The decline in the wage share: falling bargaining power of labour or technological progress? Industry-level evidence from the OECD

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Abstract:

We investigate whether the downward trend in the wage share is driven by technological change or a decline in labour's bargaining power. We present an econometric analysis using industry-level data for 14 OECD countries for the 1970-2014 period and test whether the determinants of the wage share differ between manufacturing and service industries, between workers of different skill groups and across countries with different bargaining regimes. Our findings suggest that the wage share declined due to a fall in labour's bargaining power driven by offshoring to developing countries and changes in labour market institutions such as union density, social government expenditure and minimum wages. In contrast, the effect of technological change is not robust. While we find evidence for a negative effect on medium-skilled workers, our results cast doubt on the hypothesis of skill-biased technological change.

JEL codes: E25, F66, J50

Keywords: income distribution, collective bargaining, trade unions, technological change, globalisation

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1. Introduction

There has been a significant decline in the share of wages in GDP in both developed and developing countries since the 1980s. The decline in the wage share also coincided with an increase in personal income inequality driven by increasing top-income shares and stagnant income at the bottom of the distribution. There is evidence that these two trends are related as profit income mainly accrues to people at the top of the income distribution (García-Peñalosa and Orgiazzi, 2013; Jacobson and Occhino, 2012). Additionally, a declining wage share is also alarming for future prospects in income distribution: Given the high inequality in wealth, a decline in the wage share suggests that personal income inequality will persist.

Previous research has highlighted two main hypotheses to explain the decline in the wage share. The skill-biased technological change hypothesis argues that the wage share declined due to technological progress that led to substitution of capital for low-skilled labour (Bassanini and Manfredi, 2014; Bentolila and Saint-Paul, 2003; Hutchinson and Persyn, 2012; Karabarbounis and Neiman, 2014; O'Mahony et al., 2018). The bargaining power hypothesis posits that changes in the relative bargaining power between capital and labour are responsible for the trend (Askenazy et al., 2018; Damiani et al., 2018; Jayadev, 2007; Kristal, 2010; Rodrik, 1998; Stockhammer, 2017).[1] Globalisation is often analysed as a third factor but can be considered as either facilitating technological progress or altering bargaining power. We contribute to this literature by presenting an econometric analysis of the determinants of the wage share (labour compensation as a ratio to value added) using industry-level panel data for 14 OECD countries (Australia, Austria, Belgium, France, Finland, Germany, Ireland, Italy, Japan, the Netherlands, Spain, Sweden, the UK, the US) between 1970 and 2014.[2] Our questions are twofold: First, is the decline in the wage share driven by changes in bargaining power or technological change? Second, how does the impact of technological change and bargaining power differ for workers of different skill groups and in countries with different bargaining regimes?

Previous research using industry-level data to analyse the determinants of the wage share is scarce and barely controls for the impact of bargaining power (e.g. Bassanini and Manfredi, 2014; Bentolila and Saint-Paul, 2003; Dao et al., 2017; Elsby et al., 2013; Hutchinson and Persyn, 2012; Karabarbounis and Neiman, 2014). In contrast, research focusing on changes in bargaining power mainly uses country-level data, which cannot fully account for the impact of skill-biased technological change, as it does not differentiate between high and low-skilled industries or workers (e.g. Kristal, 2010; Stockhammer, 2017).[3] Some recent contributions use country-level measures of bargaining power to explain industry-level wage shares, but such measures do not capture industry specific trends (Askenazy et al., 2018; Damiani et al., 2018; O'Mahony et al., 2018). We fill this gap by conducting an analysis that controls for the effect of bargaining power and technological change on the wage share using industry-level data. To measure bargaining power we exploit previously unexplored data for union density, minimum wages, the female employment share and narrow offshoring at the industry level. These industry-specific bargaining measures allow us to assess whether causes for the decline in the wage share differ between manufacturing and service industries, for workers of different skill levels within these industries and also increase the precision of our estimates. Additionally, we draw on literature in industrial relations and political economy to assess how the determinants of bargaining power differ in countries with different bargaining regimes (Soskice, 1990; Visser, 2006), a factor which has not received much attention in previous research on functional income distribution.

We find evidence that the wage share declined due to a fall in labour's bargaining power, driven by the decline in union density and social government expenditure. Union density is particularly relevant for low-skilled workers in coordinated bargaining regimes, whereas social government expenditure has a stronger impact in regimes characterised by firm-level bargaining. Additionally, globalisation in the form of offshoring to emerging and developing economies has eroded the bargaining power of labour and the wage share. While we also find some evidence of a negative impact of technological change, the effect is not robust over time. Furthermore, it is least relevant for low-skilled workers, in contrast to the skill-biased technological change hypothesis, although we do find some evidence of a negative impact on medium-skilled workers. Our results imply that rising inequality is not an inevitable outcome of technological progress but can be altered by collective bargaining institutions, fiscal and labour market policies.

Sections 2.1 and 2.2 present a simple model which illustrates the impact of technological progress, labour market institutions and globalisation on the wage share. Section 2.3 highlights how these effects are mediated by the skill level of the workforce and the bargaining regime, while section 2.4 summarises the main implications of the model in form of empirically testable hypotheses. Section 3 reviews the empirical literature and Section 4 introduces the data and stylised facts. Section 5 outlines the econometric model and estimation strategy, and Section 6 reports estimation results. Section 7 presents robustness tests and Section 8 concludes.

2. Determinants of the wage share – technological change or bargaining power?

Our model is based on Bentolila and Saint-Paul (2003). Output (Y) is produced using capital (K) and labour (L) via a differentiable production function that is homogenous of degree one, allowing for capital- (A) as well as labour augmenting technological change (B): $Y = f(AK, BL)$.

It is usually assumed that firms are profit maximising price takers, so that labour is paid its marginal product. Under these restrictive assumptions the wage share (S) can be expressed as a function of the capital-output ratio ($k = \frac{K}{Y}$) and capital augmenting technological change (A) alone (Bentolila and Saint-Paul, 2003).

$$S = g(A, k) \tag{1}$$

Optimal k, i.e. the choice of the production technology, will be a function of the (variable) input prices as well as (constant) technological parameters. Consequently, equation (1) captures changes in the wage share that result from changes in the relative price of capital as well as the effect of technological change (A and B).

2.1 The technological change hypothesis

The technological change hypothesis posits that the wage share declined due to capital augmenting technological change (an increase in A) and/or an increase in the capital-output ratio (k). Previous research argues that technological progress was labour augmenting after World War II and became capital augmenting since the 1980s (Bassanini and Manfredi, 2014; European Commission, 2007). A similar argument posits that technological progress contributed to a decline in the price of capital relative to labour (Dao et al., 2017; Karabarbounis and Neiman, 2014). If firms are optimising, this will lead to a substitution of capital for labour and an increase in the capital-output ratio (k). Importantly, the impact of A and k on the wage share depends on the elasticity of substitution between capital and labour (Bentolila and Saint-Paul, 2003). Only if the elasticity of substitution is above one will an increase in k or A have a negative impact on the wage share, as more output is being produced with less labour employed. In contrast, if the elasticity is below one, technological change would increase the wage share. The case of unit elasticity (e.g. Cobb-Douglas production) precludes an impact of k or A on the wage share. Therefore, the technological change hypothesis is derived from a particular model which includes a parameter restriction on the elasticity of substitution.

Technological progress, the main determinant of A and k, is often assumed to be exogenous. Additionally, some authors suggest that increasing labour costs can induce the adoption of labour-saving technology (Acemoglu, 2003; Hein, 2014). Another determinant of A and k is globalisation. There are two main channels: First, trade can lead to (trade induced) leaps in technology, thereby effectively raising A (e.g. Bloom et al., 2016). Second, globalisation can affect capital intensity as firms in capital abundant countries offshore labour intensive tasks to benefit from lower wages in labour abundant countries (Dao et al., 2017; Elsby et al., 2013). This reduces the demand for labour in advanced economies and increases the capital intensity of production, thus raising k. Again, the impact of both processes on the wage share depends on the elasticity of substitution.

2.2 The bargaining power hypothesis

If we lift the restrictive assumption of fully competitive labour markets, bargaining power between capital and labour becomes an additional variable that determines factor distribution. If workers bargain for employment as well as wages, for example in an efficiency bargaining regime, an increase in the bargaining power of labour increases the wage share for a *given* level of A and k.

The bargaining power hypothesis attributes the decline in the wage share to a decline in the bargaining power of labour. Traditionally, the main determinants of labour's bargaining power are labour market institutions. These can be categorised into direct and indirect factors; direct factors strengthen workers' voice in negotiations, whereas indirect factors improve their fall-back options in case negotiations break down. For an example of the latter, an increase in social welfare services improves labours' position because workers can rely on a provision of basic services in case of job loss (Harrison, 2002; Stockhammer, 2017). Direct measures of bargaining power include union density, strike activity, collective bargaining coverage and minimum wages (Bentolila and Saint-Paul, 2003; European Commission, 2007; ILO, 2011; Kristal, 2010). Bargaining also has a gender dimension. A higher share of women in an industry is likely to be negatively correlated with the average wage due the persistence of gender wage gaps, which may reflect lower collective voice of women (Seguino and Braunstein, 2019).

Lastly, globalisation impacts bargaining positions. Deregulation of trade barriers increases the mobility of capital by reducing relocation and offshoring costs and thereby increasing the credibility of the firing threat (Harrison, 2002; Jayadev, 2007; Rodrik, 1998). For advanced economies, it is particularly the ease of offshoring to low-wage countries that is expected to reduce workers' bargaining power. Consequently, not only the volume of offshoring but also the wage level of trade partners matters. Furthermore, globalisation can put domestic workers in direct competition with foreign workers through an increase in migration. The impact of migration on the wage share is theoretically ambiguous and depends on whether migrants substitute or complement natives. If unions or equal pay legislation are weak, leading to a segmented labour market, lower wages paid to migrants may have a negative impact on the wage share. Importantly, these aspects of globalisation would impact the wage share for a given level of capital intensity.

2.3 The relevance of skill differences and bargaining regimes

The impact of technological progress and labour market institutions on the wage share might differ by skill groups and bargaining regimes. Technological change is expected to have a negative effect on low-skilled and a positive effect on high-skilled labour if capital is a substitute for the former, while it complements as the latter. This is referred to as skill-biased technological change (European Commission, 2007). Additionally, the job polarization literature suggests a negative impact of technological change specifically on medium-skilled workers. According to this argument technological progress in the last decades was driven by Information and Communication Technology (ICT) that allowed to replace workers by machines for tasks that are easily automated, which are mainly performed by medium-skilled workers (Autor and Dorn, 2013; Dao et al., 2017).

The industrial relations literature has emphasised that the effect of labour market institutions might also differ by skill-groups. Surprisingly, this has been largely ignored in contributions on functional income distribution. There is evidence that a strong labour union presence reduces wage dispersion and restrains top executive remuneration (Jaumotte and Osorio Buitron, 2015). Consequently, union density is expected to be most relevant for low- or medium-skilled workers, whereas the effect on high-skilled workers might even be negative, especially if this group includes executives. Additionally, the effect of union density will depend on the institutional environment, in particular the level of collective bargaining coverage and the degree of coordination. A high level of bargaining coverage guarantees that gains achieved by union members are shared with the wider workforce (Visser, 2006), which suggests a stronger impact of union density when bargaining coverage is high. In contrast, if bargaining coverage is low unions might not be as effective. Our hypothesis is that in such environments indirect measures of bargaining power, such as social government expenditure, might be more relevant for labour, as they provide a ‘social wage’ that applies to the whole workforce. Conversely, Jaumotte and Osorio Buitron (2015) argue that high collective bargaining coverage relative to union density, as in Spain and France, can increase unemployment if wage demands of unions become excessive, with negative effects on the wage share.

Another factor is the degree of coordination. There is a substantive literature on the link between the degree of bargaining coordination and wage restraint. The usual claim is that unions in coordinated regimes internalise the negative impact of higher wages on employment and therefore engage in wage moderation (Soskice, 1990). However, this overlooks that coordinated labour unions might be more effectively acting as an interest group in comparison to uncoordinated regimes. McHugh (2002) argues that bargaining power is higher in coordinated regimes, especially if unions are able to push for a legal bargaining framework that is more favourable to labour (see also Kerr, 1954).[4] This position is also shared by practitioners. Labour unions often stress that uncoordinated bargaining results in "downward spirals in terms of working conditions and wages", whereas employer organisations claim that decentralisation is a necessary tool "enabling companies to adapt to the increasing pressure of global competition" (Eurofound, 2015, p. 1).

Besides the legal framework, general economic conditions also have an impact on bargaining power. It is well known that unions act differently in recessions in comparison to normal times, as they often agree to concessions and even wage reductions to save jobs (Juris, 1969). A reduction in (real) wages at constant employment rates reduces the wage share and thus we might expect a smaller, or potentially even a negative effect of labour unions on the wage share during economic downturns.

2.4 Empirical hypotheses

Summing up, there is substantive controversy about the relevance of technological change and bargaining power for the decline of the wage share (S). It is essentially a debate about whether capital augmenting technological change (A) and changes in capital intensity (k), or a shift in bargaining power (γ) are the main drivers of the trend. Technological progress ($tech$) is the main determinant of A and k, while changes in labour market institutions (LMI) are the main determinants of γ, whereas globalisation ($glob$) impacts all three factors, A, k and γ:

$$S = h[A(tech, glob), k(tech, glob), \gamma(LMI, glob)] \tag{2}$$

This implies that globalisation can affect the wage share via two channels. First, globalisation can alter the capital intensity of production (thus raising k) or increase capital efficiency (raising A). We refer to this as the globalisation-technology channel. Second, globalisation can affect the relative bargaining power of labour, thus changing γ. We refer to this as the globalisation-bargaining channel. In Section 5 we present an econometric model that allows to disentangle these two channels.

The impact of changes in bargaining power and technology depend on the skill level of the workforce and the bargaining regime. We derive the following hypotheses:

H1: Capital augmenting technological change (A) and capital intensity (k) have a negative effect on the wage share.

H1a: The effects of technological change and capital intensity are negative for low-skilled and medium-skilled workers, while they might be positive for high-skilled workers.

H2: An increase in the bargaining power of labour increases the wage share.

H2a: An increase in union density has a stronger (more positive) effect on low-income/ low-skilled labour in comparison to high-income/ high-skilled labour.

H2b: The impact of union density on the wage share is stronger when collective bargaining coverage and coordination are high. In uncoordinated bargaining regimes country-level indirect measures of bargaining power might be more relevant than union density.

H1 restates the technological change hypothesis – it will hold if firms are profit maximising and the elasticity of substitution between capital and labour is above one. Hypothesis H1a follows from H1: the negative effect of technological change will be most apparent for low-skilled workers (according to the skill-biased technological change hypothesis) and medium-skilled workers (according to the job polarization literature) as those skill-groups have the highest elasticity of substitution (Autor and Dorn, 2013; European Commission, 2007). In the extreme case of an elasticity of substitution above one for low- or medium-skilled workers and below one for high-skilled workers, the technology effect on the wage share for different types of workers might go in opposing directions. The impact on the overall wage share depends on whether the negative effect on low-/medium-skilled workers outweighs the positive effect on high-skilled workers. Therefore, it is essential to look at the effect of technological change on different skill groups to test the technological change hypothesis, but we must also consider the effect on the total wage share to assess the aggregate impact.

Hypothesis 2 expresses the bargaining power hypothesis. The relative bargaining power of labour is altered by changes in LMI or globalisation. Hypotheses H2a and H2b refer to the effect of union density as the most common measure of bargaining power. H2a implies a differentiated effect of union density on high-income/high-skilled labour as unions reduce wage dispersion and moderate excessive wages of managerial staff (Jaumotte and Osorio Buitron, 2015). The literature is somewhat divided regarding hypothesis H2b, but there is evidence that unions have higher bargaining power when bargaining coverage and coordination are high (McHugh, 2002). Conversely, if unions are weak due to a low level of coverage and coordination, country-level indirect measures of bargaining power, such as social government expenditure, might be more important.

3. Empirical Evidence

The most prominent evidence for the technological change hypothesis is provided by Karabarbounis and Neiman (2014). According to their estimates, about half of the global decline in the wage share can be explained by a change in the relative price of capital, which led to increasing capital intensity worldwide. However, overall empirical evidence remains inconclusive. Out of 15 studies that estimate determinants of the wage share with industry- or country-level data, seven found no or even a positive impact of technology, implying an elasticity of substitution that is smaller than or equal to one as summarised in Table 1.

<place Table 1 here>

More importantly, studies whose primary focus lies on the estimation of the elasticity of substitution between capital and labour consistently find values below one and closer to 0.4, which is inconsistent with the technological change hypothesis (Chirinko, 2008; Chirinko and Mallick, 2017).

Studies focusing on the bargaining power hypothesis find substantive evidence for the impact of labour market institutions on the wage share. Among indirect bargaining factors, welfare state retrenchment is found to be an important determinant (Harrison, 2002; Jayadev, 2007;

Onaran, 2009; Stockhammer, 2017). However, the measure used in previous research is aggregate government spending, which does not reflect changes in the composition of spending.[5] Several empirical papers have confirmed the impact of direct measures of bargaining power, such as strike activity, collective bargaining arrangements and minimum wages on the wage share (Argitis and Pitelis, 2001; Bentolila and Saint-Paul, 2003; European Commission, 2007; ILO, 2011; Kristal, 2010; Stockhammer, 2017). Askenazy et al. (2018), using a dataset similar to ours, obtain a positive effect of macro-level unemployment on industry-level profit shares. However, they do not control for other bargaining or technology variables. A similar strategy is followed by O'Mahony et al. (2018) and Damiani et al. (2018). Both studies regress the wage share at the industry level on capital intensity and bargaining power variables at the country level which are interacted with an industry-specific indicator. While O'Mahony et al. (2018) find only weak evidence of LMI, Damiani et al. (2018) find that legislation that favours the use of temporary contracts reduces the wage share, particularly during the Great Recession. Union density is the most commonly used variable with the best data availability and the most robust positive effect on the wage share in estimations using country-level data (Damiani et al., 2018; ILO, 2011; Stockhammer, 2009; 2017). However, IMF (2007), Dao et al. (2017) and European Commission (2007) find no significant effect of union density in most specifications. A recent contribution analyses the effect of female labour force participation on the wage share (Seguino and Braunstein, 2019).

All these studies are either based on country-level data or use industry-level data for variables reflecting technological change but country-level data for labour market institutions. Country-level data does not account for differences in technology across industries or industry-level heterogeneity of bargaining power. We capture both processes at the industry level and are thus able to provide a more accurate comparison of size effects.

Previous research using country-level data finds substantial negative effects of globalisation on the wage share, measured by trade openness (imports plus exports as a ratio to GDP), foreign direct investment (FDI) or offshoring (European Commission, 2007; Dao et al., 2017; Harrison, 2002; Jayadev, 2007; Onaran, 2009; Stockhammer, 2017). Research using industry-level data finds negative effects of offshoring or trade in high wage countries, while there are mixed results for FDI (Bassanini and Manfredi, 2014; Dao et al., 2017; Lin and Tomaskovic-Devey, 2013; Onaran, 2011; 2012). However, except for Onaran (2011; 2012), none of these articles differentiates offshoring by origin of imports, which is important to test the impact on bargaining power.

4. Data and stylised facts

We compile a comprehensive unbalanced panel database for 14 high-wage OECD economies drawing on seven publicly available international databases for sectoral data which we augment by country-level data. We measure the wage share as labour compensation as a ratio to value added adjusted for the labour income of the self-employed, imputed based on the assumption that their hourly labour income is equal to the average hourly labour compensation of the employees in the sector.[6] The well-documented decline in the aggregate country-level wage share is mirrored at the sectoral level, albeit with differences between manufacturing and services sectors as well as high- (HS) and low-skilled (LS) sector groups as can be seen in Figure 1 below for selected countries.

<place Figure 1 here>

74% of all sectors experienced a decline in the wage share between 1980 and 2007, and 65% experienced a decline that is larger than 3%-points. This confirms previous findings that attribute the decline of the country-level wage share to a decline of the wage share within sectors (Dao et al., 2017; Karabarbounis and Neiman, 2014). The wage share declined most strongly and consistently across countries in service sectors like Post and Telecommunications, Utilities, and Retail Trade, as well as manufacturing sectors like Metals and Paper, Printing and Publishing. Most of these industries (except Retail Trade and Metals) are classified as high-skilled; the fact that they experienced the strongest decline in the wage share contrasts with expectations based on the skill-biased technological change hypothesis.

When looking at labour compensation of high-, medium- and low-skilled workers as a ratio to value added we can see a stronger skill bias in the trend, in line with the skill-biased technological change hypothesis. Low-, medium- and high-skilled refers to workers with primary, secondary and tertiary education, respectively.

<place Figure 2 here>

The share of high-skilled workers' labour compensation in value added increased in some countries; however, the picture is dominated by declining shares of both medium- and low-skilled workers. Unfortunately, availability for this series is limited to the 1995- 2009 period.

We use total factor productivity (TFP), ICT and non-ICT capital services as a ratio to value added as our measures of technological progress in line with the previous literature (Bassanini and Manfredi, 2014; Bentolila and Saint-Paul, 2003).[7] We observe a steady increase in ICT capital intensity and TFP across all sectors and countries. This trend is in line with the premise of the technological change hypothesis. Conversely, non-ICT capital intensity appears to be stagnant or even declining in several countries, which contrasts with this hypothesis. The latter variable dominates the trend of total capital intensity which is reported in Figure 3.

<place Figure 3 here>

Data for union density is based on Visser (2016) and only available at an aggregated level of sectoral classification and not available for each year.[8] While our results should thus be seen as indicative, they are nevertheless important as our analysis constitutes the first attempt to analyse the impact of union density on sectoral wage shares for a large group of countries. Union density declined in all sector groups in France, Germany, the UK, the USA and Austria, while the decline is more moderate, albeit still visible, in Italy and Sweden. Union density followed an inverted U-shape pattern in Spain between 1980 and 2010, however not exceeding the comparatively low level of 20% at the aggregate level. Union density is highest in manufacturing sectors and lowest in low-skilled service sectors. Measured at the country level, it declined most strongly in Austria (34%-points between 1970 and 2014), followed by the UK and Germany (24 and 20%-points respectively). This is in line with the premise of the bargaining power hypothesis.

<place Figure 4 here>

In extensions to our baseline model we use additional measures of bargaining power: i) the female share in employment, which is measured as the share of hours worked by women in total hours worked at the industry level and is based on the KLEMS database; ii) social government spending, which is our only country-level measure of bargaining power, and consists of in-kind social government expenditure plus cash transfers as a ratio to total government spending; iii) minimum wages, which are calculated as the national minimum wage divided by the average labour compensation per person engaged at the industry level;

iv) excess collective bargaining coverage, measured as country-level collective bargaining coverage divided by industry-level union density.

Variables accounting for globalisation show similar patterns across all countries. Narrow offshoring, measured as intra-industry intermediate imports in the using sector, based on the World Input-Output Database (WIOD; Timmer et al., 2015), increased in all countries in both high- and low-skilled manufacturing sectors. We differentiate offshoring by origin of imports based on three country groups defined as ‘high-wage’ countries (countries as in our panel plus Canada and Denmark), ‘Eastern Europe’ (EU10 and Russia), and ‘rest of the world’ (RoW), which mainly consists of ‘low-wage’ emerging and developing countries. While offshoring to Eastern Europe and the RoW increased most significantly, the majority of offshoring is still among the ‘high-wage’ countries. The years of the Great Recession are the only exception to the otherwise increasing trend, which resumed in 2010 in all countries. The highest growth rates are in the 1990s in Sweden and Germany, driven by high-skilled manufacturing sectors which generally have a higher share of intermediate imports than low-skilled manufacturing sectors. This trend is consistent with the premise of both the bargaining power and the technological change hypothesis.

All variable definitions and data sources are reported in Appendix 1.

<place Figure 5 here>

5. Econometric model and methodology

Our baseline specification is based on equation (2) but in contrast to the static model in the theoretical literature, we use a dynamic model, in line with the sluggish adjustment of our variables[9]:

$$S_{c,i,t} = \alpha_S S_{c,i,t-1} + \alpha_T \ln(TFP)_{c,i,t} + \alpha_{k1} \ln(k_{nonICT})_{c,i,t} + \alpha_{k2} \ln(k_{ICT})_{c,i,t}$$
$$+\alpha_G GROWTH_{c,i,t} + \alpha_L LMI_{c,i,t-1} + \alpha_{GLOB} GLOB_{c,i,t-1} + \varepsilon_{c,i,t} \quad (3)$$

S is the adjusted wage share in sector i of country c. In alternative specifications we also use labour compensation of high-, medium- and low-skilled workers as a ratio to sectoral value added as our dependent variable.

TFP denotes total factor productivity, while k_{ICT} and k_{nonICT} are ICT and non-ICT capital services as a ratio to value added. Following the production function literature, all three variables are taken in logarithms (Bassanini and Manfredi, 2014). In line with the technological change hypothesis, we expect a negative effect of k and TFP on the wage share.

Furthermore, we include $GROWTH$, measured as the logarithmic change in real value added, to account for the counter-cyclicality of the wage share (Askenazy et al., 2018). The latter arises because profits decline faster during recessions than wages, which are typically fixed by long-term contracts. It can also be interpreted as capturing hiring and firing costs (Bentolila and Saint-Paul, 2003). We capture the effect of globalisation ($GLOB$) by narrow offshoring in the baseline and we also include migration at the country-level in alternative model specifications. Our theoretical model (equation 2) implies that globalisation affects the wage share either via the technology or via the bargaining channel. If globalisation changes the production structure through the outsourcing of labour intensive tasks this will be reflected in k_{ICT} and k_{nonICT}, whereas the adoption of new technologies due to globalisation will be captured by TFP. In our econometric model, α_{GLOB} captures the effect of globalisation on the wage share for given TFP, k_{ICT} and k_{nonICT}, i.e. for given technological conditions. Put differently, α_{GLOB} measures the impact of globalisation on bargaining power and subsequently on the wage share (the globalisation-bargaining channel). Hence, we expect a negative effect.[10]

LMI is a vector of variables related to industrial relations and labour market institutions including union density, minimum wages and social government spending. An increase in any of these measures is expected to have a positive impact on the wage share. We also include the female employment share which is expected to have a negative effect.

Due to the impact of the Great Recession on industrial relations and wage determination as well as a structural break in the dataset, our preferred approach is to perform estimations for two separate time periods 1970–2007 and 2008–2014.[11] For example, unions might aim at maintaining employment during a recession and even coordinate wage cuts. Furthermore, TFP usually shows strong declines in a recession which might be the result of a fall in aggregate demand rather than negative technology shocks. However, we also provide estimations for the whole period of 1970-2014. Estimations including narrow offshoring start in 1995 due to data availability.

Given that technological change is likely to be a function of past or current values of the wage share, we have to take potential endogeneity into account (Acemoglu, 2003; Hein, 2014). Similarly, workplaces characterised by higher bargaining power of labour might effectively resist offshoring, thereby leading to a negative effect of a higher wage share on offshoring (Barthelemy and Geyer, 2001). Accounting for reverse causality requires the use of instrumental variables. We use the General Method of Moments (GMM) estimator introduced by Arellano and Bond (1991) because it provides readily available ‘internal’ instruments based on lagged values of the explanatory variables.

To arrive at our baseline model we adopt an estimation strategy that starts with a general specification and the most robust estimator (one-step difference GMM) and work our way toward a parsimonious model with the most efficient estimator (two-step difference GMM with standard errors adjusted for heteroscedasticity and Windmeijer (2005) small sample error correction), following Kiviet, et al. (2017). We start with the estimation of an unrestricted Autoregressive Distributed Lag model including the contemporaneous and lagged value of all explanatory variables and the first and second lag of the dependent variable. All estimations include year dummies to account for unobserved shocks and mitigate cross-sectional dependence. We begin by modelling all variables as endogenous, thereby allowing our explanatory variables to be functions of the wage share in the current period. Subsequently, we perform a ‘testing down’ procedure by dropping statistically insignificant variables with the lowest t-statistic, until we are left with at least one measure per variable. This is the reason why union density as well as offshoring measures enter with a lag in our baseline, likely because changes in these variables take time to exert an impact on the wage share. This process of general to specific modelling is particularly important for the GMM estimator, since its applicability relies on a dynamically complete model without autocorrelation in the residuals. For this reason, a second lagged dependent variable remains in the model if tests suggest the presence of autocorrelation in the residuals (e.g. specification 3, Table 3). Thereafter, we test whether some of our variables can be treated as predetermined (i.e. functions of the past rather than the current wage share) or exogenous by including one-by-one more recent lags of the variable as an additional instrument and testing for its validity by applying the Incremental Hansen test. This procedure indicates that union density is exogenous, while the other variables are endogenous. Next, we reduce the number of instruments to see whether our results change (Roodman, 2009). This results in four instruments per variable for estimations going back to the 1970s and three instruments per variable otherwise (starting from the second lag for the endogenous variables).

6. Estimation Results

Our tests of hypotheses H1 and H2 are reported in Table 2. Specification (1) in Table 2 is estimated for the 1973-2007 period (starting year is 1973 rather than 1970 due to lags and instruments). All variables have the expected signs – capital intensity, TFP and growth have a negative impact on the wage share in line with the technological change hypothesis, whereas union density has a positive coefficient, in line with the bargaining power hypothesis.

<place Table 2 here>

Given that several of our variables of interest, specifically offshoring, are available only from 1995 onwards, we split our sample, estimating two separate regressions for the periods 1973-1996 and 1997-2007. This reveals inconsistency of parameters over time. Our results in specification (2) for the 1973-1996 period are robust compared to 1973-2007. However, results for the period 1997-2007 in specification (3) paint a very different picture: all variables with the exception of growth and union density turn statistically insignificant. So far, we have not accounted for the impact of globalisation and thus the model might be misspecified. Consequently, we include offshoring to 'high-wage' countries, Eastern Europe, and the rest of the world (RoW) in specification (4). Offshoring to the RoW, growth and union density are statistically significant with the expected sign. An increase in offshoring to the RoW by 1%-point (approximately 1 standard deviation) would reduce the wage share by almost 2%-points. Similarly, an increase in union density by 25%-points (approximately 1 standard deviation) would increase the wage share by 2%-points. k and TFP remain statistically insignificant, irrespective of the inclusion of offshoring into the estimation equation. This implies a large variation in the size and even the sign of the coefficients for k and TFP in samples including different countries or periods. Nevertheless taking the coefficients at face value an increase by one standard deviation in TFP, k_{ICT} and k_{nonICT} would reduce the wage share by 0.9%-points, 0.2%-points and 12%-points respectively. Particularly the relatively large economic impact of k_{nonICT} has to be interpreted cautiously, given the lack of robustness for this variable (see also specification 1, Table A3 in the appendix). Specification (4) constitutes our baseline estimation.

The insignificant effects of TFP and k after 1996 cast doubt on the technological change hypothesis H1. In contrast, union density remains statistically significant in the period after 1996. The positive effect of union density and the negative effect of offshoring to the RoW are in line with the bargaining power hypothesis (H2) and highlight the necessity to differentiate offshoring by origin of imports due to the specific characteristics of global value chains between high- and low-wage economies. The coefficient for offshoring captures the effect of globalisation on the bargaining power of workers because we control for the effect of globalisation on technology by including k and TFP.

Next, we repeat our analysis for the post-2008 period in specifications (5). Interestingly, while growth stays significant, union density is now statistically significant with a negative sign, while offshoring is insignificant although it maintains its negative sign. This indicates that the Great Recession strongly altered underlying bargaining relations. In particular, it implies that an increase in union density reduces the wage share in the years after the financial crisis. As discussed in Section 2.3 this can be reconciled with the argument that unions accept wage moderation to protect jobs during a recession. Due to the specificities associated with the crisis period, we re-estimate our model for the 2012-2014 period in specification (6), thus omitting the years characterised by the Great Recession and the Euro Crisis. While inference is difficult with such a short period, we now observe a positive (though insignificant) coefficient for union density, further suggesting that the negative effect is driven by the crisis years. Overall the results for the post-crisis period remain inconclusive.

Lastly, we report an estimation for the full period of 1973-2014 in specification (7). This estimation is least reliable due to changes in the sectoral composition over time and the merging of different releases of the KLEMS database (i.e. KLEMS 2012 and KLEMS 2017). Nevertheless, indicative results confirm our previous insights. We find negative effects of growth, TFP and capital intensity, and positive effects of union density. All variables display a reduced coefficient in comparison to estimations for the 1973-2007 period (specification 1), likely reflecting the insignificant effects over the period after the Great Recession.

Specifications presented in Table 3 test our hypotheses regarding the effect of technological change and bargaining power on different skill groups (H1a and H2a).

<place Table 3 here>

Specifications (1-3) in Table 3 report our baseline for high-, medium- and low-skilled workers' labour compensation in sectoral value added. We also include the share of the labour force that has attained the level of education defined by the skill group at the country level as an explanatory variable in order to account for shifts in labour supply. The results for capital intensity and TFP contradict the skill-biased technological change hypothesis (H1a). First, we find statistically significant negative effects of TFP and capital intensity only for medium-skilled workers. Interestingly, estimations for manufacturing and service sectors separately (specifications 4-5 in Table 3), reveal that these results are mainly driven by service sectors, especially those classified as high-skilled.[12] Low-skilled workers, supposedly those with the highest elasticity of substitution by capital, are least affected by TFP, which, while being insignificant, even has a positive sign in specification (3), Table 3.

While the negative impact of technological change on medium-skilled workers can be explained by the process of automation of routine tasks, the lack of a significant effect on low-skilled workers as well as in low-skilled manufacturing industries contradicts hypothesis H1a. It suggests that the declining share of low-skilled workers' labour compensation is a result of changes in bargaining power, rather than technological progress. In contrast, the negative impact of TFP was mainly experienced by medium-skilled workers in high-skilled service sectors.[12]

Turning to the effect of bargaining power on workers of different skill groups, the positive effect of union density is driven by the effects on low-skilled workers in manufacturing sectors (specification 3-4 in Table 3). Furthermore, union density appears to have a negative impact on the wage share of high-skilled workers which include executives (specification 1, Table 3). This is consistent with hypothesis H2a and implies that union density reduces wage dispersion (Jaumotte and Osorio Buitron, 2015).

The effect of offshoring to the RoW is always negative, although it is borderline insignificant for low-skilled labour and statistically significant only for high-skilled workers. This suggests that offshoring harmed workers of all skill groups.

We proceed by testing the impact of bargaining power across different bargaining regimes (hypothesis H2b), and the impact of additional factors determining bargaining power that were discussed in Section 2. Table 4 reports the results.

<place Table 4 here>

Specification (1) in Table 4 applies an interaction term for union density (union density_coord) which takes the value 1 for countries where wage bargaining is coordinated at the industry or national level[13]: Austria, Belgium, Finland, Germany, Ireland, Italy, Japan, the Netherlands, Spain, and Sweden, i.e. excluding Australia, France, the UK and the US (Visser, 2016). The positive and significant coefficient of the interacted variable suggest that union density has a stronger impact on the wage share in countries with more coordinated bargaining regimes. Indeed, the effect for countries with mainly firm-level and some sector-level bargaining (Australia, France, the UK, the US) is insignificant. This is in line with hypothesis H2b and suggests that unions in coordinated regimes are more effectively acting as an interest group (McHugh, 2002).

To further investigate this hypothesis, we test whether excess bargaining coverage, i.e. bargaining coverage as a ratio to union density at the sector level, negatively affects the wage share in specification (2). In contrast to Jaumotte and Osario Buitron (2015) we find a positive significant effect of this variable. The other variables, including union density, remain significant as well, suggesting an additional positive impact of bargaining coverage relative to union density on the wage share. Given the strong empirical association between the level of coordination and bargaining coverage (Visser, 2006), this finding further confirms hypothesis H2b. It is also in line with the argument that a high collective bargaining coverage implies that gains from negotiations are shared with the wider workforce (Visser, 2006).[14]

Specification (3) controls for the share of in-kind social government spending and cash transfers as a ratio to total government spending. Applying an interaction term, we find that this measure is specifically important for countries with a relatively low level of collective bargaining coverage, classified as having an average collective bargaining coverage below 50%, such as Japan, Ireland, the UK and the US (Govt_LBC). While the effect is insignificant for other countries, this result has to be seen as indicative given that the variable is measured at the country level. However, it provides further tentative evidence for hypothesis H2b: in countries where gains from successful wage negotiations are not shared with the wider workforce because of a low level of bargaining coverage, the more relevant measure of bargaining power are indirect measures reflecting labour’s fall-back options in the form of social government expenditure. This result is also robust in estimations spanning the 1973-2007 period.

Specifications (4)-(9) in Table 4 test the impact of alternative measures of bargaining power as discussed in Section 2. Specification (4) includes the female share in employment. We find a negative effect on the wage share, which is driven by low-skilled workers in manufacturing industries. Estimations for the period 1970-2007 are reported and the results are also robust for the 1997-2007 period with respect to the effect of the female share in employment but render offshoring insignificant.[12] Specification (5) includes national minimum wages as a ratio to sectoral average wages for a pool of nine countries that had introduced minimum wages by 2007 (Australia, Belgium, France, Ireland, Japan, the Netherlands, Spain, the UK and the US). Our findings suggest a strong positive impact of higher minimum wages on the wage share for the 1995-2007 period and this result is also confirmed for the 1970-2007 period. It is worth noting that minimum wages appear to be relevant for workers of all skill groups and across service and manufacturing sectors alike.[12] Interestingly, once we include minimum wages, union density turns insignificant, while still maintaining its positive coefficient.

Specifications (6)-(9) test the effect of migration, defined as the share of foreign-born employees in the total labour force and measured at the country level, on the wage share. Theory suggests that the effect should be strongest for low-skilled workers who will suffer the most from wage competition by migrants. However, while the coefficient is negative, we obtain no statistically significant effect on either the total wage share or workers of different skill levels. This suggests that migration does not exercise a negative effect on the wage share, once globalisation and bargaining power is controlled for. Indeed, offshoring to the RoW remains statistically significant with a negative sign in specification (6), indicating that capital mobility, rather than labour mobility has a negative impact on the wage share.

However, the results should be taken as indicative, as the migration variable is not at the sector level. Further research, in particular based on individual data is required for more conclusive evidence. We also added imports of final and capital goods and exports to the baseline specification, and estimated additional specifications with foreign direct investment (outward and inward FDI) instead of offshoring as an alternative measure of globalisation, but we did not obtain significant effects.[12]

Finally, in Table 5 we assess the economic significance of our estimates based on specification (4) in Table 2 by multiplying the average change of our explanatory variables by their respective coefficients. The results refer to the impact on an average industry in an average country.

<place Table 5 here>

Offshoring to the RoW, which mainly consists of low-wage countries, emerges as the most important explanatory variable, accounting for 44% of the decline in the wage share between 1997 and 2007, while union density accounts for 23% and growth for 2%. Based on these statistically significant variables we can explain around 69% of the decline in the wage share. Thus, around two-thirds of the change in the wage share is due to changes in the bargaining power of labour, captured by offshoring to low-wage countries and a decline in union density. We do not include statistically insignificant variables in the calculation of economic effects due to the high uncertainty regarding the size and the sign of the coefficients.

7. Robustness tests

We present several robustness tests which are reported in Table A3 in the appendix. Specification (1) uses labour compensation of employees as a ratio to value added as the dependent variable, i.e. without adjusting for self-employed workers. Our results remain largely robust and indicate a larger coefficient for union density in comparison to our baseline. This is to be expected as self-employed workers are usually not part of labour unions. k_{ICT} displays a statistically positive coefficient in this specification, casting further doubt on the technological change hypothesis.

Due to the issues related to the measurement of TFP (see footnote 8) we estimate our baseline (specification 4, Table 2) excluding TFP. The results, reported in specification (2) in Table A3, do not change our baseline results qualitatively.

Next, we exclude growth from our model, as TFP might already be capturing business cycle effects on the wage share. Results, reported in specification (3), suggest model misspecification, as we do not pass the overall Hansen test for instrument validity. Union density turns statistically insignificant, while offshoring remains robust. TFP remains statistically insignificant.

Specification (4) in Table A3 estimates our baseline using the system- rather than the difference-GMM estimator, thereby taking advantage of additional moment conditions. This estimator increases efficiency, but its applicability requires 'effect stationarity', i.e. constant correlation between the unobservable fixed-effects and our covariates. As reported in specification (4) we reject the null hypothesis of instrument validity (Hansen test p-value of 0.003). This is driven by the Incremental Hansen test on the instruments used in the level equation (p-value of 0.001), which negates the effect stationarity assumption and renders this estimation method unreliable. This confirms our choice of difference-GMM as our baseline estimation method.[15]

Specification (5) estimates our baseline specification using the within-estimator rather than difference-GMM. Interestingly, there is now evidence of a negative effect of TFP on the wage share, while offshoring to the RoW turns insignificant. Union density, which is treated as exogenous in our baseline, remains robust. This further confirms our choice of the difference-GMM estimator and implies that accounting for endogeneity is essential. Comparison of the coefficient for the lagged dependent variable shows the expected downward bias for the within-estimator in comparison to our baseline estimation, thus providing further indication for its accuracy.

In specifications (6-7) we apply the mean-group estimator to account for potential bias due to parameter heterogeneity between groups, which becomes a particular issue in panels with a long time dimension (Damiani et al., 2018; Pesaran et al., 1999). It is thus applied to estimations for the long sample 1970-2007 and 1970-2014. This estimator circumvents the problem of parameter heterogeneity by estimating the model separately for all cross sections and then averaging the coefficients. However, as it does not allow to account for endogeneity (Pesaran et al., 1999), the overall effect is an average of potentially biased coefficients. Taking the coefficients at face value, we confirm the main insights from our previous estimations using the long sample (specification 1, Table 2). Union density has a positive effect on the wage share with a significantly increased coefficient in comparison to the GMM estimation. According to specification (7), an increase in union density by 1%-point would increase the wage share by 0.4%-points.

A common concern for instrumental variable estimators is weak instrument bias. This is an issue when the variables are non-stationary, as in this case there should be little correlation between the differenced series and their lags which are used as instruments. We test for this issue in two ways. First, we conduct the Im-Pesaran-Shin (2003) and the modified inverse chi-square unit root tests (Choi, 2001) on variables that are treated as endogenous or predetermined in the GMM estimation and thus are instrumented by their lags. Both tests are shown to be robust when the panel has a large cross-sectional dimension, as in our case (Choi, 2001). Results suggest that most variables are stationary (Table A4 in the appendix).

There is some contradictory evidence between the two test results for TFP, labour compensation of medium-skilled workers as a ratio to value added and for outsourcing to eastern Europe and the RoW. However, in contrast to other variables, wage share by skill-group and offshoring are only available from 1995 onwards, which casts doubt on the reliability of these unit root tests.

Second, we test directly whether our instruments are relevant predictors of our endogenous variables by regressing the explanatory variables (e.g. the first difference of capital intensity in period t) on their instruments (the level of capital intensity in periods t-2 to t-4). This procedure manually reproduces the instrumentalisation performed as part of the GMM estimation. In all regressions the coefficients for at least one of the instruments is statistically significant.[16] F-statistics of these regressions are reported in Table A5, row 2. For TFP the F-test provides strong evidence for instrument relevance despite potential concerns regarding the stationarity of the variable based on the unit root tests. Next, we additionally include all other instruments and year dummies in the regression. F-statistics on the joint significance of all instruments are reported in Table A5, row 4. Both tests indicate that the instruments are relevant.[17]

Overall, these robustness tests confirm our previous results with respect to the bargaining variables. Measures of technological change remain insignificant in most specifications, and often change signs. This confirms the lack of sufficient evidence for the technological change hypothesis.

8. Conclusion

Our findings support the hypothesis that a reduction in the bargaining power of labour played a key role for the decline in the wage share. The declining wage share is related to the strong deterioration in union density, minimum wages, welfare state retrenchment, and the increase in female employment in the presence of gender wage gaps. Unions are particularly effective in increasing low-skilled workers' wage share in value added. However, the relevance of these factors depends on the underlying bargaining regime and our analysis reveals that labour unions are most effective when bargaining is coordinated and collective bargaining coverage is high. In contrast to previous findings based on country-level data (Jaumotte and Osorio Buitron, 2015), we find that excess bargaining coverage does not have a negative impact on the wage share. However, in countries where collective bargaining coverage is low, country-level measures like social government spending are more important determinants of labour's bargaining power. We also confirm a significant negative effect of globalisation on the bargaining power of labour and subsequently on the wage share. The increased fall-back options of capital in the form of offshoring to low-wage countries, rather than migration, is the most important driver of this process.

In contrast we find scant evidence for the technological change hypothesis. There is some evidence for a negative effect of technological change, as measured by total factor productivity and (ICT-) capital intensity, on the wage share between 1973-1996. The effect of technological change is statistically insignificant (and becomes positive in some specifications) in the later 1997-2007 period. There are several potential explanations for such time inconsistency of technological parameters within the standard model. A parameter switch would result from changes in the elasticity of substitution between capital and labour. The elasticity might change due to the automation of routine tasks or an increasing level of education among the workforce, pushing the two factors of production more in the direction of complements rather than substitutes. The only group for which we are able to confirm a negative effect of technology between 1997 and 2007 are medium-skilled workers. While this finding is consistent with the automation of routine tasks, the insignificant effect on low-skilled workers as well as in low-skilled industries casts further doubt on the general validity of the skill-biased technological change hypothesis during this period. Additionally, we find that the Great Recession led to instability in the existing relationships between the wage share and its determinants. None of our explanatory variables remains robust in estimations for the 2008-2014 period, which is mainly due to changes in the coefficients during the 2008-2011 period. Further analysis and more data is necessary to assess whether the drivers of functional income distribution changed after the Great Recession.

We conclude that the workhorse model of recent studies (Bassanini and Manfredi, 2014; Bentolila and Saint-Paul, 2003; Hutchinson and Persyn, 2012; Karabarbounis and Neiman, 2014) which relies on profit maximising firms faced with a high elasticity of substitution does not appropriately describe recent wage share trends. Rather than changes in relative prices and capital augmenting technological progress, changes in bargaining power and access to low-wage labour markets determined employment and wage setting in the years leading up to the Great Recession. This indicates the limitations of purely technology focused approaches to functional income distribution and suggests that factors affecting bargaining power should be given more attention in future research.

Our findings have important policy implications. Rising inequality is not an inevitable outcome of technological change or globalisation. Tackling income inequality requires a restructuring of the institutional framework in which bargaining takes place and a level playing field where the bargaining power of labour is more in balance with that of capital. The impact of globalisation is likely to be significantly moderated by stronger bargaining power of labour via an improvement in union legislation, increasing minimum wages, improving and enforcing equal pay legislation, increasing the social wage via public goods and social security and international labour standards. Finally, our results suggest that a simple attempt to reduce income inequality through skill-upgrading will not work as medium-skilled workers have experienced the strongest negative impact of technological change among all workers, although low-skilled workers experienced the strongest decline in the wage share.

Endnotes

[1] Recent contributions based on firm-level data propose another hypothesis according to which the decline of the wage share is a consequence of increasing market concentration, driven by a reallocation of production towards a small number of highly productive firms (Autor et al., 2017). However, contrasting evidence suggests that concentration is negatively linked to productivity, establishes stagnating or declining levels of concentration outside of the U.S. and finds a significant within-firm decline of the wage share (Guschanski and Onaran, 2018; Gutiérrez and Philippon, 2017). While testing this hypothesis requires the use of firm-level data, our analysis accounts for factors that enabled highly productive firms to reduce the within-firm wage share, insofar as these factors are not related to their size, such as network effects or increasing returns to scale.
[2] The time period and choice of countries is determined by data availability at a detailed sectoral level across seven industry-level databases and several other country-level databases.
[3] Lin and Tomaskovic-Devey (2013) and Onaran (2011; 2012) use industry-level data, but while these studies focus on a single country, we perform our analysis for a panel of selected OECD countries and are therefore able to account for methodological issues related to endogeneity.
[4] As an example for such a legal framework, McHugh (2002) explicitly considers immunities, i.e. protection of employees from financial losses incurred by the employer during labour disputes. For example, in the UK, which is characterised by uncoordinated (firm-level) bargaining, unions were not able to protect the reduction of immunities throughout the 1980s and 1990s when their membership dwindled.
[5] Kristal (2010) uses government civilian spending, which nevertheless does not specify spending that is particularly important for the bargaining power of labour such as in-kind benefits and cash transfers.
[6] EU KLEMS 2009 and 2012 (for estimations until 2007) and KLEMS 2017 (for estimations after 2007) are the main industry-level databases used. Where data from EU KLEMS is not available or where the wage share is constant for several years in a row (indicating lack of data in the national accounts) we link the wage share from KLEMS with the growth rate of the adjusted wage share from the World Input-Output Database (WIOD) and the OECD Structural Analysis database (OECD STAN). The three series have correlations of 0.91 and above. We exclude observations where the percentage change in the wage share exceeds 30% in one year. These outliers mostly appear in the UK and Sweden. However, our results are largely robust to the inclusion of outliers.
[7] Both proxies come with their caveats: TFP is derived as a residual from a model where factors are remunerated according to their marginal product (Timmer et al., 2007). Therefore, including this variable seems tautological in a study whose aim is to analyse the determinants of income distribution. Indeed, similar considerations apply to the measurement of capital. Capital is measured either as an aggregation of depreciated investments on an initial capital stock or by a user cost approach (capital services). Previous research mainly uses capital services (Bassanini and Manfredi, 2014; European Commission, 2007). However, the user costs approach is 'based on the assumption that marginal costs reflect marginal productivity' (Koszerek et al., 2007, p. 23). Finally, ICT capital is part of the general capital stock and therefore captures substitution processes that are not necessarily driven by technological change. However, alternatives to these measures are limited.
[8] We linearly interpolate the series between available years and extrapolate by using the growth rate of data available for the next higher level of aggregation – e.g. data on total manufacturing union density for individual manufacturing sectors.
[9] The estimation of a static model produces autocorrelated residuals.
[10] Identifying how much of the changes in k and TFP are driven by globalisation would require two-stage estimations. However, we are interested in isolating the effect of globalisation on bargaining power and subsequently on the wage share rather than disentangling the drivers of technological change.
[11] While previous releases of the EU KLEMS database could be made compatible by the use of concordance tables, this is not possible with the KLEMS 2017 version due to changes in variable definitions. This induces a structural break in our dataset. Additionally, several variables are not available for three countries in the sample (Australia, Ireland and Japan) after 2009. Thus, estimations after 2007 are performed on a reduced sample. We exclude the following sectors from all estimations: Agriculture, Hunting, Forestry and Fishing, Mining and Quarrying, Coke and Refined Petroleum, as well as mostly publicly owned sectors (Public Administration and Defence; Compulsory Social Security; Education; Human Health and Social Work Activities). This is because wage setting in these industries may not be determined by the same forces as other sectors. For example, value added in Agriculture and Mining will fluctuate with changes in commodity prices. Furthermore, we exclude the real estate sector whose value added largely constitutes imputed rents (Timmer et al., 2007). Table A2 in the appendix contains the industry classification used.
[12] Results are available upon request.

[13] This group is defined by countries whose degree of coordination consistently exceeds 2 based on the ICTWSS database (Visser, 2016). We have also experimented with an interaction term isolating countries where bargaining is coordinated and collective bargaining coverage is high (implying that we exclude Ireland, Italy, Japan, and Spain from the previous group). Our results remain robust, but the coefficient for the interacted group declines, suggesting that the degree of coordination, rather than bargaining coverage, is the decisive factor.

[14] However, excess bargaining coverage turns insignificant in estimations for the 1973-2007 period. Similarly, estimations with bargaining coverage alone (i.e. not as a ratio to union density) did not yield significant results, possibly because this variable is only available at the country level.

[15] The economic reason for the inapplicability of the system-GMM estimator could be, for example, that the correlation between unobservable technological coefficients and capital intensity (k) changed over time. In the theoretical framework of a constant elasticities of substitution production function such a technological coefficient could be the distribution parameter. In the difference-GMM specification this parameter is eliminated when taking first differences (e.g. Bassanini and Manfredi, 2014).

[16] The only exception is the regression for growth where past growth does not have a statistically significant impact on the first difference of growth. However, the F-statistic is still passed at the 1%-level for this regression. Detailed estimation results are available upon request.

[17] Unfortunately, in analysing the F-statistics we cannot rely on usual thresholds, such as proposed by Stock and Yogo (2005), as they are not applicable to GMM estimations. Therefore, we consider a statistically significant coefficient for the lags to be more relevant than the F-statistic. Evidence for the second important characteristic of valid instruments, which implies that the instruments should be uncorrelated with the error term, is provided by the Hansen test and reported for each estimation.

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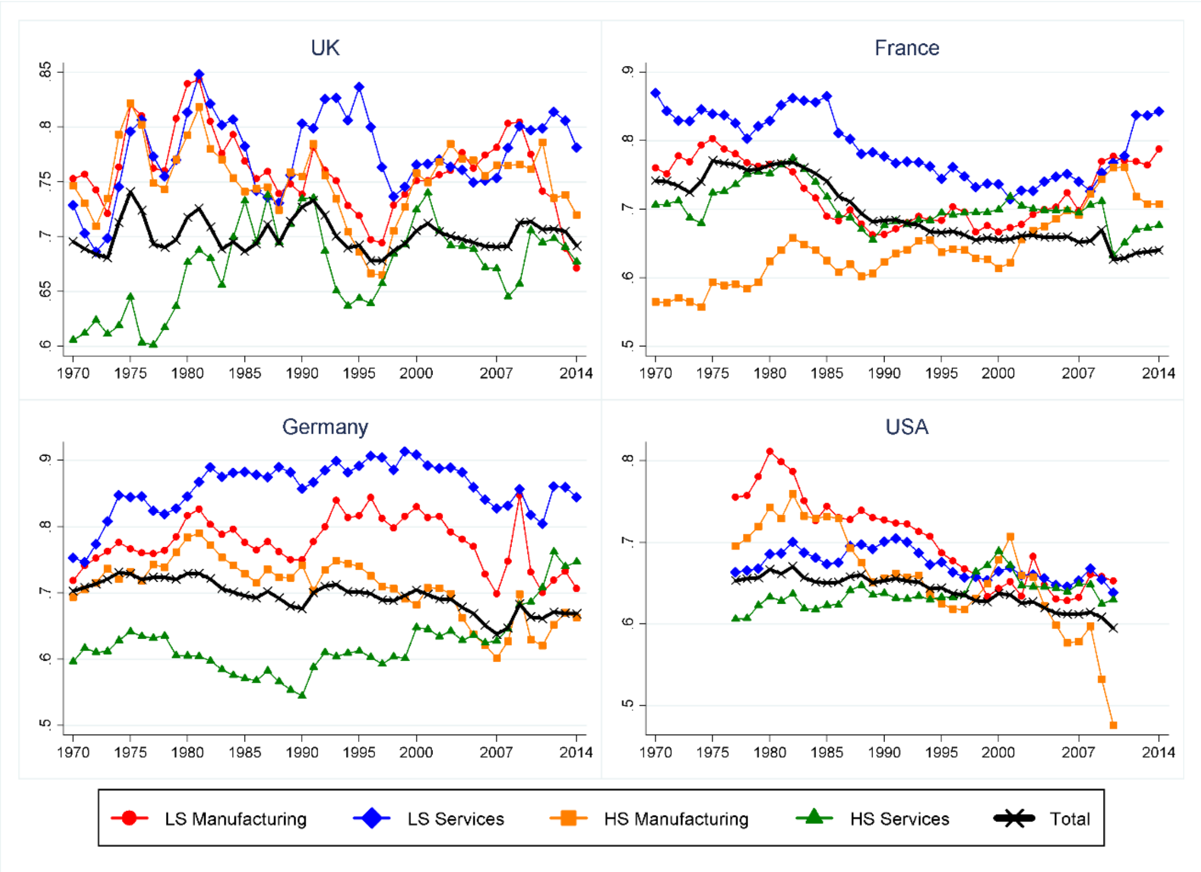
Figures and Tables

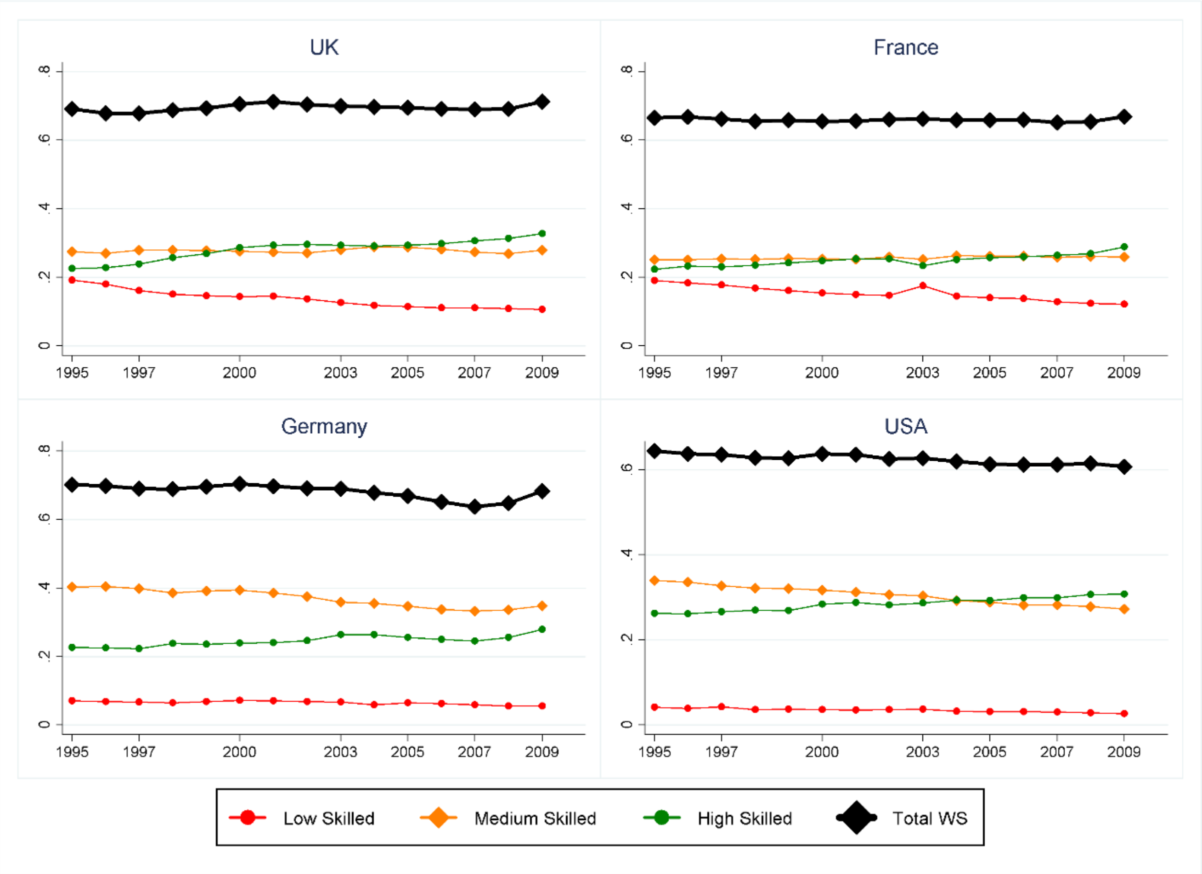
Figure 1: Wage share by sector type, selected countries 1970-2014



Notes: HS and LS stands for high and low skilled sectors respectively. For example, “LS Services” denotes labour compensation in low-skilled service industries as a ratio to value added in these industries. The graph for the total wage share includes all sectors. Sector level graphs exclude: Agriculture, Hunting, Forestry, Fishing; Mining and Quarrying; Coke and Refined Petroleum; Real Estate; and Community Social and Personal Services (including Health, Education, Defence and Arts).

Source: Own calculations based on EU KLEMS.

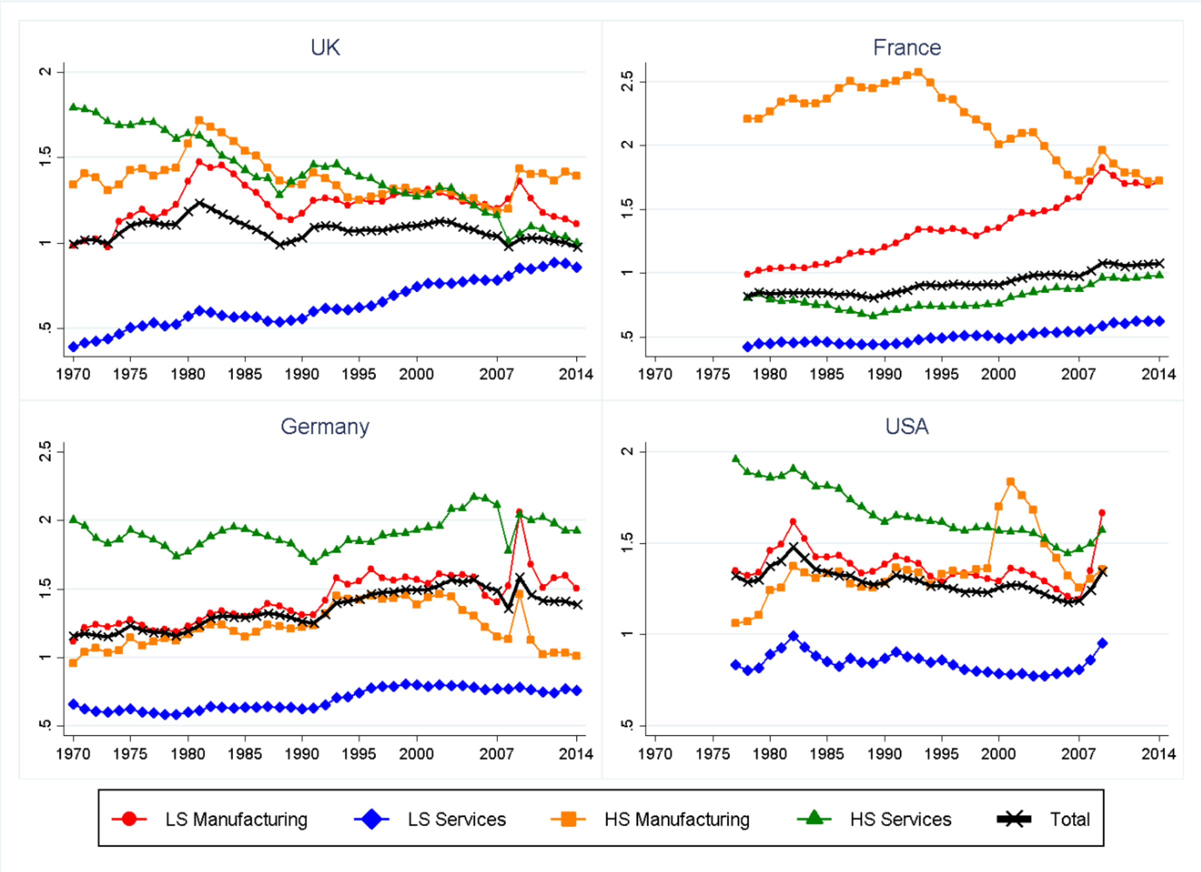
Figure 2: Wage share by skill group as defined by workers' education, 1995-2009



Notes: Low skilled: Up to lower secondary or second stage of basic education; Medium skilled: Up to Post-secondary non-tertiary education; High skilled: First and Second stage of tertiary education. For example, the red line stands for low-skilled workers' labour compensation as a ratio to total value added.

Source: Own calculations based on EU KLEMS and WIOD.

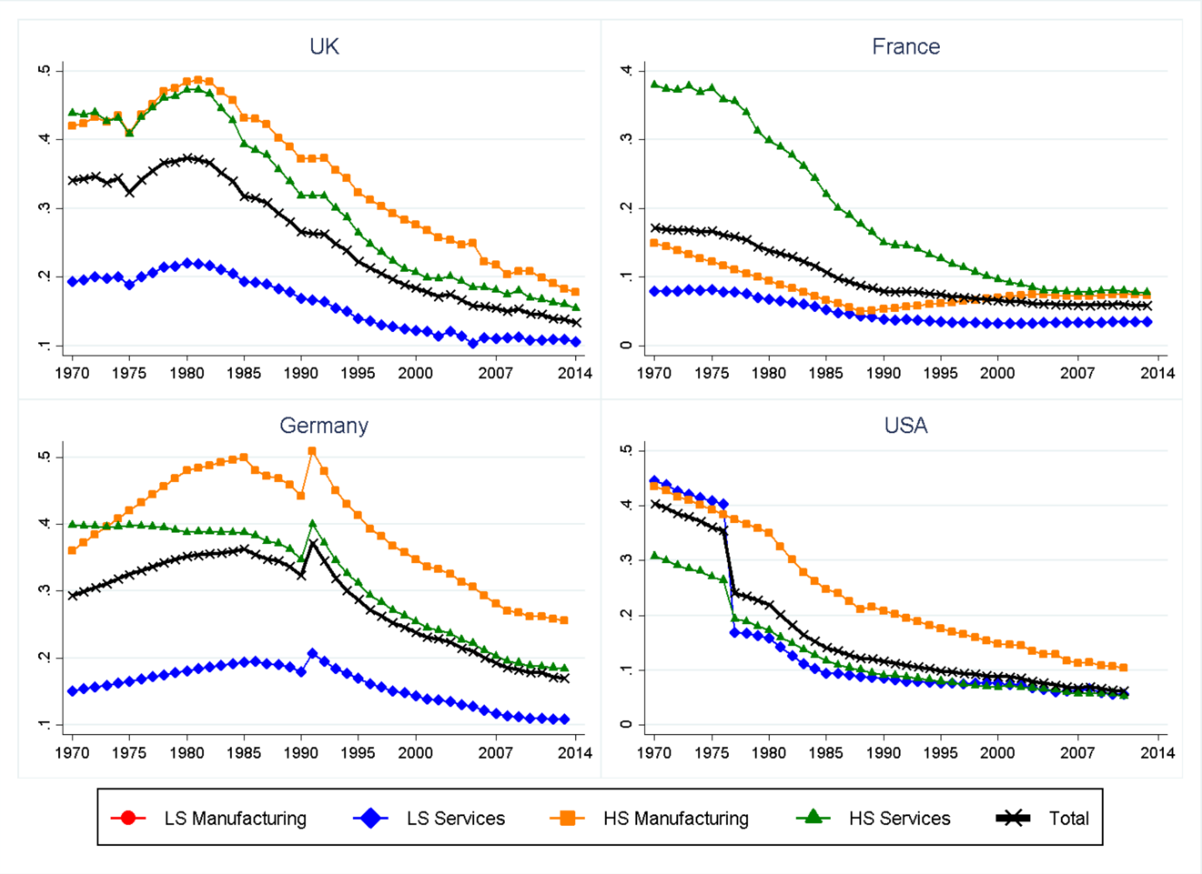
Figure 3: Capital intensity by sector type, selected countries 1970-2014



Notes: HS and LS stands for high and low skilled sectors respectively. For example, "LS Services" denotes capital stock in low-skilled service industries as a ratio to value added in these industries. The graph for the total capital intensity includes all sectors. Sector level graphs exclude: Agriculture, Hunting, Forestry, Fishing; Mining and Quarrying; Coke and Refined Petroleum; Real Estate; and Community Social and Personal Services (including Health, Education, Defence and Arts). We report capital stock rather than services because the service variable is an index that cannot be meaningfully aggregated by industry.

Source: Own calculations based on EU KLEMS.

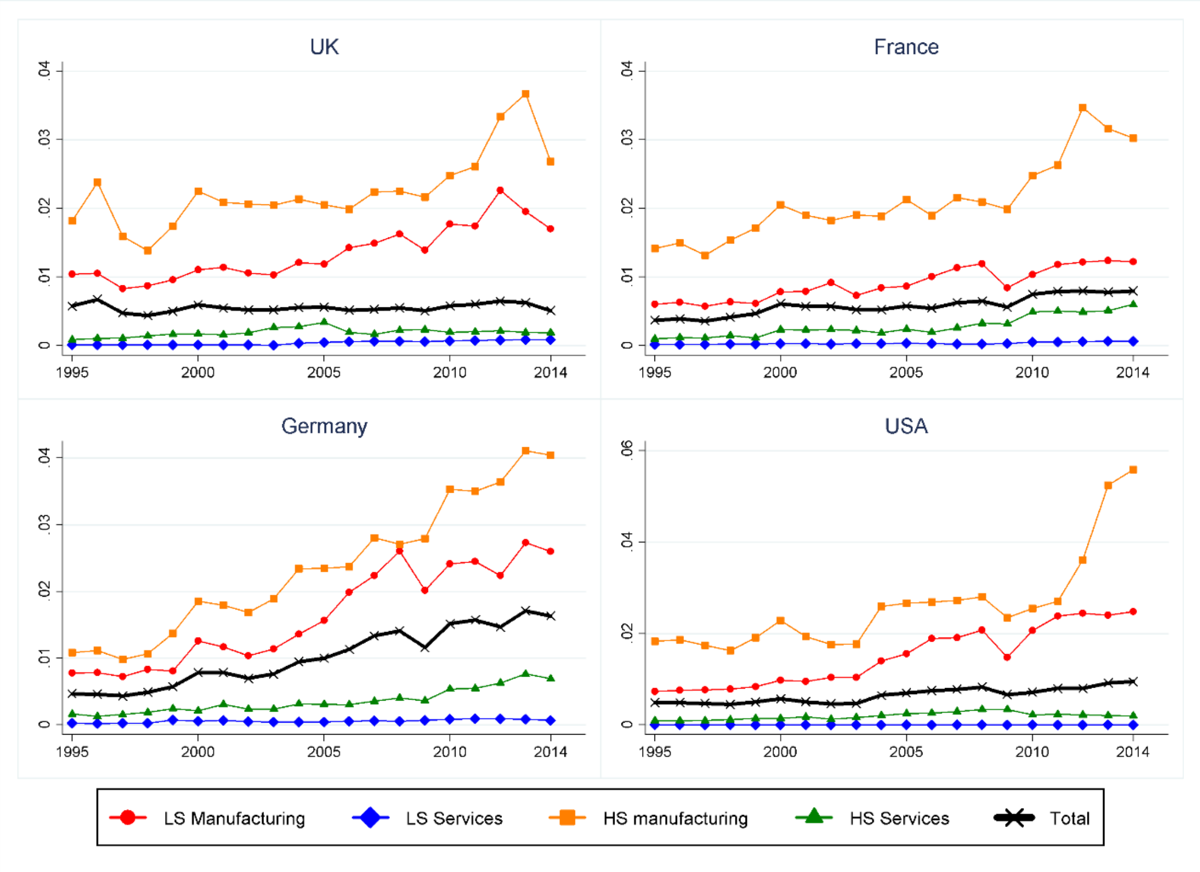
Figure 4: Union density by sector type, selected countries 1995-2014



Notes: HS and LS stands for high and low skilled sectors respectively. For example, "LS Services" denotes union density in low-skilled service industries. The graph for the total union density includes all sectors. Sector level graphs exclude: Agriculture, Hunting, Forestry, Fishing; Mining and Quarrying; Coke and Refined Petroleum; Real Estate; and Community Social and Personal Services (including Health, Education, Defence and Arts).

Source: Own calculations based on Visser (2016).

Figure 5: Offshoring to emerging and developing countries by sector type, selected countries 1995-2014



Notes: HS and LS stands for high and low skilled sectors respectively. For example, "LS Services" denotes intra-industry intermediate imports from emerging and developing countries in low-skilled service industries as a ratio to gross output in these industries. The black line for total industries includes all industries. Industry level graphs exclude: Agriculture, Hunting, Forestry, Fishing; Mining and Quarrying; Coke and Refined Petroleum; Real Estate; and Community Social and Personal Services (including Health, Education, Defence and Arts).

Source: Own calculations based on WIOD.

Table 1: Implied elasticity of substitution between capital and labour in selected articles

Article	Implied elasticity (e)
Bassanini and Manfredi (2014)	e>1
Bentolila and Saint-Paul (2003)	e>1
Demiani et al. (2018)	e<1 (K/Y); e>1 (TFP)
Doan and Wan (2017)	e<1
European Commission (2007)	e<1 (K/L); e>1 (ICT)
Elsby, et al. (2012)	e=1
Harrison (2002)	e<1
Hutchinson and Persyn (2012)	e>1
ILO (2011)	e<1
IMF (2007)	e<=1 (K/L); Non-linear for ICT
Dao et al. (2017)	e>=1
Karabarbounis and Neiman 2014	e>1
O'Mahony et al. (2018)	e>1
Stockhammer 2009	e=1
Stockhammer 2017	e<=1

Notes: The proxies commonly used to account for technological change are the capital-output ratio (K/Y), the capital-labour ratio (K/L), total factor productivity (TFP) and ICT capital intensity (ICT). If conflicting results regarding the value of *e* were found the variables are indicated in brackets (e.g. in Demiani et al. 2018 the implied elasticity is below one for capital intensity and above one for TFP). Results for IMF (2007) are based on estimations for the aggregate wage share using instrumental variables. They find evidence for an elasticity above one when they conduct estimations for high- and low-skilled sectors separately.

Table 2: Baseline specification and robustness of results over time

	1	2	3	**4**	5	6	7
$growth_t$	-0.205***	-0.222***	-0.407**	**-0.267****	-0.286***	-0.134	-0.174***
	(0.001)	(0.001)	(0.010)	**(0.042)**	(0.000)	(0.309)	(0.004)
TFP_t	-0.242***	-0.234***	-0.142	**-0.062**	0.047	-0.308	-0.211***
	(0.001)	(0.001)	(0.288)	**(0.175)**	(0.722)	(0.187)	(0.007)
ICT_t	-0.041***	-0.042**	-0.008	**-0.001**	0.009	-0.042	-0.017**
	(0.008)	(0.018)	(0.708)	**(0.883)**	(0.854)	(0.442)	(0.037)
ICT_{t-1}	0.021*	0.021*					
	(0.100)	(0.099)					
$nonICT_t$	-0.202***	-0.170***	-0.075	**-0.053**	0.099	-0.060	-0.173**
	(0.004)	(0.008)	(0.492)	**(0.120)**	(0.370)	(0.768)	(0.020)
offshoring $OECD_{t-1}$				**-0.364**	0.256	-0.675	
				(0.404)	(0.648)	(0.665)	
offshoring $East_{t-1}$				**1.811**	3.311	6.913	
				(0.339)	(0.439)	(0.370)	
offshoring RoW_{t-1}				**-1.725****	-0.332	0.707	

				(0.039)	(0.694)	(0.417)	
union density$_{t-1}$	0.141***	0.146***	0.071*	**0.084***	-0.288**	0.106	0.098*
	(0.000)	(0.003)	(0.087)	**(0.063)**	(0.022)	(0.607)	(0.063)
wage share$_{t-1}$	0.640***	0.703***	0.544***	**0.747*****	0.474***	0.412	0.595***
	(0.000)	(0.000)	(0.006)	**(0.000)**	(0.000)	(0.242)	(0.000)
wage share$_{t-2}$	-0.057***	-0.072**					-0.060***
	(0.007)	(0.013)					(0.004)
Hansen (p-val)	0.200	0.423	0.220	**0.154**	0.233	0.598	0.044
AR1 (p-val)	0.000	0.000	0.002	**0.000**	0.000	0.167	0.000
AR2 (p-val)	0.760	0.976	0.271	**0.952**	0.148	0.952	0.749
Instruments	56	45	27	**36**	32	28	63
Sectors	300	276	300	**300**	193	193	267
F-test	33.882	34.565	11.269	**12.196**	14.696	6.854	26.792
Observations	7835	4552	3837	**3284**	1351	579	8136
Period	73-07	73-96	97-07	**97-07**	08-14	12-14	73-14

Notes: The dependent variable is the sectoral adjusted wage share. Estimation method is ‘difference GMM’ with one instrument column per variable. P-values below the estimation coefficients in parenthesis. ***, **, * denote statistical significant at the 1%, 5% and 10% level. Hansen (p-val) is the p-value of the Hansen test of overidentifying restrictions for all instruments. AR1 and AR2 (p-val) is the p-value of the Arellano-Bond test for autocorrelation of first and second order in the residuals. Instruments denote the number of instruments used. Sectors, F-test and Observations is the number of cross sections, the F-test statistic and the number of observations. Baseline specification in bold.

Table 3: The effect of technological change and bargaining power on different skill groups

	1	2	3	4	5
skill group	HS	MS	LS	All	All
sector type	All	All	All	MANU	SERV
$growth_t$	-0.030	-0.088	-0.079	-0.361	-0.235*
	(0.521)	(0.173)	(0.240)	(0.113)	(0.067)
TFP_t	0.009	-0.068**	0.006	-0.059	-0.095*
	(0.676)	(0.033)	(0.714)	(0.369)	(0.066)
ICT_t	-0.001	-0.004	0.005	-0.009	0.000
	(0.802)	(0.422)	(0.213)	(0.505)	(0.996)
$nonICT_t$	0.015	-0.047**	-0.011	-0.077	-0.042
	(0.319)	(0.023)	(0.445)	(0.177)	(0.254)
offshoring OECD $_{t-1}$	-0.650**	-0.458	0.242	-0.101	-0.334
	(0.024)	(0.139)	(0.482)	(0.796)	(0.876)
offshoring $East_{t-1}$	2.004**	-0.043	0.744	-3.860	28.270
	(0.023)	(0.974)	(0.467)	(0.185)	(0.237)
offshoring RoW_{t-1}	-1.330**	-0.342	-0.833	-0.480	-0.130
	(0.019)	(0.649)	(0.162)	(0.726)	(0.925)
union $density_{t-1}$	-0.069***	0.018	0.105***	0.142*	0.080
	(0.002)	(0.448)	(0.000)	(0.066)	(0.241)
education_HS,MS,LS_t	0.094	-0.103***	-0.055***		
	(0.234)	(0.000)	(0.005)		
wage share $_{t-1}$	0.526***	0.762***	0.676***	0.551***	0.671***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
wage share $_{t-2}$			0.119***		
			(0.000)		
Hansen (p-val)	0.320	0.133	0.076	0.187	0.353

AR1 (p-val)	0.000	0.000	0.000	0.001	0.000
AR2 (p-val)	0.868	0.948	0.319	0.340	0.676
Instruments	37	37	36	36	36
Sectors	300	300	295	166	134
F-test	60.651	26.089	208.409	10.048	9.975
Observations	3284	3284	2934	1816	1468
Period	97-07	97-07	98-07	97-07	97-07

Notes: The dependent variable is the sectoral adjusted wage share. Estimation method is 'difference GMM' with one instrument column per variable. 'wage share_(t-1)' reflects the lagged dependent variable, i.e. the wage share of high-, medium-, low-skilled or all workers as specified in the skill-group. HS, MS and LS stands for high, medium and low skilled workers. P-values below the estimation coefficients in parenthesis. ***, **, * denote statistical significant at the 1%, 5% and 10% level. Hansen (p-val) is the p-value of the Hansen test of overidentifying restrictions for all instruments. AR1 and AR2 (p-val) is the p-value of the Arellano-Bond test for autocorrelation of first and second order in the residuals. Instruments denote the number of instruments used. Sectors, F-test and Observations is the number of cross sections, the F-test statistic and the number of observations.

Table 4: The impact of bargaining power across different bargaining regimes and other determinants of the wage share

	1	2	3	4	5	6	7	8	9
Skill-group	All	All	All	All	All	All	HS	MS	LS
$growth_t$	-0.242*	-0.372***	-0.212	-0.186***	-0.287***	-0.264	-0.015	-0.099	-0.104*
	(0.060)	(0.002)	(0.130)	(0.000)	(0.000)	(0.134)	(0.771)	(0.297)	(0.098)
TFP_t	-0.064	-0.035	-0.047	-0.329***	-0.034	-0.053	0.014	-0.078**	-0.011
	(0.159)	(0.401)	(0.318)	(0.006)	(0.559)	(0.254)	(0.610)	(0.039)	(0.561)
ICT_t	-0.006	-0.007	-0.000	-0.028	-0.007	-0.002	0.002	-0.014	0.008*
	(0.456)	(0.348)	(0.962)	(0.378)	(0.532)	(0.800)	(0.738)	(0.138)	(0.073)
$nonICT_t$	-0.045	-0.013	-0.041	-0.269***	-0.045	-0.023	0.018	-0.047*	-0.024
	(0.186)	(0.677)	(0.239)	(0.009)	(0.286)	(0.518)	(0.383)	(0.084)	(0.128)
offshoring $OECD_{t-1}$	-0.298	-0.426	-0.425		0.093	-0.557	-0.824	-0.744	0.806**
	(0.501)	(0.458)	(0.349)		(0.875)	(0.584)	(0.130)	(0.370)	(0.029)
offshoring $East_{t-1}$	2.932	3.848**	2.951		4.606	5.008**	0.600	2.834	-0.700
	(0.133)	(0.026)	(0.194)		(0.109)	(0.014)	(0.721)	(0.156)	(0.351)
offshoring RoW_{t-1}	-1.882**	-2.156***	-2.391**		-2.050*	-2.943**	-0.543	-1.990	0.286
	(0.030)	(0.010)	(0.032)		(0.087)	(0.038)	(0.604)	(0.117)	(0.504)
union $density_{t-1}$	-0.049	0.102**	0.058	0.134***	0.057	0.083	-0.066*	0.070*	0.070
	(0.504)	(0.028)	(0.221)	(0.000)	(0.294)	(0.205)	(0.068)	(0.083)	(0.152)
union density_coord $_{t-1}$	0.192**								
	(0.020)								
excess CB_{t-1}		0.003*							
		(0.072)							
$Govt_{t-1}$			-0.089						
			(0.262)						

Govt_LBC$_{t-1}$			0.206*						
			(0.079)						
female$_{t-1}$				-0.409*					
				(0.085)					
min wage$_{t-1}$					0.277***				
					(0.000)				
migration$_{t-1}$						-0.659	-0.167	-0.079	-0.204
						(0.152)	(0.602)	(0.784)	(0.273)
Education_ HS,MS,LS $_{t}$							0.445***	-0.134***	-0.044*
							(0.002)	(0.001)	(0.083)
wage share $_{t-1}$	0.721***	0.737***	0.767***	0.553***	0.686***	0.747***	0.611***	0.695***	0.645***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
wage share $_{t-2}$				-0.041*					0.118***
				(0.098)					(0.000)
Hansen (p-val)	0.192	0.325	0.215	0.121	0.471	0.052	0.337	0.001	0.001
AR1 (p-val)	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.000	0.000
AR2 (p-val)	0.982	0.467	0.989	0.515	0.346	0.935	0.913	0.740	0.411
Instruments	37	45	38	54	37	39	31	40	48
Sectors	300	300	300	242	191	259	259	259	254
F-test	12.326	13.472	10.455	21.651	5.113	15.016	48.854	23.172	141.260
Observations	3284	3189	3284	6075	1880	2833	2833	2833	2524
Period	97-07	97-07	97-07	73-07	97-07	97-07	97-07	97-07	97-07

Notes: The dependent variable is the sectoral adjusted wage share. Estimation method is 'difference GMM' with one instrument column per variable. 'wage share_(t-1)' reflects the lagged dependent variable, i.e. the wage share of high-, medium-, low-skilled or all workers as specified in the skill-group. HS, MS and LS stands for high, medium and low skilled workers. P-values below the estimation coefficients in parenthesis. ***, **, * denote statistical significant at the 1%, 5% and 10% level. Hansen (p-val) is the p-value of the Hansen test of overidentifying restrictions for all instruments. AR1 and AR2 (p-val) is the p-value of the Arellano-Bond test for autocorrelation of first and second order in the residuals. Instruments denote the number of instruments used. Sectors, F-test and Observations is the number of cross sections, the F-test statistic and the number of observations.

Table 5: Economic significance

Variables	Predicted change in the wage share based on specification (4) in Table 2	Percentage of explained change in the wage share based on specification (4) in Table 2
growth	-0.0004	1.99%
offshoring to the RoW	-0.0098	44.00%
union density	-0.0051	22.94%
Sum	-0.0154	68.93%
Memo: Actual average change in the Wage Share	-0.0223	

Appendix

Table A1: Descriptive statistics and data sources

Variable definition	Observations	Mean	Standard Deviation	Source
$\text{wage share}_{i,j} = \dfrac{\text{labour compensation}_{i,j}}{\text{value added}_{i,j}}$	10191	0.698	0.163	EU KLEMS
$\text{wage share(high} - \text{skilled)}_{i,j} = \dfrac{\text{labour compensation(high}-\text{skilled)}_{i,j}}{\text{value added}_{i,j}}$	3895	0.160	0.088	EU KLEMS
$\text{wage share(medium} - \text{skilled)}_{i,j} = \dfrac{\text{labour compensation(medium} - \text{skilled)}_{i,j}}{\text{value added}_{i,j}}$	3895	0.331	0.117	EU KLEMS
$\text{wage share(low} - \text{skilled)}_{i,j} = \dfrac{\text{labour compensation(low} - \text{skilled)}_{i,j}}{\text{value added}_{i,j}}$	3830	0.180	0.108	EU KLEMS
$\text{ICT}_{i,j} = \dfrac{\text{ICT services}_{i,j}}{\text{real value added}_{i,j}}$	9811	0.008	0.025	EU KLEMS
$\text{nonICT}_{i,j} = \dfrac{\text{non} - \text{ICT services}_{i,j}}{\text{real value added}_{i,j}}$	9811	0.019	0.039	EU KLEMS
$\text{TFP}_{i,j} = \text{Total Factor Productivity}_{i,j}$	8852	88.954	24.572	EU KLEMS
$\text{growth}_{i,j} = \Delta\ln(\text{real value added})_{i,j}$	10335	0.026	0.064	EU KLEMS
$\text{union density}_{i,j} = \dfrac{\text{union members}_{i,j}}{\text{total employees}_{i,j}}$	10142	0.419	0.255	ICTWSS 5.1
$\text{offshoring OECD}_{i,j} = \dfrac{(\text{intra} - \text{industry intermediate imports from OECD countries})_{i,j}}{\text{gross output}_{i,j}}$	4004	0.032	0.046	WIOD
$\text{offshoring East}_{i,j} = \dfrac{(\text{intra} - \text{industry intermediate imports from Eastern Europe})_{i,j}}{\text{gross output}_{i,j}}$	4004	0.002	0.004	WIOD

$\text{offshoring RoW}_{i,j} = \frac{(\text{intra} - \text{industry intermediate imports from the rest of the world})_{i,j}}{\text{gross output}_{i,j}}$	4004	0.008	0.013	WIOD
$\text{female share}_{i,j} = \frac{\text{hours worked by women}_{i,j}}{\text{total hours worked}_{i,j}}$	6888	0.294	0.146	EU KLEMS
$\text{Govt}_{i} = \frac{(\text{in} - \text{kind social government expenditure and cash transfers})_{i}}{\text{total government spending}_{i}}$	5918	0.546	0.058	OECD
$\text{min wage}_{i,j} = \frac{\text{national minimum wages}_{i}}{\text{average labour compensation per person engaged}_{i,j}}$	5274	0.383	0.185	OECD & EU KLEMS
$\text{migration}_{i} = \frac{\text{foreign born labourforce}_{i}}{\text{total labour force}_{i}}$	5962	0.051	0.037	OECD
$\text{excess bargaining coverage}_{i,j} = \frac{\text{collective bargaining coverage}_{i}}{\text{union density}_{i,j}}$	9548	3.095	4.413	ICTWSS 5.1

Note: *i* stands for industry and *j* stands for country.

Table A2: Sectoral classification and skill taxonomy

Description	ISIC3 code for estimations 1970-2007	ISIC4 code for estimations 2008-2014	Skill classification (IMF, 2007)
Manufacturing			
Food products, beverages and tobacco	15-16	10-12	low
Textiles, wearing apparel, leather and related products	17-19	13-15	low
Wood and Products of Wood and Cork	20		low
Pulp, Paper, Printing and Publishing	21-22		high
Wood and paper products; printing and reproduction of recorded media		16-18	high
Chemicals and chemical products	24	20-21	high
Rubber and Plastics	25		high
Other Non-Metallic Mineral	26		high
Rubber and plastics products, and other non-metallic mineral products		22-23	high
Basic metals and fabricated metal products, except machinery and equipment	27-28	24-25	low
Machinery and equipment n.e.c.	29	28	high
Electrical and optical equipment	30-33	26-27	high
Transport equipment	34-35	29-30	low
Manufacturing, n.e.c.; Recycling	36-37	31-33	low
Services			
Electricity, Gas and Water Supply (Utilities)	E	D-E	high
Construction	F	F	low
Wholesale and Retail Trade; Repair Of Motor Vehicles and Motorcycles		G	low
Sale, Maintenance and Repair of Motor Vehicles and	50		low

Motorcycles; Retail Sale of Fuel			
Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	51		low
Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods	52		low
Hotels and Restaurants	H	I	low
Transport and storage	60-63	49-52	high
Post and Telecommunications	64		high
Postal and courier activities		53	high
Telecommunications		61	high
Publishing, audiovisual and broadcasting activities		58-60	high
IT and other information services		62-63	high
Financial Intermediation	J	K	high
Renting of M&Eq and Other Business Activities	71-74	M-N	high

Table A3: Robustness tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$growth_t$	-0.305***	-0.400***		-0.193	-0.270***	-0.100***	-0.131***
	(0.008)	(0.008)		(0.105)	(0.000)	(0.002)	(0.002)
TFP_t	-0.001		-0.049	-0.045	-0.032***	-0.321***	-0.274***
	(0.985)		(0.408)	(0.140)	(0.000)	(0.000)	(0.000)
ICT_t	0.010*	0.003	-0.003	0.006	0.003	-0.028	-0.006
	(0.090)	(0.691)	(0.743)	(0.318)	(0.195)	(0.323)	(0.800)
ICT_{t-1}						0.007	0.039*
						(0.799)	(0.063)
$nonICT_t$	0.003	-0.023	-0.035	-0.007	-0.002	-0.042	-0.112*
	(0.902)	(0.414)	(0.472)	(0.481)	(0.787)	(0.348)	(0.054)
offshoring $OECD_{t-1}$	-0.750	-0.379	-0.092	-0.389**	-0.108*		
	(0.103)	(0.375)	(0.864)	(0.010)	(0.056)		
offshoring $East_{t-1}$	1.063	1.082	2.511	2.036*	0.369		
	(0.619)	(0.660)	(0.276)	(0.054)	(0.237)		
offshoring RoW_{t-1}	-1.758**	-1.801*	-1.889*	0.097	0.050		
	(0.030)	(0.063)	(0.051)	(0.730)	(0.742)		
union $density_{t-1}$	0.187***	0.094*	0.084	0.007	0.044**	0.259*	0.412***
	(0.000)	(0.062)	(0.119)	(0.807)	(0.035)	(0.052)	(0.004)
wage $share_{t-1}$	0.679***	0.734***	0.773***	0.931***	0.730***	0.127***	0.193***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)

wage share$_{t-2}$						-0.110***	-0.063*
						(0.001)	(0.098)
constant				0.250**	0.328***	0.385	-0.106
				(0.023)	(0.000)	(0.641)	(0.891)
Hansen (p-val)	0.200	0.141	0.050	0.003			
diffH_level (p-val)				0.001			
AR1 (p-val)	0.000	0.000	0.000	0.000			
AR2 (p-val)	0.663	0.929	0.622	0.922			
Instruments	36	33	33	58			
Sectors	300	300	300	300	300	300	267
F-test	14.269	13.151	12.698	178.173	261.959		
Observations	3284	3284	3284	3584	3584	8135	7188
Period	97-07	97-07	97-07	97-07	97-07	73-07	73-14

Notes: The dependent variable is the sectoral adjusted wage share, except for specification (1) where the wage share is not adjusted for self-employed workers. Estimation method for specifications (1-3) is 'difference GMM' (Arellano and Bond 1991) with Windmeijer small sample error correction and one instrument column per variable (collapse option). We use the system GMM estimator in specification (4), the within estimator in specification (5), the mean group estimator in specifications (6) and (7). P-values below the estimation coefficients in parenthesis. ***, **, * denote statistical significant at the 1%, 5% and 10% level, respectively. Hansen (p-val) stands for the p-value of the Hansen test of overidentifying restrictions for all instruments, diffH_level (p-val) indicates the incremental Hansen test for instruments used in the level equation. AR1 and AR2 (p-val) is the p-value of the Arellano-Bond test for autocorrelation of first and second order in the residuals. Instruments denote the number of instruments used. Sectors, F-test and Observations is the number of cross sections, the p-value of the F-test and the number of observations.

Table A4: Unit root tests

variable	Im-Pesaran-Shin (2003)	Choi (2001)
wage share	0.000	0.000
wage share$_{high-skilled}$	0.009	0.000
wage share$_{medium-skilled}$	0.773	0.000
wage share$_{low-skilled}$	0.000	0.000
TFP	1.000	0.000
ICT	0.000	0.000
nonICT	0.000	0.000
growth	0.000	0.000
offshoring_OECD	0.001	0.000
offshoring East	1.000	0.021
offshoring RoW	1.000	0.000
Δwage share	0.000	0.000
Δwage share$_{high-skilled}$	0.000	0.000
Δwage share$_{medium-skilled}$	0.000	0.000
Δwage share$_{low-skilled}$	0.000	0.000
ΔTFP	0.000	0.000
ΔICT	0.000	0.000
ΔnonICT	0.000	0.000
Δgrowth	0.000	0.000
Δoffshoring_OECD	0.000	0.000
Δoffshoring East	0.000	0.000
Δoffshoring RoW	0.000	0.000

Notes: The table shows p-values of unit root tests performed for the 1970-2007 period on variables treated as endogenous or predetermined in the GMM estimation. The null hypothesis is that all the panels contain a unit root.

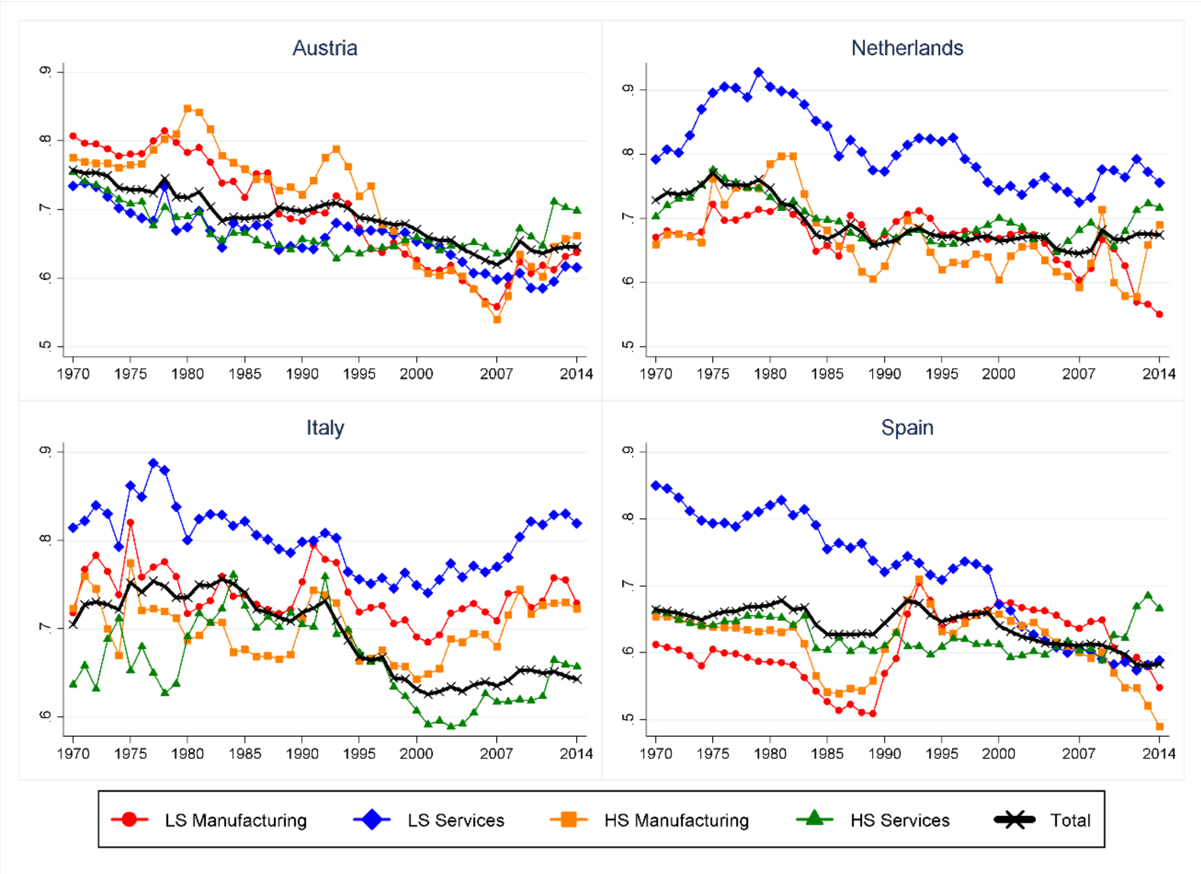
Table A5: Weak instrument tests

	Δwage share	ΔICT	ΔnonICT	ΔTFP	Δgrowth	Δoffshoring OECD	Δoffshoring East	Δoffshoring RoW
F-test (own instruments)	13.964	780.093	73.776	112.114	4.603	9.081	101.505	45.771
Observations	3279	3284	3284	3284	3283	2384	2384	2384
F-test (all instruments)	20.019	30.242	8.383	6.516	4.445	22.02	9.913	19.771
Observations	2684	2684	2684	2684	2684	2684	2684	2684

Notes: The table reports F-statistics on the joint validity of all instruments. The first row is the dependent variable and corresponds to one of the endogenous variable in the baseline estimation (specification 4, Table 2). The second row reports F-tests from a regression of the difference of the endogenous variable on its on lags in levels, without any controls. The fourth row reports F-tests from a regression of the difference of the endogenous variable on all the instruments used in the baseline regression, including the year dummies. The regressions are performed on data that enters the baseline specification and thus span the 1995-2007 period and are based on 300 country-industries across 14 countries.

Online Appendix

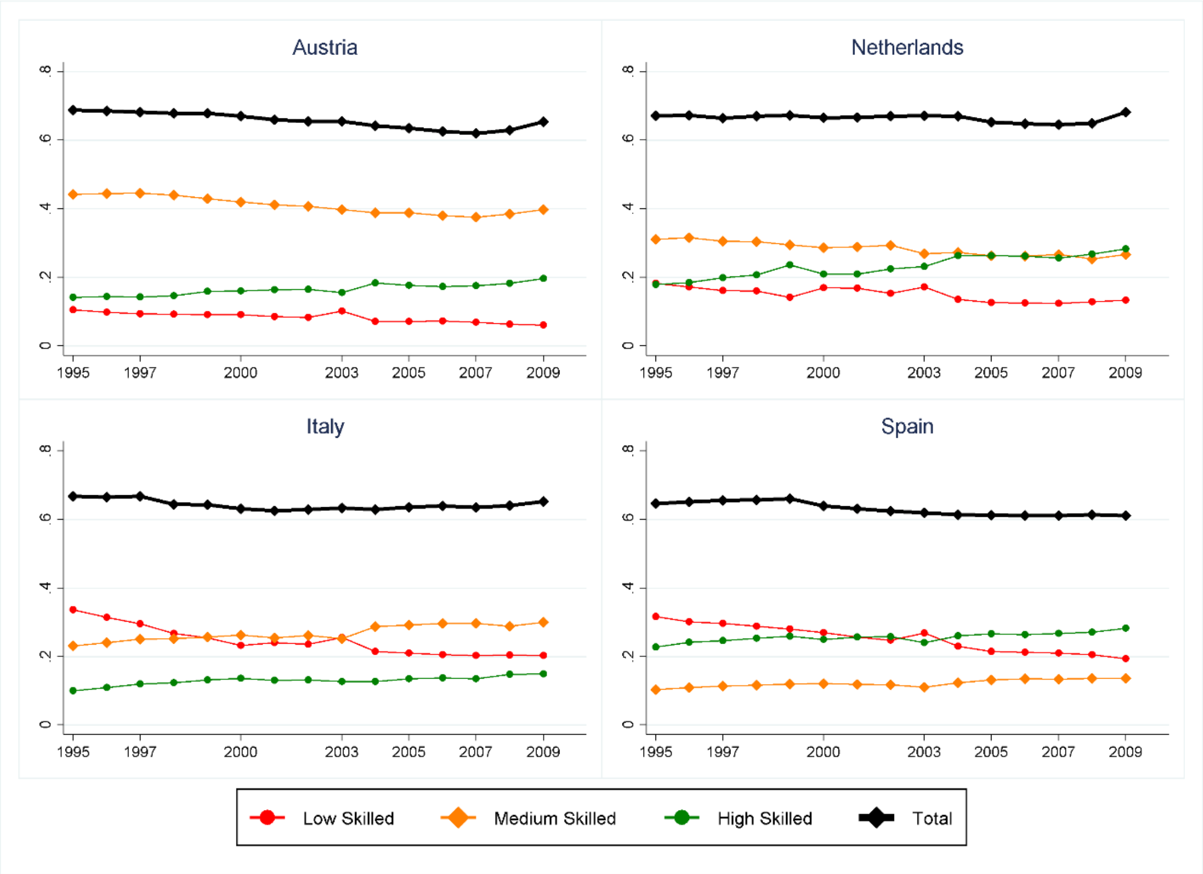
Figure A1: Wage share by sector type, selected countries 1970-2014



Notes: HS and LS stands for high and low skilled sectors respectively. For example, "LS Services" denotes labour compensation in low-skilled service industries as a ratio to value added in these industries. The graph for the total wage share includes all sectors. Sector level graphs exclude: Agriculture, Hunting, Forestry, Fishing; Mining and Quarrying; Coke and Refined Petroleum; Real Estate; and Community Social and Personal Services (including Health, Education, Defence and Arts).

Source: Own calculations based on EU KLEMS.

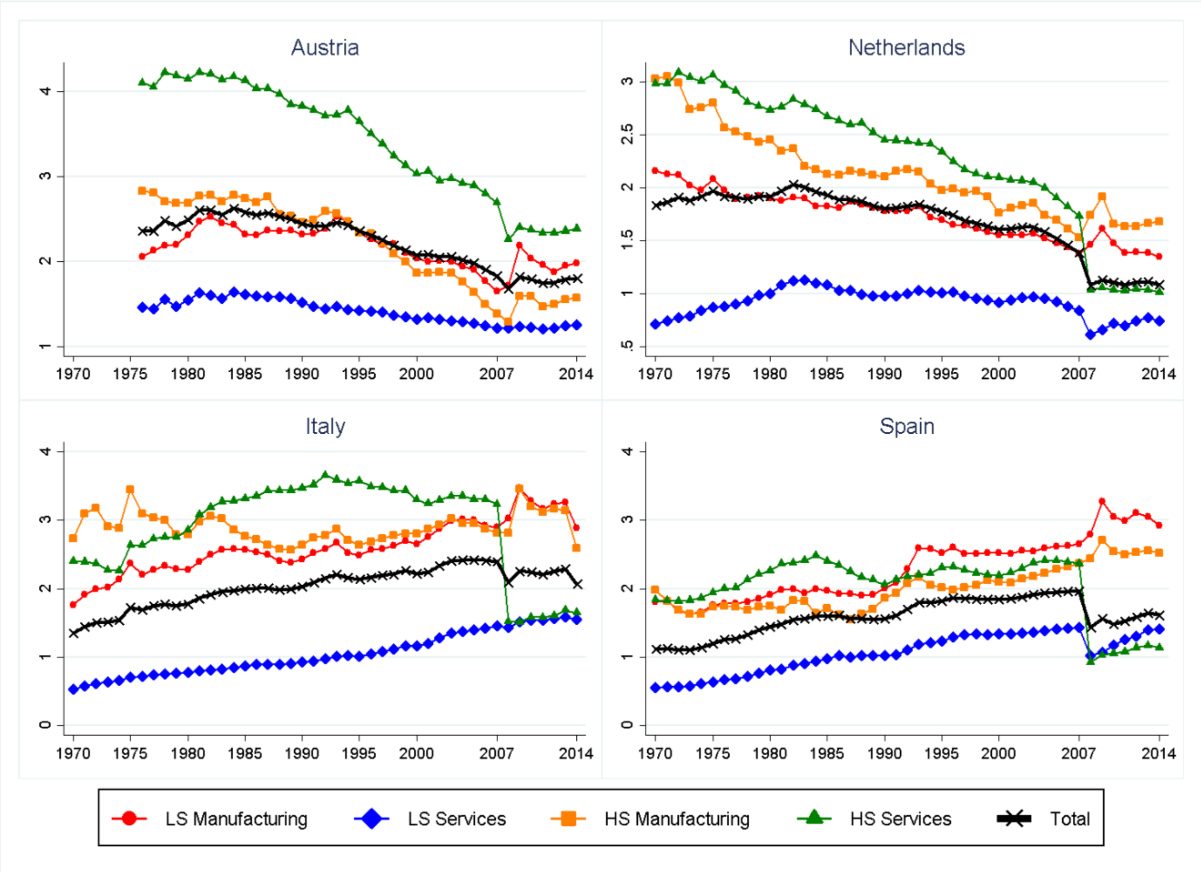
Figure A2: Wage share by skill group as defined by workers' education, 1995-2009



Notes: Low skilled: Up to lower secondary or second stage of basic education; Medium skilled: Up to Post-secondary non-tertiary education; High skilled: First and Second stage of tertiary education. For example, the red line stands for low-skilled workers' labour compensation as a ratio to total value added.

Source: Own calculations based on EU KLEMS and WIOD.

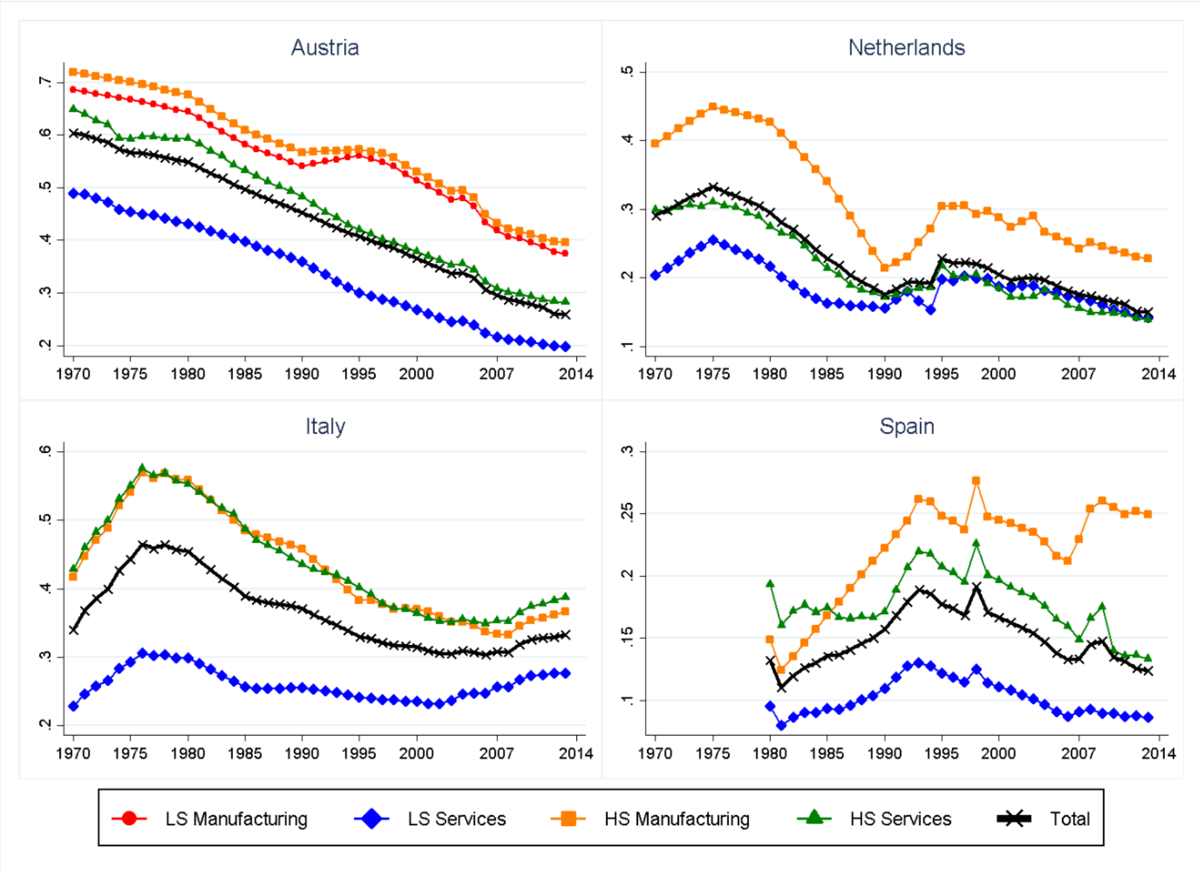
Figure A3: Capital intensity by sector type, selected countries 1970-2014



Notes: HS and LS stands for high and low skilled sectors respectively. For example, "LS Services" denotes capital stock in low-skilled service industries as a ratio to value added in these industries. The graph for the total capital intensity includes all sectors. Sector level graphs exclude: Agriculture, Hunting, Forestry, Fishing; Mining and Quarrying; Coke and Refined Petroleum; Real Estate; and Community Social and Personal Services (including Health, Education, Defence and Arts). We report capital stock rather than services because the service variable is an index that cannot be meaningfully aggregated by industry.

Source: Own calculations based on EU KLEMS.

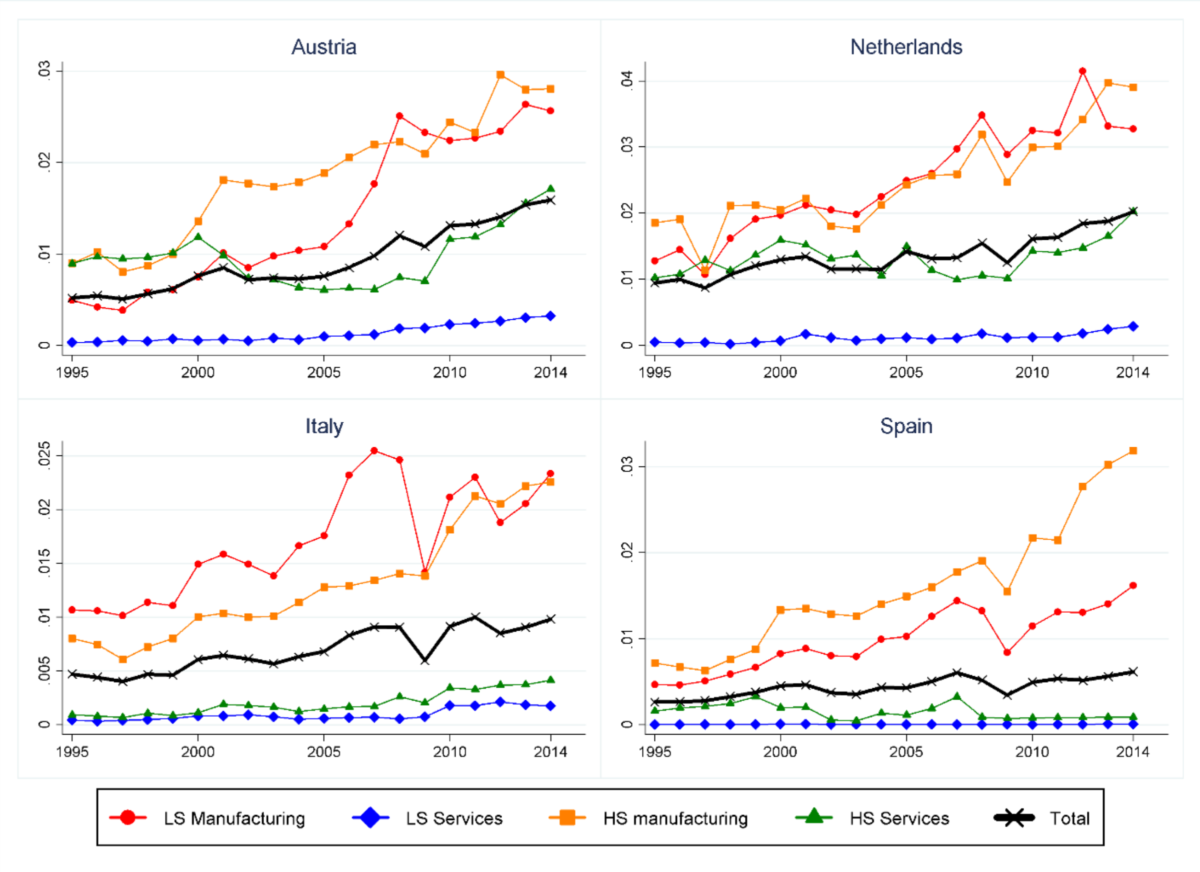
Figure A4: Union density by sector type, selected countries 1995-2014



Notes: HS and LS stands for high and low skilled sectors respectively. For example, "LS Services" denotes union density in low-skilled service industries. The graph for the total union density includes all sectors. Sector level graphs exclude: Agriculture, Hunting, Forestry, Fishing; Mining and Quarrying; Coke and Refined Petroleum; Real Estate; and Community Social and Personal Services (including Health, Education, Defence and Arts).

Source: Own calculations based on Visser (2016).

Figure A5: Offshoring to emerging and developing countries by sector type, selected countries 1995-2014



Notes: HS and LS stands for high and low skilled sectors respectively. For example, "LS Services" denotes intra-industry intermediate imports from emerging and developing countries in low-skilled service industries as a ratio to gross output in these industries. The black line for total industries includes all industries. Industry level graphs exclude: Agriculture, Hunting, Forestry, Fishing; Mining and Quarrying; Coke and Refined Petroleum; Real Estate; and Community Social and Personal Services (including Health, Education, Defence and Arts).

Source: Own calculations based on WIOD.