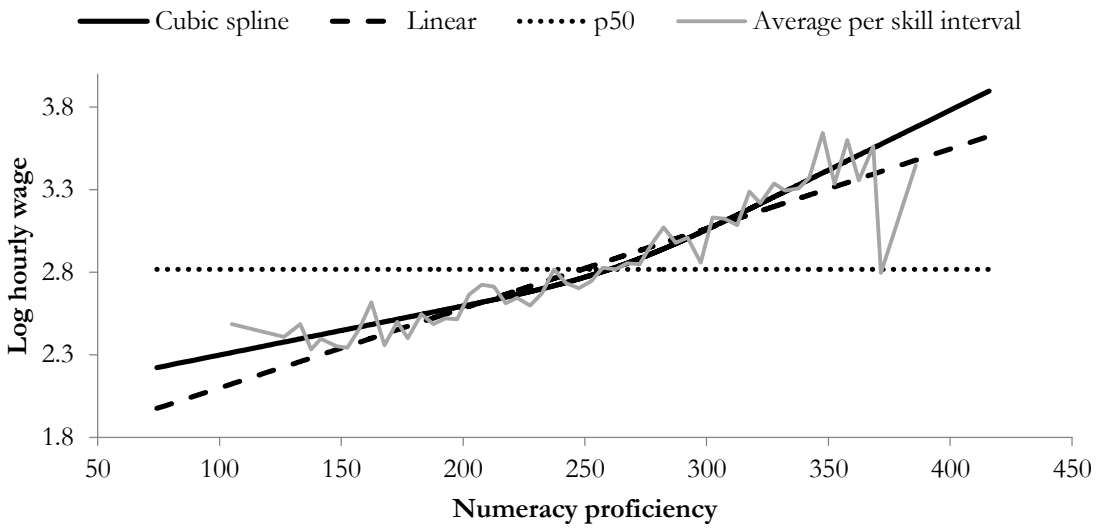
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Annex 3.A Additional figures

Figure 3.A.1: Returns to skills in the United States



Notes: The "average per skill interval" shows the average wage in each skill interval S (of 5 skill points each), as described above. The "cubic spline" shows the fitted values of a cubic spline fit (with three knots), while the dotted line shows the "linear" fit.

Chapter 4

The effect of minimum wages on employment in emerging economies: A survey and meta-analysis

Abstract

Using both qualitative and quantitative (meta-analysis) methods, this paper reviews the growing evidence on the impact of minimum wages on employment in 14 major emerging economies (Argentina, Brazil, Chile, China, Colombia, India, Indonesia, Mexico, Poland, the Philippines, the Russian Federation, South Africa, Thailand and Turkey). Overall, minimum wages are found to have only a minimal impact on employment, and there is evidence of reporting bias towards statistically significant negative results. More vulnerable groups (e.g. youth and the low-skilled) are marginally more negatively affected, and there is some indication that higher minimum wages lead to more informal employment.

4.1 Introduction

Few topics in economics have received as much attention as the minimum wage. In particular, and despite decades of research, arguments still rage about whether minimum wages have a negative impact on employment or not.[66] On balance, however, most economists would probably agree that moderate minimum wages are unlikely to undermine employment – although vulnerable groups (like youth and the low-skilled) may be more likely to suffer adverse employment effects (OECD, 2015).

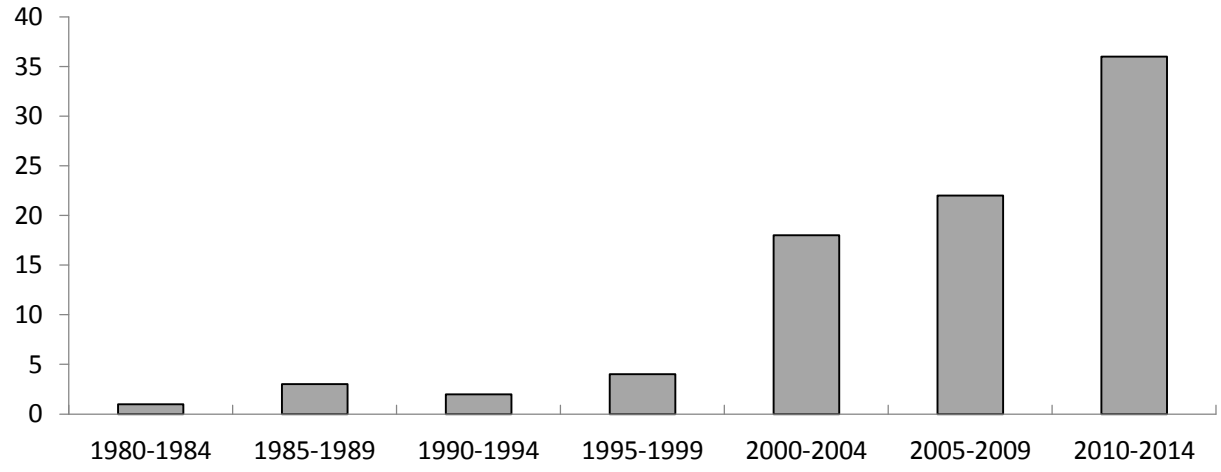
While the effect of minimum wages on employment has been heavily researched in the developed world, much less is known about their impact in emerging economies – and yet there are important reasons to believe that their impact might be very different in such settings. For example, emerging economies are often characterised by high rates of informality and low levels of compliance with the minimum wage, and so the latter might be expected to have very little or even no effect on employment. On the other hand, minimum wages in emerging economies are often set at very high levels compared to average wages and a greater proportion of the workforce is unskilled and earning at or near the minimum wage – meaning that the negative effect on employment could actually be larger than in more advanced countries.

[66] Recent exchanges in the United States bear testimony to this fact. On the one hand, Dube, Lester and Reich (2010) and Allegretto, Dube and Reich (2011, 2013) claim that minimum wages have no impact on employment, while Neumark, Ian Salas and Wascher (2014a; 2014b) strongly disagree.

The true impact of minimum wages on employment outcomes in emerging economies is therefore, to a large extent, an empirical issue. However, while the literature in this field has been growing rapidly and exponentially (see Figure 4.1), there has been virtually no attempt to date to review all this evidence systematically.

Figure 4.1: Minimum wage studies in emerging economies, 1980-2014

Number of individual country studies by year of publication



This paper aims to fill this void by reviewing the minimum wage literature for the 14 largest emerging market economies in the world (as measured by total GDP): the six BRIICS countries (Brazil, China, the Russian Federation, India, Indonesia and South Africa) as well as Argentina, Chile, Colombia, Mexico, Poland, the Philippines, Thailand and Turkey.[67] While Malaysia completes this list of the largest emerging economies, no minimum-wage studies could be identified for Malaysia and so it could not be included in the analysis. The list of countries covered in this paper also provides a good geographical spread, covering four continents: Africa, Asia, Europe and South America.

Based on both a qualitative (survey) and quantitative (meta-analysis) review of the evidence, we find that the effect of minimum wages on employment in large emerging economies is very similar to that observed in more advanced countries: overall, minimum wages seem to have no effect of economic significance on employment – although studies appear to find that more vulnerable groups (youth and the low-skilled) are marginally more adversely affected, and that higher minimum wages lead to more informal employment. There is also clear evidence of reporting bias in favour of statistically significant negative results. While we investigate whether the impact of minimum wages varies by other individual and study characteristics, the results are too sensitive to model specification to allow us to draw any robust conclusions.

Following this introduction, the paper proceeds as follows: We first provide a country-by-country qualitative survey of the minimum wage literature in emerging economies. We then proceed with a simple meta-regression analysis (MRA) both of the elasticities obtained in this

[67] The definition of what constitutes an emerging economy varies depending upon the source consulted, and so any grouping of such countries will necessarily contain some element of arbitrariness. In this paper, we have followed the IMF classification of countries.

literature, as well as of the partial correlations. These simple models are subsequently extended to test and control for reporting bias and, in the following section, we add a range of additional control variables (including study fixed effects) to run a multiple MRA. The final section discusses the results and offers some concluding remarks.

4.2 Qualitative literature review

Using standard search engines and economic literature databases, we identified 95 studies covering 14 major emerging economies: Argentina (2), Brazil (19), Chile (13), China (11), Colombia (7), India (1), Indonesia (10), Mexico (4), Poland (8), the Philippines (2), the Russian Federation (2), South Africa (9), Thailand (3) and Turkey (5).[68] While the main purpose of this paper is to carry out an MRA of the existing evidence, we believe that a qualitative (survey) review of the literature is still valuable and should be seen as a useful complement to more quantitative methods. In particular, qualitative reviews sometimes allow for a more nuanced discussion of certain issues. In addition, because not all studies we identified contain results which can be used in the meta-analysis, the qualitative survey of the literature covers a greater number of studies.

In what follows, we therefore offer a country-by-country review of the impact of the minimum wage on employment, hours worked and formality, based on the main conclusions reached by each of the papers surveyed. To guide the discussion (but also for the reader wishing to skip the detailed country-by-country discussion), Table 4.1 provides a brief summary of the main findings of this qualitative review, as well as some basic minimum wage and labour market characteristics of the countries covered to assist the interpretation of the findings. More specifically, Table 4.1 shows: the Kaitz index (i.e. the ratio of the minimum to the average wage), the employment rate, and the incidence of informal employment for each of the countries included in the study.

A few interesting, albeit very tentative, observations emerge from these summary statistics. Firstly, the employment impact of minimum wages appears to be mixed or zero in most countries studied. Secondly, when the evidence points towards a negative effect, this tends to be more common in countries with high minimum wages (as a proportion of the average wage), such as the Philippines, Thailand, Colombia, Brazil and Chile – although there are some exceptions, e.g. Indonesia and Argentina. This leads us to the third observation which is that in countries which combine a high minimum wage with a high incidence of informality, the negative employment effect appears to be muted (which is the case in both Indonesia and Argentina). Fourthly, when minimum wages are very low (as in the Russian Federation and South Africa), few negative effects on employment can be detected. Fifthly, the evidence in nearly all of the countries suggests that vulnerable groups might be more adversely affected by minimum wages. Finally, the impact of minimum wages on hours worked is much less well-researched, and the evidence appears inconclusive. Similarly, the relationship between minimum wages and formality is empirically unclear: while many studies find negative effects, some

[68] Note that the sum of individual country studies adds up to 96 and not 95 – this is because one study included in our analysis covers two countries.

positive effects of minimum wages on formality[69] have been found in Brazil, Colombia and South Africa.

Table 4.1: Summary of qualitative literature review

Panel A. Country and institutional characteristics

Country	Region	Minimum/average wage (2013)[a]	Employment rate, 15+ (2013)[b]	Informal employment[c]
South Africa	Africa	0.30	43%	33% (2010)
China	Asia	0.33	69%	33% (2010)
India	Asia	0.40	50%	84% (2009)
Indonesia	Asia	0.69	63%	73% (2009)
Philippines	Asia	0.87	59%	44% (2008)
Thailand	Asia	0.65	71%	42% (2010)
Poland	Europe	0.40	50%	5% (2010)
Russia	Europe/Asia	0.18	65%	12% (2010)
Turkey	Europe/Asia	0.38	46%	31% (2009)
Argentina	South America	0.59	56%	50% (2009)
Brazil	South America	0.45	59%	42% (2009)
Chile	South America	0.45	56%	36% (1995-99)
Colombia	South America	0.60	63%	60% (2010)
Mexico	South America	0.28	57%	54% (2009)

Panel B. Minimum wage effects

	Effect of an increase in the MW on			Vulnerable groups more negatively affected?
Country	Employment	Hours	Formality	
South Africa	Mostly zero/mixed	Mixed	Mixed/positive	Little research (mixed)
China	Mixed	Little research (mixed/positive)		Yes
India	Mixed			
Indonesia	Mixed	Mixed/positive	Mixed	Yes
Philippines	Negative	Little research (negative)		Yes
Thailand	Mixed	Little research (positive)		Yes
Poland	Negative	Mixed		Yes
Russia	Zero (or small)		Mixed/negative	Yes
Turkey	Mixed	Mixed	Little research (negative)	Yes
Argentina	Mixed		Little research (negative)	Yes
Brazil	Mostly negative (small)	Zero/mixed or negative	Mostly negative or zero/mixed	Mostly not
Chile	Mostly negative	Little research (negative)	Little research (negative)	Yes
Colombia	Mostly negative	Little research (negative)	Mixed	Yes
Mexico	Mixed			Mixed

a. The calculation of minimum and average wages is based on the ILO *Global Wage Report* data. For the Philippines, the average wage is calculated as the average of 2012 and 2014, while the minimum wage is calculated as the employment-weighted average of the regional minimum wages (taken from the Philippine Statistics Authority). For Argentina, the average wage is obtained from INDEC (2013). Data refer to 2008 for China and 2012 for India.
b. Source: OECD for Brazil, Chile, Colombia, Mexico, Poland, Russia and Turkey; ILO for Argentina, China, India, Indonesia, Philippines, South Africa and Thailand. 2014 for India.
c. Source: ILO (2011), Charmes (2011) (for Chile), DOLE (n.d.) for the Philippines, Central Statistical Office for Poland. The data refer to persons in informal employment, except in Russia and the Philippines, where it refers to persons employed in the informal sector/economy.

[69] It is important to note that no universal definition of the informal sector is used across the studies. Some authors define the informal sector as all self-employed workers (Chun & Khor, 2010; and Magruder, 2013), while others explicitly exclude this category (Wedenoja, 2013; Lemos, 2009a). Other definitions include: (i) not having a signed labour card (Carneiro & Corseuil, 2001; Lemos, 2009a; Wedenoja, 2013); (ii) not having a written contract (Bhorat, 2014; Dinkelman & Ranchhod, 2012); or (iii) not being registered in the social security system (Pelek, 2011).

4.2.1 Argentina

In contrast to many other Latin American countries, the minimum wage literature in Argentina is very limited – which is surprising given that Argentina has a relatively high minimum wage. The results of Groisman (2012, 2015) indicate that a rise in the minimum wage increases the probability of becoming unemployed or inactive for workers with salaries below the minimum wage, but that this impact is only significant for unregistered workers. The findings also suggest that formal sector workers have a higher chance of switching to the informal sector after a minimum wage increase. Both the effects on employment and on informality are found to be stronger for women, although overall the economic size of the effect on informality is negligible.

4.2.2 Brazil

In contrast to Argentina, a relatively large number of studies have investigated the impact of the minimum wage on employment in Brazil. Earlier research tended to find small- to medium-sized negative effects of the minimum wage on employment (Foguel, 1998; Foguel, Ramos & Carneiro, 2001; Carneiro, 2001; Fajnzylber, 2001; Soares, 2005; Neumark, Cunningham & Siga, 2006). One exception was a study by Carneiro and Corseuil (2001) who look at the period between 1982 and 1999 and use a difference-in-differences model. They find much larger negative employment effects, ranging between -3% and -13% for a 10% increase in the minimum wage. A later series of studies carried out by Lemos (2004a, 2004b, 2005a, 2005b, 2007, 2009a, 2009b) found no, or negligible, effects – a result confirmed by Broecke and Vandeweyer (2015) for more recent years.

Two studies have also investigated the effect of Brazil's state wage floors, but both found that compliance with these state minimum wages is extremely low and that they have had no effect on labour market outcomes (Moura & Neri, 2008; Corsueil, Foguel & Hecksher, 2013). While some studies looked at more vulnerable groups, most of them do not find that they are more negatively affected (Lemos 2007, 2009a, 2009b), although one obtains mixed results (Fajnzylber, 2001) and another finds that vulnerable groups (youth and the low-skilled) are slightly more negatively affected (Broecke & Vandeweyer, 2015).

The relationship between minimum wages and hours worked has barely been investigated in the context of Brazil, and findings are contradictory: Lemos (2004a) and Broecke and Vandeweyer (2015) find small negative effects, while Lemos (2007, 2009a) finds no effect at all, and Neumark *et al.* (2006) obtain mixed results at the household level.

Similarly, the evidence on the impact of minimum wages on formality is inconclusive in Brazil. On the one hand, Carneiro (2001, 2004), Carneiro and Corseuil (2001), Foguel *et al.* (2001), Jales (2015) and Broecke and Vandeweyer (2015) find that increases in the value of the minimum wage tend to decrease formal employment and increase informal employment. On the other hand, Lemos (2009a) finds no proof of employment effects in either formal or informal sectors, while Lemos (2004c, 2009b) also finds some evidence that increases in the minimum wage reduce, rather than increase, employment of informal workers. Similarly, Fajnzylber (2001) finds larger negative employment effects in the informal sector (meaning that informality has a tendency to fall as minimum wages increase) and Foguel (1998) finds a positive effect of

minimum wages on formality. Finally, Soares (2005) and Corseuil, Foguel and Hecksher (2013) find no effect on formality.

4.2.3 Chile

Research on the employment effect of the minimum wage in Chile mainly points to a negative impact (Paredes & Riveros, 1989; Chacra Orfali, 1990; Martinez, Morales & Valdes, 2001; Infante, Marinakis & Velasco, 2003; Cowan, Micco, Mizala, Pagés & Romaguera, 2004; Beyer & Dussaillant, 2009; Miranda, 2013), although one older study (Solimano, 1988) finds a positive impact on employment, and two others find no or mixed results (Castañeda, 1983; Montenegro & Pagés, 2004).

The evidence from Chile also suggests that the negative impact of minimum wages on employment is more significant for more vulnerable groups. Paredes and Riveros (1989, 1993), Chacra Orfali (1990) and Cowan *et al.* (2004) all conclude that the minimum wage is more likely to have a negative impact on young people and people with lower educational attainment. Beyer and Dussaillant (2009) find that the minimum wage has a negative effect on youth employment, with young people mainly transitioning from work to unemployment or inactivity (rather than into study). Montenegro and Pagés (2004) find that unskilled workers experience negative employment effects, while for skilled workers the impact is positive. The minimum wage is also found to have a negative effect on the employment of low-wage workers (Castañeda, 1983; Paredes & Riveros, 1989).

While most Chilean studies do not make a distinction between formal and informal employment when assessing the impact of minimum wages, Wedenoja (2013) argues that the minimum wage increases informality. Similarly, only one study investigates the effect of minimum wage increases on hours worked, and finds that the effect is negative (Grau & Landerretche, 2011).

4.2.4 China

The impact of minimum wages on labour market outcomes in China has received significant attention from researchers in recent years. Studies analysing aggregate employment generally point to a small negative impact (Fang & Lin, 2013; Xiao & Xiang, 2009; Wang & Gunderson, 2012) – although Mayneris, Poncet and Zhang (2014) argue that increases in the minimum wage have no impact on aggregate employment because of their positive impact on productivity.

Effects have also been found to differ significantly between the different Chinese regions which vary in their degree of development. Whereas Wang and Gunderson (2011, 2012) find that the minimum wage has no effect on employment in the Eastern (most developed) region and a negative impact in the slower growing Central and Western regions, the exact opposite is found by Ni, Wang and Yao (2011) and Fang and Lin (2013). The distinction between urban and rural migrant workers is made in many studies, with rural workers mostly experiencing stronger negative effects (Ding, 2010; Fang & Lin, 2013; Luo, Zhou & Wu, 2011). Negative employment effects are also found to be greater for low-skilled and female workers (Fang & Lin, 2013; Jia, 2014). Using firm-level data, both Ding (2010) and Huang, Loungani and Wang (2014) find stronger adverse effects on low-wage firms. Finally, there is some evidence that the impact might vary by sector, with negative effects for the manufacturing sector and positive effects for the construction sector (Luo *et al.*, 2011; Shi, 2011).

When focusing on hours worked rather than on employment, a positive effect of the minimum wage is found by Xiao and Xiang (2009) – a finding confirmed by Jia (2014) although only for low-skilled men. No research in China has focused on the impact on informality.

4.2.5 Colombia

The majority of evidence on minimum wages in Colombia shows a negative impact on employment and a positive impact on unemployment (Bell, 1997; Hernandez Diaz & Pinzon Garcia, 2006; Arango & Pachón, 2004; Aguirre Botero, 2011; Sánchez, Duque & Ruiz, 2009), which is perhaps not too surprising given the high level of the minimum wage in Colombia. Only one paper looked at the effect on hours worked, and found a negative effect which is stronger for younger and high-skilled workers (Arango & Pachón, 2004).

According to Aguirre Botero (2011), youth are most likely to be affected by minimum wages and, in particular, those with low levels of education or experience, as well as those living in less educated families. These stronger effects on youth employment are confirmed by Hernandez and Lasso (2003), Arango and Pachón (2004) and Sánchez *et al.* (2009), but not by Hernandez Diaz and Pinzon Garcia (2006). Stronger effects are also found for female and low-skilled workers (Arango & Pachón, 2004; Bell, 1997; Hernandez Diaz & Pinzon Garcia, 2006; Sánchez *et al.*, 2009).

While Mora Rodriguez (2007) finds that the probability of participation in the informal sector decreases as the minimum wage rises, Sánchez *et al.* (2009) show that informality increases.

4.2.6 India

There has been virtually no research on the effect of minimum wage legislation on employment in India, which is likely to be a consequence of the complexity of the country's minimum wage system and its limited coverage and enforcement (Belser & Rani, 2012). The only study this review encountered is Soundararajan (2014), who analyses the impact of the minimum wage on employment in the construction industry. Exploiting the difference in minimum wages and the number of labour inspectors across regions, the author finds a negative effect on employment for low levels of enforcement, and a positive effect for high levels of enforcement.

4.2.7 Indonesia

The evidence on the effect of minimum wages on employment in Indonesia is mixed, with Chun and Khor (2010) and Alatas and Cameron (2008) finding no impact, Comola and de Mello (2011) finding a positive impact, Rama (2001) finding a negative impact, and Islam and Nazara (2000) finding evidence for both negative and positive effects. Suryahdi, Widyanti, Perwira and Sumarto (2003), focusing on the formal sector, find a negative impact on employment, which is stronger for females, low-skilled youth and part-time workers, while there is evidence of positive effects on white collar employment. According to Del Carpio, Nguyen and Wang (2012), only female non-production[70] workers and low-skilled production workers in small firms face negative

[70] According to Del Carpio *et al.* (2012), production workers are workers who work directly in the production process, such as forklift operators, whereas non-production workers perform supporting tasks, such as administration.

effects of minimum wages. Similarly, Sugiyarto and Endriga (2008) find negative effects on unskilled workers, but not on skilled ones.

A positive impact on hours worked is found, although not for female workers in rural areas (Pratomo, 2014; Chun & Khor, 2010). Only a few papers focus on the possible effect of minimum wages on formality and the evidence is inconclusive. On the one hand, Comola and De Mello (2011) find that the positive effect on aggregate employment is driven by a positive impact on informal employment which fully offsets the negative impact on formal employment. This confirms the finding of Chun and Khor (2010) that the negative impact on low-wage formal sector workers does not translate into aggregate employment losses. On the other hand, Magruder (2013) shows that minimum wages increase full-time paid work and decrease self-employment, which is evidence for increased formalisation.

4.2.8 Mexico

For Mexico, evidence on the employment effects of minimum wages is scarce and inconclusive – both overall as well as for more vulnerable groups. No research in Mexico has looked at the impact of the minimum wage on either hours worked or formality. Bell (1997) finds that there are no significant effects on aggregate manufacturing employment, even when a distinction between skilled and unskilled workers is made, while Samaniego de Villareal and Samaniego Breach (1988) point to a negative relationship between minimum wages and manual employment, and Garza Cantú and Bazaldúa (2002) also find a negative impact of minimum wage rises on aggregate employment. When looking at different wage groups, however, the latter authors show that people with low wages experience positive effects from a minimum wage increase, while the impact on higher wage earners is negative. When defining vulnerable groups in terms of age and sex, Feliciano (1998) finds that there is no impact on aggregate male employment, while it is positive for older men. The impact on aggregate female employment is negative and increases with age.

4.2.9 Poland

Most research in the Polish context finds a negative effect of minimum wage rises on employment (Melnyk, 1996; Ruzik, 2007; Bukowski, 2010; Majchrowska & Żółkiewski, 2012; Kamińska & Lewandowski, 2015; and Baranowska-Rataj & Magda, 2015).

While there are some contradictory findings, the evidence also seems to suggest that the negative employment effects are greater for youth and in less developed regions. Majchrowska, Broniatowska and Żółkiewski (2015) and Ciżkowicz, Kowalczuk and Rzońca (2014) are two papers which do not find a negative effect on youth employment, although the former paper does find a more adverse effect in less-developed regions where there is a higher minimum-to-average wage ratio. By contrast, Majchrowska and Żółkiewski (2012) find that the minimum wage effect is particularly strong for young workers over the period 2005-10, which saw large rises in the minimum wage, as well as in poorer regions. Kamińska and Lewandowski (2015) also find that job separations following minimum wage hikes occur primarily among young workers and Baranowska-Rataj and Magda (2015) confirm the negative impact on youth employment.

Only a handful of papers have investigated the impact of the Polish minimum wage on hours worked, and the evidence is mixed. Kamińska and Lewandowski (2015) find a negative impact

on hours worked among workers for whom the minimum wage became more binding, but Baranowska-Rataj and Magda (2015) find no effect. None of the Polish papers we reviewed looked at the effect on informality, but then the rate of informality is quite low in Poland and therefore less of an issue.

4.2.10 Philippines

We could find only two papers which have estimated the impact of minimum wages on employment in the Philippines. Canales (2014) finds that workers affected by minimum wage increases experience a reduction in hours worked as well as in the probability of employment. Lanzona (2014) also finds a negative effect of the minimum wage on employment, particularly among youth, low-skilled workers and women.

4.2.11 Russian Federation

Research on the effect of minimum wages in the Russian Federation is very limited, which is likely to be because of the low level of the minimum wage in comparison to average wages. It is therefore not surprising that the only two papers which look at the employment impact of minimum wages in the Russian Federation find no, or very little, effect. Kobzar (2009) finds no significant effect on either aggregate employment or unemployment, and the lack of statistically significant effect on unemployment is confirmed by Muravyev and Oshchepkov (2013). When focusing on different sub-groups, the latter authors find that the minimum wage has no impact on female unemployment, but does have a negative impact on youth unemployment. Both papers also look at the effects on the share of workers in informal employment. While Kobzar (2009) finds no effect, Muravyev and Oshchepkov (2013) find a significant positive effect (i.e. minimum wage hikes are associated with an increase in informal employment).

4.2.12 South Africa

Although minimum wages were only introduced in South Africa in 1999, there are already several studies analysing their effects, albeit with conflicting conclusions. While most studies find no effect on the employment of farm workers (Murray & van Waelbeek, 2007; Conradie, 2003, 2005), Bhorat, Kanbur & Stanwix (2014) find that minimum wages reduce the probability of being a farm worker – a finding confirmed by Bhorat, Cassim, Kanbur, Stanwix & Yu (2016). For domestic workers, the evidence is also mixed: individual-level data point to no significant effect on the probability of being a domestic worker (Dinkelman & Ranchhod, 2012; Bhorat, Kanbur & Mayet, 2013), but regional-level analysis shows a negative impact on domestic employment (Hertz, 2005). Bhorat *et al.* (2013) look at all sectors with a minimum wage and find no effect on employment in any of them.

The effect on hours worked also differs between sectors. Murray and van Waelbeek (2007) argue that adjustments in the agricultural sector mainly happen at this intensive margin. This is confirmed by Bhorat *et al.* (2014) who find that average hours worked drop after a minimum wage increase. However, their results also show that average hours increase in the most vulnerable regions, which they attribute to a decline in part-time jobs. The results for domestic workers are again mixed, with Dinkelman and Ranchhod (2012) and Bhorat *et al.* (2013) finding no significant effects on hours worked, and Hertz (2005) finding a negative impact. Bhorat *et al.*

(2013) only find a significant negative effect on hours worked in the retail and security sectors. For youth, Bhorat *et al.* (2016) find mixed evidence, depending on the sector they are employed in: hours worked decline with minimum wage increases in the private security, agriculture and domestic worker sectors, while they increase in the taxi sector.

In South Africa, minimum wages are found to lead to increased formalisation for both agricultural and domestic workers (Bhorat *et al.*, 2014; Dinkelman & Ranchhod, 2012). For youth, increased formalisation is only found in the retail sector (Bhorat *et al.*, 2016). However, the impact on formality is found to differ between people of different sex and ethnicity, with a negative effect (which is stronger the lower the level of education) for coloured and black women, a positive effect for coloured men, and no effect for white and black men, or for white women (Millea, Rezek & Pitts 2012).

4.2.13 Thailand

Del Carpio, Messina and Sanz-de-Galdeano (2014) look at minimum wage increases in Thailand over the period 1998-2010 and find small disemployment effects for women, older workers and the low-skilled, but a small positive effect on average hours worked. Ariga (2016) finds that the minimum wage hikes of 2012 and 2013 had a positive effect on employment – although these findings were questioned by Lathapipat and Poggi (2016).

4.2.14 Turkey

Analysis of the impact of minimum wages on the Turkish labour market is scarce and shows mixed results. Ozturk (2006) and Papps (2012) find a negative impact on employment, while Korkmaz and Coban (2006) find no impact.

Papps (2012) identifies young and rural workers as those who are most negatively affected by the minimum wage. This differs from the results of Pelek (2011), who finds no effect on low-skilled youth employment and a positive impact on the employment rate of young workers with tertiary education. Whereas Günsoy and Tekeli (2013) find no significant effect of minimum wages on female employment, Ozturk (2006) shows that the low female participation rate can to a large extent be attributed to minimum wages because the latter reduces the availability of flexible, part-time jobs.

The results on the impact of the minimum wage on hours worked are also contradictory: Ozturk (2006) finds a positive effect on hours worked, while Papps (2012) finds a negative effect.

Given that young and low-skilled workers have relatively high probabilities of being employed in the informal sector in Turkey, Pelek (2011) looks at the effect of minimum wages on the share of formal work for different skill groups of young workers. She finds a positive effect of minimum wages on informal work for the low-skilled and, to a lesser extent, for medium-skilled young workers.

4.3 Meta-regression analysis

While a qualitative (survey) review may be useful in getting an overall sense of the results obtained in the literature, it is difficult to draw robust statistical conclusions from it. In particular, a more systematic and quantitative approach is necessary in order to obtain an estimate of the

"average" size and significance of the minimum wage effect on employment, and much will depend on subjective interpretation (both of the authors and the reviewer). Such interpretation is further complicated by the fact that a qualitative review of the literature does not allow us to test for the existence of bias in the reporting of the results.

This section therefore attempts to quantify the impact of minimum wages on employment through a more objective meta-regression analysis (MRA), as described by Stanley and Jarrell (1989) and Stanley and Doucouliagos (2012). As discussed below, a meta-analysis will enable us to run some formal tests for the presence of reporting bias in the literature. It will also allow for a more systematic investigation of whether the effect of minimum wages on employment varies by sub-group studied and/or depends on the methodology employed.

Meta-analyses are becoming increasingly popular to summarise the large number of studies on minimum wages and employment – although none has specifically looked at emerging economies. Meta-analyses focusing on developed countries include Card and Krueger (1995), Doucouliagos and Stanley (2009), Boockmann (2010), Leonard, Stanley and Doucouliagos (2014) and Belman and Wolfson (2014a, 2014b). Nataraj, Perez-Arce, Kumar and Srinivasan (2014) look at low-income countries and only cover two emerging economies (India and Indonesia). Chletsos and Giotis (2015) include a few studies from emerging economies, including Indonesia (6), Brazil (4), Mexico (2), China (1), Colombia (1) and Poland (1) – but do not distinguish these countries from the other, (largely) developed countries they include in their study.

4.3.1 Basic meta-analysis

We run two different types of meta-analysis in this paper. The data collected for the first meta-analysis consist of all coefficients on the minimum wage variable in regressions where the dependent variable is employment and where the estimates obtained are in the form of elasticities. As shown in Table 4.2, this results in a total of 746 estimates from 28 studies and seven countries (Brazil, Chile, China, Colombia, Indonesia, Mexico and Poland).[71] The approach taken was to include all elasticities presented in each paper, and not just the authors' preferred results. This was to minimise the risk of subjectivity creeping into the analysis and is in line with best practice in the recent meta-analysis literature (Disdier & Head, 2008; Stanley & Doucouliagos, 2012).

Table 4.2 further shows that the average (unweighted) elasticity from these studies is -0.047. In other words: a 10% increase in the minimum wage decreases employment by 0.47%, which is a relatively small effect.[72] However, the estimates vary considerably between countries: a small positive effect is found in China and Indonesia, and relatively strong negative effects are observed in Mexico, Colombia and also Poland.[73] While most estimates are negative, only a third

[71] See Appendix 4.A for the list of studies included in the elasticities meta-analysis.

[72] To put these estimates into context, it is useful to refer back to the famous summary of the minimum wage literature in the United States carried out by Brown, Gilroy and Kohen (1982), which concluded that the disemployment effects of the minimum wage were small and almost exclusively limited to teenagers (aged 16-19 years). For this group, Brown *et al.* (1982) estimated that a 10% increase in the minimum wage reduced employment by 0-1.5%.

[73] For a number of countries, these findings point in different directions than the qualitative literature review suggested. However, this may not be entirely surprising since the focus is now on the subset of studies which report elasticities. It may also to some extent reflect subjectivity in the interpretation of findings by the authors of the studies we analysed in the survey review.

of all coefficients are significantly different from zero and, as shown in Figure 4.2, the majority (significant or not) are very close to zero.

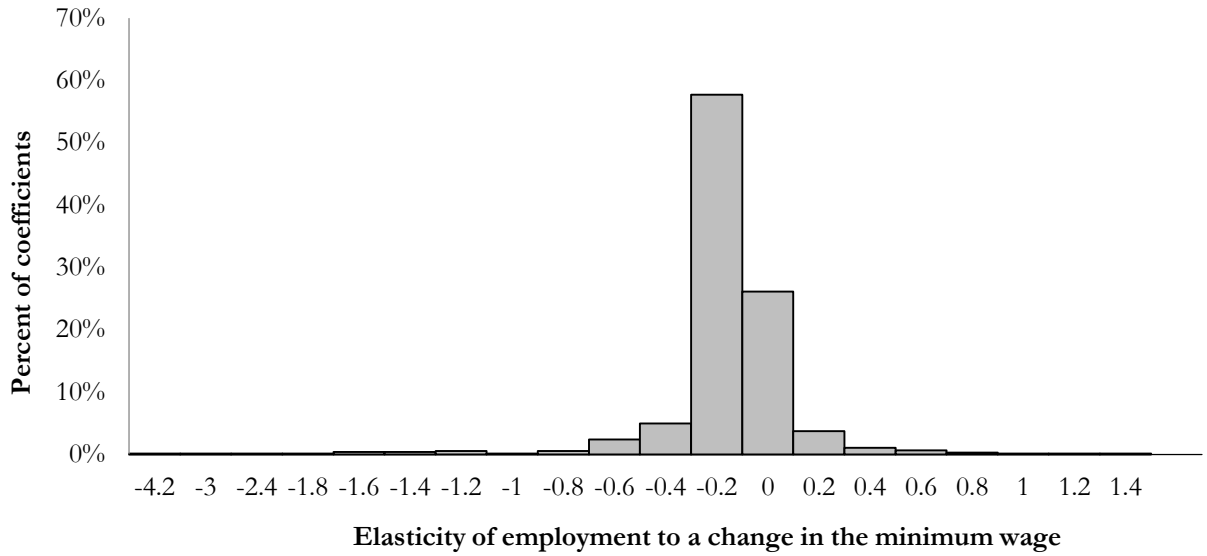
Table 4.2: Summary statistics: Elasticities

	N	Studies	Mean	Share negative	Share significant[a]	
					Negative	Positive
Brazil	315	10	-0.005	0.68	0.22	0.06
Chile	21	3	-0.026	0.57	0.24	0.19
China	220	7	0.004	0.60	0.19	0.08
Colombia	25	1	-0.378	0.92	0.64	0.04
Indonesia	84	3	0.029	0.70	0.35	0.19
Mexico	48	3	-0.460	0.73	0.48	0.06
Poland	33	2	-0.145	0.91	0.48	0.03
All	746	28[b]	-0.047	0.68	0.27	0.08

a. An elasticity is said to be significant when its p-value is smaller than 0.05.

b. Because Bell (1997) studies both Colombia and Mexico, the total number of studies (28) does not equal the sum of the number of studies per country (29).

Figure 4.2: Distribution of elasticities used for the meta-analysis



Notes: The data underlying this figure consist of 746 estimates from 28 studies and for 7 countries (Brazil, Chile, China, Colombia, Indonesia, Mexico and Poland) which could be expressed as elasticities and are used in the first meta-analysis reported in Section 4.3.1. The values on the x-axis represent the upper bound of a bin with width 0.2.

This elasticities meta-analysis is our preferred approach because it provides an estimate of the economic effect of minimum wages on employment. However, the big disadvantage of this method is that a large number of observations which are not reported as elasticities need to be thrown away, which also results in a diminished country coverage. One way of recovering some of the other estimates and boosting the sample size for the analysis is to use the "partial correlations" instead of the coefficients (Stanley & Doucouliagos, 2012). The advantage of using partial correlations is that they are unit-less, and therefore comparable across studies. However, they are not usually reported in studies and need to be calculated using the following formula:

$$r = \frac{t}{\sqrt{t^2 + df}} \tag{4.1}$$

Where *t* denotes the t-statistic of the regression coefficient and *df* the related degrees of freedom. Similarly, the standard error of the partial correlation needs to be calculated as:

$$\sqrt{\frac{1 - r^2}{df}} \tag{4.2}$$

One challenge with this approach is that the degrees of freedom are not always reported clearly in studies and therefore need to be inferred from the information provided by the authors. This is particularly challenging when the models include fixed effects. But, according to Stanley and Doucouliagos (2012), the calculation of the partial correlation is relatively robust to uncertainty about the degrees of freedom. A final problem with using partial correlations is that, of course, they are not a measure of an economic effect, but merely a measure of the strength and direction of the association between two variables.

Table 4.3 shows that this approach boosts the sample size by nearly 50% to 1,083 observations from 56 studies, and adds five countries to the analysis: Argentina, Russia, South Africa, Thailand and Turkey.[74] As with the elasticities meta-analysis, all partial correlations were included and not just those based on the authors' preferred results. Table 4.3 shows that the average partial correlation across all 12 countries is -0.052. While negative (i.e. the minimum wage has an adverse effect on employment), this is on the small side of partial correlations usually found in the minimum wage literature, according to the analysis carried out by Doucouliagos (2011). The average partial correlation is negative in all countries, except Russia and Turkey. It is also small in all countries, except in China (where it is moderate at -0.1) and in Mexico and Thailand (where it is large at -0.175 and -0.182, respectively). As in the elasticities analysis, most (two-thirds) of the partial correlations obtained from the emerging economies literature are negative but, apart from in Colombia, Mexico, Poland and Thailand, only a small share of these is statistically significant. Moreover, over half of the partial correlations can be classified as small according to Doucouliagos' (2011) criteria (i.e. smaller or equal to ±0.045) (see Figure 4.3). All in all, these results therefore confirm the analysis based on the elasticities sub-sample: while negative, the impact of minimum wages on employment appears to be small overall.

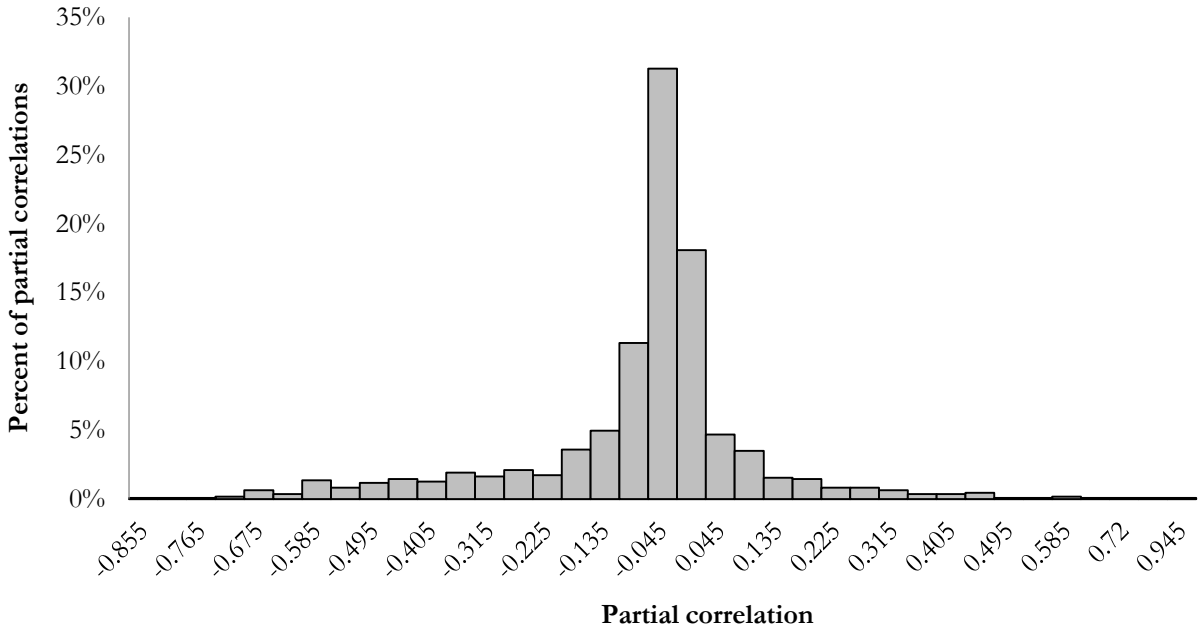
[74] See Appendix 4.A for the list of studies included in the partial correlations meta-analysis.

Table 4.3: Summary statistics: Partial correlation coefficients

	N	Studies	Mean	Share negative	Share significant[a]	
					Negative	Positive
Argentina	18	1	-0.011	0.72	0.28	0.00
Brazil	384	14	-0.025	0.67	0.20	0.04
Chile	19	5	-0.051	0.68	0.32	0.05
China	230	9	-0.100	0.57	0.25	0.10
Colombia	23	1	-0.048	0.91	0.57	0.04
Indonesia	155	8	-0.010	0.61	0.19	0.13
Mexico	49	3	-0.175	0.71	0.41	0.06
Poland	91	5	-0.091	0.97	0.82	0.01
Russia	2	1	0.040	0.00	0.00	0.00
South Africa	74	6	-0.009	0.57	0.23	0.08
Thailand	11	1	-0.182	0.73	0.45	0.00
Turkey	27	3	0.001	0.67	0.26	0.04
All	1083	56	-0.052	0.67	0.29	0.06

a. A partial correlation is said to be significant when its p-value is smaller than 0.05.

Figure 4.3: Distribution of partial correlations used for the meta-analysis



Notes: The data underlying this figure consist of 1,083 estimates from 56 studies and for 12 countries (Argentina, Brazil, Chile, China, Colombia, Indonesia, Mexico, Poland, Russia, South Africa, Thailand and Turkey) which could be expressed as partial correlations and are used in the second meta-analysis reported in Section 4.3.1. The values on the x-axis represent the upper bound of a bin with width 0.045.

4.3.2 Testing for reporting bias

One potential problem with the analysis so far is that the results may partially reflect reporting bias[75] rather than a true effect of the minimum wage on employment. Indeed, in their analysis of the effect of minimum wage rises in the United States, Doucouliagos and Stanley (2009) found that such bias was an important contributor to the average reported minimum wage effect in the literature. In this section, we therefore carry out some formal tests for the presence of reporting bias in the research on minimum wages in emerging economies.

To do this, we need to adopt a more formal model to estimate the average impact of minimum wages on employment. More specifically, we relate the effect size *e* obtained in study *i* to the overall effect size β_0 (intercept) using the following equation:

$$e_i = \beta_0 + \varepsilon_i \tag{4.3}$$

This, in essence, is what gives us the results reported in Tables 4.2 and 4.3. However, if reporting bias is present, then the effect size is likely to be related to its standard error. The reasoning behind this is that authors using small samples need larger estimates to achieve the desired significance level and may therefore resort to data-mining and/or specification search in order to achieve the desired result.

A common method to inspect the presence of such bias visually is to draw a "funnel plot", which shows the relationship between the effect size (e_i) on the x-axis and the precision of the estimate (as measured by the inverse of the coefficient's standard error, se_i) on the y-axis. One would expect this relationship to be funnel-shaped since more precise estimates (which are plotted higher up the y-axis) should be closer to the "true" population effect, while less precise estimates (which are plotted lower down the y-axis) will be scattered more widely around the true effect. The graph's symmetry is essential for assessing reporting bias: if the plot leans more heavily towards one side than the other, than this is indicative of reporting bias.

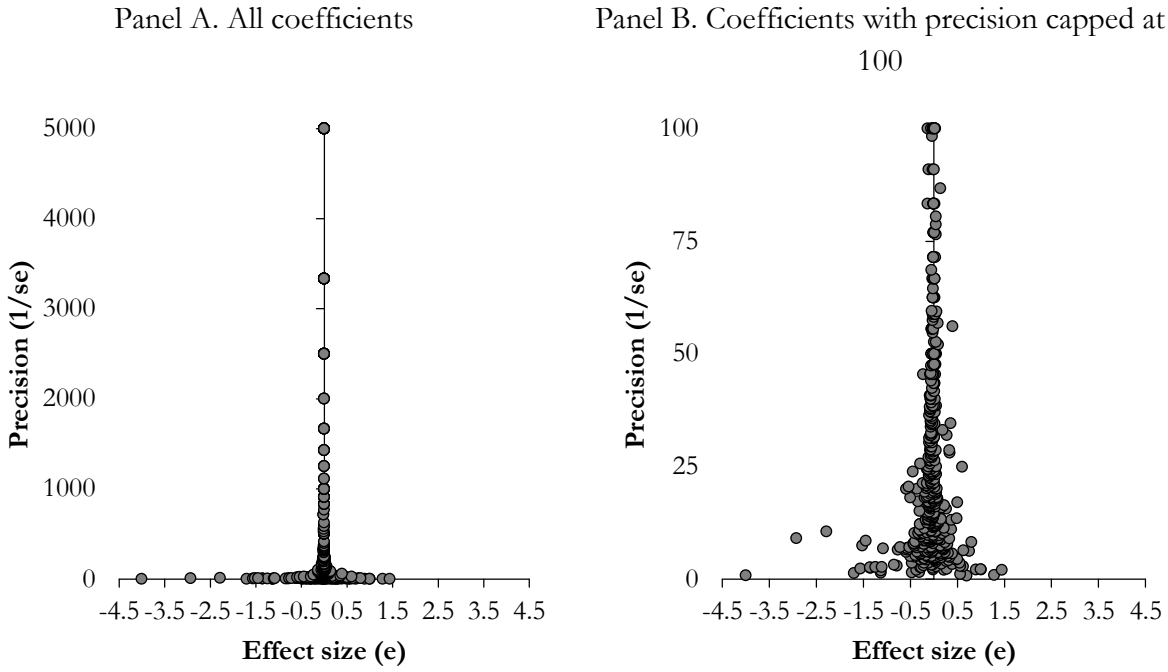
Panel A of Figure 4.4 shows a funnel plot based on the minimum wage elasticities summarised in Table 4.2, and suggests that reporting bias may not be an issue in the studies selected for our meta-analysis. However, because of the very high precision of some of the estimates, the scale of the y-axis makes it difficult to visually inspect what goes on near the base of the funnel plot. Panel B therefore reproduces the figure presented in Panel A, but caps the precision at 100 (equivalent to keeping 65.4% of the observations included in Panel A). With the exception of a few outliers on the left, Panel B again seems to suggest that reporting bias may not be a major issue.[76] Similarly, it is difficult to infer the existence of any reporting bias from Figure 4.5, which reproduces the funnel plot for the partial correlations sample.

However, eyeballing reporting bias from a funnel plot is not fool-proof, and so we extend the meta-analyses run in the previous section to control for the possible presence of such bias. We do this by adding the standard error of the coefficient, se_i, to the regression:

[75] We prefer to use the term reporting bias instead of publication bias because many of our estimates are obtained from working papers which are not published in peer-reviewed journals.

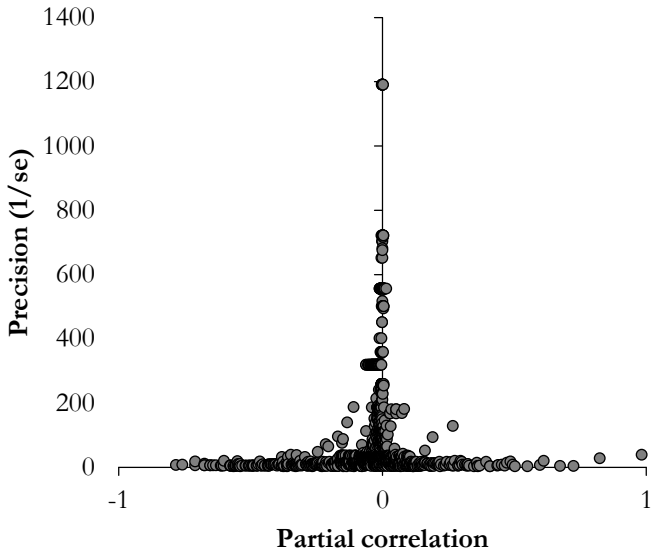
[76] We have tested whether our results are sensitive to the inclusion of these outliers. The results (not reported here but available upon request) indicate that the overall reporting bias in Table 4.5 reduces somewhat, but that this does not change the overall conclusions reached in this paper.

Figure 4.4: Funnel plots of estimated minimum wage elasticities



Notes: The data underlying the figure in Panel A consist of 746 estimates from 28 studies and for 7 countries (Brazil, Chile, China, Colombia, Indonesia, Mexico and Poland) which could be expressed as elasticities and are reported in Table 4.2. Panel B shows the subset of these estimates with precision 1/se capped at 100 and includes 65.4% of all the estimates included in Panel A.

Figure 4.5: Funnel plot of estimated minimum wage partial correlations



Notes: The data underlying the figure consist of 1,083 estimates from 56 studies and for 12 countries (Argentina, Brazil, Chile, China, Colombia, Indonesia, Mexico, Poland, Russia, South Africa, Thailand and Turkey) which could be expressed as partial correlations and are reported in Table 4.3.

$$e_i = \beta_0 + \beta_1 se_i + \varepsilon_i \quad (4.4)$$

In this regression, β_0 denotes the "true" elasticity and β_1 indicates the presence or not of reporting bias. If β_1 is statistically significant, then reporting bias is present but if it is small, then it is not something to be much concerned about. If β_1 is statistically insignificant and the reporting bias large, then it may still indicate the presence of reporting bias – but that it is highly variable, which is why it is estimated so imprecisely. Note that β_1 does not actually represent the magnitude of the reporting bias, but should be estimated as $\beta_1 \overline{se}$.

Because the studies included in the meta-analysis use different sample sizes and methods, the error term in equations (4.3) and (4.4) is likely to be heteroscedastic. To control for this, each observation in equation (4.4) can be weighted by the inverse of its standard error, so we obtain the following weighted least squares model:

$$t_i = \beta_o \frac{1}{se_i} + \beta_1 + \nu_i \quad (4.5)$$

Where t_i is the conventional t-ratio of the reported effect, and β_o and β_1 are the coefficients to be estimated. β_o remains the estimate of the average effect, while β_1 (now the constant) indicates the presence (or not) of reporting bias and, as before, the size of this reporting bias (expressed in elasticities rather than in t-ratios) is computed as $\beta_1 \overline{se}$. In addition, the within-study dependence can be accounted for by using cluster-robust standard errors.

The results of these various tests for reporting bias are presented in Table 4.4, both for the elasticities sample (Panel A) and the partial correlations sample (Panel B). Column (i) contains the results of equation (4.1) and, as discussed above, these are identical to the average effects estimated in Section 4.3.1. Column (ii) controls for reporting bias by estimating equation (4.2) – i.e. by including the standard error of the coefficients to the regression. The effect size becomes much smaller as a result of this, and even turns insignificant in the elasticities regression. There is also clear evidence of (negative) reporting bias, and the estimated magnitude of this bias is -0.021 (i.e. nearly half the effect size found in Column (i)). Finally, Column (iii) estimates the weighted least squares regression of model (4.3) with cluster-robust standard errors. In both the elasticities and the partial correlations models, the estimated effects are now of no economic significance, while there is still strong evidence of negative reporting bias. In fact, the estimated size of the reporting bias is at least as large as the effect size found in Column (i). Overall, two conclusions can be drawn from this analysis: (i) the literature on minimum wages in emerging economies tends to be biased towards reporting negative employment effects; and (ii) once this bias is controlled for, no minimum wage effect of economic significance can be detected.

4.3.3 Multiple meta-regression analysis

The first advantage of MRA is that it allows us to test and control for reporting bias. The second advantage is that it allows us to control simultaneously for a whole host of other variables which might have an independent effect on the outcome of interest, and which could bias the estimate of the minimum wage effect if omitted from the regression. For example, minimum wage studies (and estimates within studies) vary amongst one another both in terms of the populations they cover (e.g. youth, low-skilled, female, etc.) and how the models are specified (definition of the

minimum wage variable used, level of disaggregation of data, etc.) – and these sample and specification characteristics could, in turn, have an independent impact on the magnitude of the minimum wage elasticity (or partial correlation).

We therefore extend equation (4.5) to include a vector of *j* such moderator variables, Z_{ij} (which are also divided by the coefficient's standard error because the model is estimated by weighted least squares).

$$t_i = \beta_1 + \beta_o \frac{1}{se_i} + \sum_{j>0} \beta_0^j \frac{Z_{ij}}{se_i} + \nu_i \tag{4.6}$$

In addition, Stanley and Doucouliagos (2012) argue that the model should be augmented with a set of *K*-variables which identify factors that influence the propensity that an estimate gets published or reported. Stanley and Doucouliagos (2012) rationalise this as a way of approximating the Inverse Mills Ratio for each estimate used in the MRA, where publication bias is understood as a type of sample selection bias. Equation (4.6) therefore becomes:

$$t_i = \beta_1 + \beta_o \frac{1}{se_i} + \sum_{j>0} \beta_0^j \frac{Z_{ij}}{se_i} + \sum_{j>0} \beta_1^j K_{ij} + \nu_i \tag{4.7}$$

We assume that the *K*- and *Z*-vectors overlap completely, because we believe that the additional control variables might potentially affect both the expected effect of the minimum wage on employment (the *Z*-vector) and the propensity of a study being selected for publication (the *K*-vector). In practice, we control for sample characteristics by including dummy variables for the following categories: low-skilled[77]; youth[78]; low-wage[79]; male and female (with the omitted category consisting of estimates which do not distinguish between the genders); formal and informal (again, with the omitted category consisting of non-discriminating estimates); and country (with Brazil as the omitted category). As model controls, we include dummies for: the average year to which the data refer[80]; whether the study has been published in a peer-reviewed journal or not; the type of minimum wage variable used (Kaitz index, nominal MW, other – with the real MW as the omitted category); and the level of observation of the data (individual, firm, country or other – with regional-level data as the omitted category). Because adding *K*-variables on top of the *Z*-variables results in a high degree of multicollinearity, we only retain those *K*-variables which are statistically significant (i.e. we use a general-to-specific modelling technique). Note that when adding the *K*-variables, the reporting bias needs to be estimated as the combination of the intercept and all the statistically significant *K*-variables – i.e. $\overline{\left(\beta_1 + \sum_{J>0} \beta_1^J K_J\right) se}$.

[77] While the definition of low-skilled differs somewhat between papers, this category includes: less educated, unskilled or people with incomplete high school education.

[78] The definition of young people differs between papers, but tends to cover people aged 15-29 years.

[79] The definition of low-wage workers differs between papers, e.g. low-wage, below the minimum wage, between one and two times the minimum wage.

[80] Where studies span more than one year, the average year of the study is calculated and included as a control variable in the meta-analysis. In practice, we distinguish between papers which use data: older than 1990 (base category); from between 1990 and 1999; and since 2000.

Table 4.4: Testing for reporting bias

(i)		(ii)		(iii)	
$e_i=\beta_0+\varepsilon_i$		$e_i=\beta_0+\beta_1 se_i+\varepsilon_i$		$t_i=\beta_o\ 1/(se_i)+\beta_1+\nu_i$ (with clustered s.e.)	
Panel A. Coefficients					
β_0 (effect size)	-0.047***	β_0 (effect size)	-0.013	β_0 (effect size)	-0.0003***
	(0.012)		(0.013)		(0.0001)
		β_1 (reporting bias)	-0.486***	β_1 (reporting bias)	-0.782**
			(0.087)		(0.290)
Observations	746	Observations	746	Observations	746
		Size of reporting bias	-0.021***	Size of reporting bias	-0.054**
Panel B. Partial Correlations					
β_0 (effect size)	-0.052***	β_0 (effect size)	-0.024***	β_0 (effect size)	-0.001
	(0.006)		(0.007)		(0.003)
		β_1 (reporting bias)	-0.357***	β_1 (reporting bias)	-0.973***
			(0.060)		(0.274)
Observations	1083	Observations	1083	Observations	1083
		Size of reporting bias	-0.028***	Size of reporting bias	-0.075***

Notes: Standard errors are reported in parentheses. $\boldsymbol{\beta_1}$ indicates the presence of reporting bias, but the size of the coefficient does not give an indication of the magnitude of the reporting bias. The latter is reported at the bottom of each panel, and is calculated as $\boldsymbol{\beta_1 \overline{se}}$.

*** Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

One additional source of potential omitted variable bias in the model just discussed stems from the fact that estimates from the same study may be influenced by some common unreported or unobserved factors. We therefore also run regressions to which we add study fixed effects, γ_s (divided by the standard error) – as in equation (4.8).[81, 82] The obvious drawback of including these fixed effects is that controls for methodological characteristics (as well as the country fixed effects) can no longer be added separately to the meta-regression. This is because estimates within any one study are generally obtained using the same model specification (and for the same country), and so will largely be absorbed by the study fixed effects. Note that the country effects can still be retrieved from the means of the corresponding study fixed effects, and so these will be reported alongside the other results. An additional complication with introducing study fixed effects is that the effect size becomes more complicated to interpret. More specifically, the effect size should now be estimated as the average of the fixed effects coefficients ($\beta_o + \frac{\sum_s \gamma_s}{1+N_s}$), where N_s is the number of dummies (not counting the excluded one):

$$t_i = \beta_1 + \beta_o \frac{1}{se_i} + \sum_{j>0} \beta_0^j \frac{Z_{ij}}{se_i} + \sum_{j>0} \beta_1^j K_{ij} + \sum_{s>0} \frac{\gamma_s}{se_i} + v_i \quad (4.8)$$

Finally, in the partial correlations regressions, it is also important to control for the assumptions made by authors in calculating their standard errors. This is because, while the partial correlation coefficient is a function of the degrees of freedom and t-statistic when the latter is calculated on the assumption of an independent and identically distributed (i.i.d.) error term, this is no longer the case once this assumption is dropped. In practice, we therefore include a dummy variable in the regression coded as zero for standard errors calculated under the assumption of i.i.d. error terms and as one otherwise.

The results of these additional regressions are presented in Table 4.5, both for the elasticities (Panel A) and the partial correlations (Panel B). Starting with the elasticities analysis, Column (i) (i.e. without fixed effects or *K*-variables) indicates a negative effect similar in size to that reported in Table 4.4 (i.e. the "raw" effect with no controls for reporting bias) and which is only marginally statistically significant. Once *K*-variables are included in the model (Column (ii)), this effect remains similar in size (-0.055), but turns statistically insignificant. It is important to stress that this effect is no longer a general effect across countries and other characteristics, but rather the effect for the base group (i.e. with all dummy variables set at their base category). In other words, it is the meta-estimate of the elasticity for skilled, older, higher-wage workers of indeterminate gender in Brazil (without differentiation as to whether they work in the formal or informal sector).[83]

[81] Note that these are added only as *Z*-variables.

[82] In the case of Bell (1997), which covers two different countries, we include two separate fixed effects (one for each country).

[83] To obtain an estimate more comparable to that presented in Table 4.4, one would first need to calculate the following mean for each group *d* of dummy variables: $\frac{Precision + \sum_{j=1}^{N_d}(Precision + D_j)}{1+N_d} = Precision + (1 + N_d)^{-1} \sum_{j=1}^{N_d} D_j \sum_{j=1}^{N_d} D_j$. The grand mean of these individual group means would then provide an estimate comparable to the precision (effect size) term presented in Table 4.4. For the model presented in Column (i) of Table 4.5 this gives an estimate of -0.062 – i.e. an estimate similar in size to that presented in Table 4.4.

Finally, adding study fixed effects (Columns (iii) and (iv) of Table 4.5) turns the effect size marginally positive, but economically insignificant: a 10% increase in the minimum wage is associated with a 0.03% to 0.04% increase in employment. This time, the effect size can be interpreted as an average effect across countries (although the other dummy variables are still set at their base category[84]). Turning to the partial correlations, the effect size obtained in Panel B is always small and positive, and is statistically significant in three of the four specifications. Overall, the multiple MRA findings therefore confirm the analysis from the previous section: there is little evidence that the minimum wage in emerging economies has had a detectible on employment.

Turning to the reporting bias, the elasticities analysis (Panel A of Table 4.5) provides evidence of a negative and statistically significant reporting bias, which is almost identical in size to that estimated in the last column of Table 4.4. Similarly, the estimated reporting bias in the case of the partial correlations analysis (Panel B of Table 4.5) is remarkably consistent with the estimates reported in Table 4.4 – although one of them (in the regression with fixed effects and without *K*-variables) is statistically insignificant. Again, therefore, the findings of the multiple MRA confirm the conclusions of the basic meta-analysis reported in Section 4.3.2.

In theory, the multiple MRA should also allow us to assess whether the impact of the minimum wage varies by sample and/or specification characteristics. Here, unfortunately, we find that the results tend to be sensitive to the choice of model. There is some indication from the elasticities analysis in Table 4.5 that youth and the low-skilled tend to be more negatively affected by increases in the minimum wage – but the effect is relatively small, and the finding is not confirmed by the partial correlation analysis. There is also some indication that increases in the minimum wage tend to lead to small increases in informal employment – although most of the estimates are statistically insignificant, and one estimate in the partial correlations analysis is unrealistically high. The results also suggest that published studies and those using the Kaitz index as a minimum wage variable are slightly more likely to be associated with a larger positive effect of the minimum wage on employment.[85] No definite conclusions can be drawn about any of the other characteristics (although it is worth remembering that one would not necessarily expect the same results across the elasticities and partial correlations analysis because the latter covers a much larger set of studies).

A final remark concerns the effects by country. The models without study fixed effects suggest that only in studies for Poland is the effect of minimum wages found to be consistently more negative than in studies for Brazil. However, the analysis in the models without study fixed effects is complicated by the fact that all estimated country effects need to be estimated relative to the base country (Brazil). While the country fixed effects drop out of the models with study fixed effects, it is possible to retrieve the former from the relevant study fixed effects. These are reported in Table 4.6 and are slightly easier to interpret since they do not need to be analysed with reference to any base category. The results indicate that minimum wage studies for Mexico,

[84] However, a grand mean effect using the equation in footnote 83 gives very similar estimates (0.002 and -0.001 for columns (iii) and (iv), respectively, of Table 4.5).

[85] That being said, Card, Katz and Krueger (1994) argue that the Kaitz index imports some endogeneity into the measurement of the minimum wage and thus onto the right-hand side of the equation being estimated. This could help explain this finding.

Colombia and Poland most often report negative effects of the minimum wage on employment, while positive effects are most often found in studies for China, Indonesia and South Africa.

Table 4.5: Multiple meta-regression analysis

		Panel A. Coefficients				Panel B. Partial Correlations			
		(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Study fixed effects				✓	✓			✓	✓
Z-variables		✓	✓	✓	✓	✓	✓	✓	✓
K-variables[a]			✓		✓		✓		✓
Minimum Wage[b]	Precision	-0.064*	-0.055	0.004***	0.003***	0.009	0.051***	0.041***	0.040***
		(0.035)	(0.033)			(0.022)	(0.013)		
Skill	Low-skilled	-0.001	-0.002*	-0.002**	-0.002*	0.002	0.001	0.002	0.002
		(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Age	Young	-0.001*	-0.001***	-0.001***	-0.002***	0.000	-0.001	-0.001	-0.001
		(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.002)	(0.002)
Wage	Low-wage	-0.006	-0.006	-0.009	-0.009	0.027	0.014	0.014	0.014
		(0.006)	(0.006)	(0.006)	(0.006)	(0.018)	(0.013)	(0.013)	(0.013)
Gender	Female	-0.001	0.002	-0.003	-0.003	-0.002	-0.006	-0.009*	-0.008
		(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)
	Male	-0.014	-0.051***	-0.011	-0.037***	0.001	-0.001	-0.003	-0.007
		(0.013)	(0.015)	(0.015)	(0.011)	(0.003)	(0.003)	(0.004)	(0.005)
Formality	Formal	0.004*	0.003	0.003	0.003	0.004	0.000	-0.009	-0.009
		(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.006)	(0.012)	(0.012)
	Informal	0.003	0.002	0.004**	0.004**	0.060	0.136*	0.046	0.045
		(0.002)	(0.002)	(0.002)	(0.002)	(0.048)	(0.074)	(0.039)	(0.039)
Country	China	-0.038***	-0.057***			0.038	-0.005		
		(0.008)	(0.005)			(0.043)	(0.043)		
	Indonesia	0.043	0.045			0.028	0.001		
		(0.047)	(0.046)			(0.026)	(0.025)		
	Mexico	0.065	0.157**			-0.001	-0.034		
		(0.059)	(0.059)			(0.038)	(0.031)		
	Colombia	0.022	0.080			-0.017	-0.068**		
		(0.070)	(0.069)			(0.039)	(0.032)		
	Poland	-0.123*	-0.149**			-0.036*	-0.036**		
		(0.062)	(0.058)			(0.019)	(0.016)		
	Chile	0.071*	0.105***			-0.008	-0.024***		
		(0.035)	(0.035)			(0.006)	(0.008)		
	South Africa					0.025	0.016		
						(0.022)	(0.018)		
	Turkey					-0.021	-0.033**		
						(0.015)	(0.014)		
	Argentina					-0.016	-0.029**		
						(0.018)	(0.014)		
	Thailand					-0.057	-5.273***		
						(0.044)	(0.026)		
	Russia					0.112***	0.087***		
						(0.022)	(0.019		

Table 4.5: Multiple meta-regression analysis (continued)

		Panel A. Coefficients				Panel B. Partial Correlations			
		(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Study fixed effects				✓	✓			✓	✓
Z-variables		✓	✓	✓	✓	✓	✓	✓	✓
K-variables[a]			✓		✓		✓		✓
Time	1990-1999	0.060*	0.052			-0.008	-0.029***		
		(0.034)	(0.033)			(0.005)	(0.009)		
	>=2000	0.065*	0.053			0.000	-0.030***		
		(0.034)	(0.033)			(0.006)	(0.007)		
Published	Yes	0.002*	0.003**			0.006*	-0.004		
		(0.001)	(0.001)			(0.004)	(0.005)		
MW Variable	Kaitz	0.010***	0.008**			0.002***	0.002***		
		(0.003)	(0.003)			(0.001)	(0.000)		
	Nominal	0.042	0.056			-0.031	-0.015		
		(0.034)	(0.033)			(0.021)	(0.018)		
	Other	-0.002*	0.001			0.000	0.001*		
		(0.001)	(0.002)			(0.001)	(0.001)		
Observation level	Firm	-0.005	-0.002			-0.010	0.021		
		(0.036)	(0.035)			(0.029)	(0.030)		
	Individual	-0.001	0.001			0.002	0.001**		
		(0.001)	(0.001)			(0.001)	(0.001)		
	Country	-0.132*	-0.451**			-0.020	0.064		
		(0.076)	(0.202)			(0.069)	(0.073)		
Error (corrected)[c]						-0.009	-0.020**		
						(0.018)	(0.010)		
N		746	746	746	746	1083	1083	1083	1083
Reporting bias[d]		-0.054*	-0.056***	-0.055***	-0.052***	-0.081***	-0.013***	-0.107	-0.106*

a. The K-variables are not reported in the table. A general-to-specific approach is used for the K-variables, and only significant K-variables are kept in the regression.

b. In the fixed effects models, the reported precision coefficients are estimated as the weighted mean of the coefficients on the study fixed effects ($\boldsymbol{\beta_o} + \frac{\sum_s \gamma_s}{1+N_s}$)- and therefore no error can be calculated. Significance of the coefficient is estimated using an F-test of joint significance of the fixed effects.

c. Error (corrected) is a dummy variable indicating when the standard errors are corrected (i.e. White, serial correlation, heteroscedasticity, etc.).

d. In the models without K-variables effects, reporting bias is estimated as in Table 4.4. In the models with K-variables, reporting bias is estimated as $\overline{\left(\boldsymbol{\beta_1} + \sum_{j>0} \boldsymbol{\beta_1^j} \boldsymbol{K_j}\right)\boldsymbol{se}}$ and the significance is tested using an F-test of the associated coefficients.

Standard errors, in parentheses, are clustered at the study-level.

*** Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 4.6: Country fixed effects estimated from the corresponding study fixed effects

	Panel A. Coefficients		Panel B. Partial Correlations	
	(iii)	(iv)	(vii)	(viii)
Argentina			-0.010	-0.011
Brazil	-0.002 **	-0.002 **	0.000 ***	0.001 ***
Chile	-0.023	-0.015	0.019 ***	0.024 ***
China	0.036 ***	0.033 ***	0.105	0.099
Colombia	-0.046 ***	-0.045 ***	0.000	0.000
Indonesia	0.013 ***	0.012 ***	0.055 ***	0.056 ***
Mexico	-0.004	-0.018 ***	-0.047	-0.064 **
Poland	-0.103 ***	-0.099	-0.050 ***	-0.047 ***
Russia			0.145	0.150
South Africa			0.227 ***	0.223 ***
Thailand			-0.036	-0.038
Turkey			0.065	0.068

Notes: Country effects are obtained from the corresponding study fixed effects estimated in the models from Table 4.5. The column headings correspond to those in Table 4.5. Significance is estimated from an F-test of the relevant study fixed effects.

*** Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

4.4. Conclusion

The impact of minimum wages on employment is primarily an empirical matter and, in advanced economies, countless studies have addressed this issue – with some consensus emerging that moderate increases in a minimum wage (which is set at a reasonable level to start with) are unlikely to lead to significant employment losses. For policymakers in emerging economies, however, evidence from developed countries may not be of much use because the characteristics of their labour markets are very different. Recognising this issue, more and more researchers have begun to investigate the impact of minimum wages in emerging economies and the number of studies has been growing exponentially. While this boom in research is a welcome development, there has been very little attempt so far at taking stock of the emerging findings – which is what this paper has sought to address.

Based on evidence for 14 large emerging economies, both the qualitative (survey) review (covering 95 studies) and the meta-analyses of elasticities and partial correlations (covering 28 and 56 studies, respectively) showed that minimum wages have had little detectable impact on employment. While more vulnerable groups appear to be more adversely affected by minimum wage rises, the effects tend to be small on average. These findings are very much in line with the growing consensus around the impact of minimum wages on employment in more advanced economies.

From a research perspective, the main novelty of this paper has been the application of meta-analysis techniques to the minimum-wage literature in emerging economies. While meta-analyses have been commonly used to summarise large numbers of minimum wage studies in the context of developed countries, to date no such exercise had focused exclusively on emerging economies. The paper also constitutes an important contribution to the policy debate on minimum wages. More specifically, the results seem to indicate that, like in more developed

countries, regular and modest increases in the minimum wage are unlikely to have a significant negative impact on employment in emerging economies.

Some caution is nevertheless required. While the finding of no employment effect is remarkable given the large differences in labour market characteristics between emerging and more advanced economies, the reasons why the minimum wage has no employment effect may in fact be very different. In developed countries, the possible explanations which have generally been advanced for the lack of effect include: employers with monopsonistic power, the efficiency wage hypothesis, or the fact that firms use adjustment mechanisms other than employment to adapt to a higher minimum wage. In emerging economies, however, the reason for not finding any employment effect could be very different. In particular, the role of non-compliance should be explored in future research as a possible explanation given that, in many emerging economies, a substantial share of workers still earn less than the minimum wage (Bhorat & Stanwix, 2013).

Compliance may be low because: the minimum wage is either set too high or too low (Saget, 2008; Lee & Sobeck, 2012; Rani, Belser, Oelz & Ranjbar, 2013); the system is too complex (Cunningham, 2007; Rani et al., 2013); there are no legislated fines/punishments for non-compliance; or the minimum wage is simply not enforced, possibly due to a lack of resources (Kristensen & Cunningham, 2006). Another important reason why the minimum wage might be difficult to enforce in emerging economies is the existence of a large informal sector. In such contexts, increases in the minimum wage may have no effect on employment overall because a fall in formal sector employment may simply be compensated for by a rise in informal sector employment. Indeed, we presented some tentative evidence that higher minimum wages may lead to more informal employment (although the effect was of little economic significance).

A second reason to be cautious about the policy implications of this paper is that the findings presented apply to large emerging economies only – which could be another explanation for why no employment effect could be detected. Indeed, minimum wages might be expected to have a more significant impact on employment in small, open economies – and so the conclusions reached here may not be applicable in those contexts.

The analysis has been valuable from a stock-taking point of view – however, it has also raised a large number of new questions. Firstly, minimum wage analyses (including those in advanced economies) often take the minimum wage as a given and look at the impact of increases in that minimum wage on employment. Very few studies ask the question of what would happen in a world without minimum wages (albeit for obvious, methodological reasons). Secondly, while this study reviewed 95 studies, differences in sub-samples and, in particular, methods used across papers often made it difficult to compare the results across studies. Indeed, the elasticities meta-analysis could only draw on a sub-sample of 28 studies which reported findings in the form of elasticities. More consistency and rigour in reporting findings from minimum wage studies are therefore required. Thirdly, there should be a more systematic attempt to investigate the impact of minimum wages on labour market outcomes other than employment, including hours worked and formality, as well as on different sub-groups.

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Annex 4.A. Papers included in meta-analyses

	Elasticities	Partial Correlations
Alatas & Cameron (2008)		x
Baranowska-Rataj & Magda (2015)		x
Bell (1997)	x	x
Bhorat, Kanbur & Mayet (2013)		x
Bhorat, Kanbur & Stanwix (2014)		x
Bhorat, Cassim, Kanbur, Stanwix & Yu (2016)		x
Broecke & Vandeweyer (2015)	x	x
Carneiro (2004)		x
Castañeda (1983)		x
Chun & Khor (2010)		x
Comola & de Mello (2011)		x
Del Carpio, Mesina & Sanz-de-Galdeano (2014)		x
Del Carpio, Nguyen & Wang (2012)	x	x
Dinkelman & Ranchhod (2012)		x
Fang & Lin (2013)	x	x
Feliciano (1998)	x	x
Foguel (1998)	x	x
Foguel, Ramos & Carneiro (2001)		x
Garza Cantú & Bazaldúa (2002)	x	x
Grau & Landerretche (2011)		x
Groisman (2015)		x
Hertz (2005)		x
Huang, Loungani & Wang (2014)	x	x
Islam & Nazara (2000)	x	x
Kamińska & Lewandowski (2015)		x
Kobzar (2009)		x
Lemos (2004a)	x	x
Lemos (2004b)	x	x
Lemos (2004c)	x	x
Lemos (2005a)	x	x
Lemos (2005b)	x	x
Lemos (2007)	x	x
Lemos (2009a)	x	x
Lemos (2009b)	x	x
Luo, Zhou & Wu (2011)		x
Magruger (2013)		x
Majchrowska & Żółkiewski (2012)	x	x
Martinez, Morales & Valdes (2001)	x	x
Mayneris, Poncet & Zhang (2014)	x	x
Melnyk (1996)	x	x
Millea, Rezek & Pitts (2012)		x
Miranda (2013)	x	x

Montenegro & Pagés (2004)	x	x
Neumark, Cunningham & Siga (2006)		x
Ni, Wang & Yao (2011)	x	x
Ozturk (2006)		x
Papps (2012)		x
Pelek (2011)		x
Rama (2001)		x
Ruzik (2007)		x
Shi (2011)	x	x
Soares (2005)		x
Suryahadi, Widyantu, Perwira & Sumarto (2003)	x	x
Wang & Gunnderson (2011)	x	x
Wang & Gunderson (2012)		x
Xiao & Xiang (2009)	x	x

Doctoral dissertations from the Faculty of Economics and Business, see: http://www.kuleuven.ac.be/doctoraatsverdediging/archief.htm.