Offshoring to China and the skill structure of manufacturing labour demand in developed countries

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Abstract: The aim of this paper is to examine the impact of manufacturing offshoring to China on the skill structure of labour demand, for a sample of 19 developed countries, each consisting of 14 manufacturing industries, over the years 1995-2009. A system of factor demand equations is estimated, by using data from the World Input-Output Database, which allow for distinguishing between three skill categories of labour. Besides constructing the widely used narrow and broad offshoring measures, an additional measure is proposed, in order to capture the effects on labour demand when the offshored task was formerly outsourced domestically. The overall results show that offshoring negatively affects demand for all skill types of labour, but low and medium skilled labour demand are hardest hit. By estimating the effects of the additional offshoring measure, this pattern becomes more pronounced. This implies that by including this new measure in the analysis, the widening gap between lower and higher skilled labour can be attributed to offshoring to a larger extent.

1. Introduction

Globalisation has progressed at a fast pace over the last few decades, but also its nature has changed. While formerly trade consisted of final goods, it increasingly comprises intermediate goods as firms' production processes have become fragmented. This new phase in globalisation is referred to as the "second great unbundling" (Baldwin, 2006). While the first great unbundling marked the end of the necessity of making goods close to where they are consumed, in the second unbundling phase, even the different stages of making a good can be widely dispersed throughout the world (Baldwin, 2006). This phenomenon is called offshoring and can be defined as the relocation of production stages abroad. This can be done within the boundaries of a firm (vertical fragmentation), but also beyond it (foreign outsourcing) (Bowen, Hollander and Viaene, 2012).

At the same time as these developments have occurred in international trade, the gap between low and high skilled workers in terms of wages and job opportunities in developed countries has widened (Foster-McGregor, Stehrer & de Vries, 2013). This must be due to an increase in the relative demand for high skilled labour, as the relative supply of high skilled labour also increased (Strauss-Kahn, 2004). While this was first believed to be caused solely by the rise in the use of computers and other high-tech equipment, known as skill biased technological change which made particularly low skilled jobs obsolete, the new trend in international trade has spurred policy debates focusing on offshoring as an alternative explanation for the increased worker inequality within countries. In high-income countries, according to the idea underlying offshoring, firms move lower skilled intensive production stages to low wage countries (Hertveldt & Michel, 2013). This has led to the belief that offshoring worsens the position of low skilled workers in the labour market, thereby affecting the within-industry skill structure of labour demand. This would imply that offshoring can at least partly explain the divergence between low and high skilled labour.

From a theoretical perspective, it is however by no means clear which labour type is harmed by offshoring. This is because offshoring results in cost-savings, which are largest for industries that have relatively low skilled intensive production stages, which can induce an expansion of production that would be largest for the low skilled intensive industries, and hence increase relative demand for this labour type (Grossman & Rossi-Hansberg, 2008). This paper empirically examines if and to what extent the change in the skill structure of labour demand is due to offshoring.

This study builds on the existing literature by using a widely used econometric model, based on a flexible cost function, to estimate the impact of offshoring on relative factor demand. The use of the relatively recently compiled World Input-Output Database (WIOD) with data on intermediate goods trade and labour markets at the industry level, allows for including 19 developed countries in the analysis. Data is extracted for the time period 1995-2009. Furthermore, the WIOD distinguishes between three skill types of labour (low, medium and high skilled labour), resulting in the estimation of multiple equations. While the debate is increasingly focusing on offshoring of services, this analysis is restricted to offshoring in manufacturing industries, as the amount of services offshoring was still relatively small compared to manufacturing offshoring in the period under study (Amiti & Wei, 2005). This study comes closest to Foster-McGregor et al. (2013), as the same database and main methodology is used, although they examine offshoring to all countries. The reason why I consider offshoring to one specific country is that the impact of offshoring might depend on the host country, and policy implications can be concerned with bilateral trade agreements. As the debate is primarily focused on offshoring to China due to its rapidly increasing role in globalisation, I will only consider offshoring to China.

This paper contributes to Foster-McGregor et al. (2013) and most other existing literature by aligning theory with empirics. The division between theoretical and empirical papers is large in the topic of offshoring. This has led some empirical studies to overlook assessing the potential positive effects of cost-savings, by estimating only the effects of offshoring for a given level of output. This paper therefore examines the effects of offshoring unconditional on output in addition to estimating the standard model. Also in contrast to the existing literature, the expected effects of the non-offshoring variables, based on microeconomic theory, and the interpretation of their estimated coefficients are elaborated on. The main extension of the existing literature is however the construction of a new measure for offshoring, which is meant to complement to, not substitute for, the classical measures. The underlying reason for proposing an additional measure is that not all effects of offshoring on domestic labour demand might be captured by the existing measures. These measures namely focus on labour market effect in the industry that offshores, while ignoring potential effects in other industries. More specifically, the new measure aims to capture the effect of relocating an activity abroad that was formerly already outsourced domestically.

The results show a negative effect on low and medium skilled labour demand, and also a negative but smaller effect on high skilled labour. This implies that offshoring increases the worker gap, which is in line with the findings of Foster-McGregor et al. (2013) and the majority of the existing literature. This result is not changed when taking into account expansion of production. The additional measure for offshoring makes the effects more pronounced, although not highly significantly. This implies that by including this newly proposed measure in empirical analyses, the gap between lower and higher skilled labour can be attributed more to offshoring, albeit only to a small extent.

The remainder of this paper is organised as follows. Section 2 briefly discusses the most relevant empirical literature. In section 3, the theory behind the existence of fragmentation of production is discussed, followed by a detailed outline of a theoretical model that links offshoring with labour demand. The methodology for the empirical analysis is presented in section 4, while section 5 describes the data that is used and explains the construction of the measures for offshoring. Section 6 discusses the expectations of the results from which hypotheses are derived. Section 7 presents the results and in the next section, section 8, a robustness check is performed. Finally, section 9 concludes and presents a discussion of the results.

2. Empirical literature review

Together with the increased debate on the effects of offshoring, as discussed in the introduction, a large amount of empirical research on this topic has emerged. The majority of the papers has focused on the effects of offshoring from one country to any other country on labour demand in this single country. Feenstra and Hanson (1996), who pioneered in this topic, find that in the United States, offshoring contributed to the increase in the relative wages of higher skilled workers that occurred in the 1980s. Hijzen, Görg and Hine (2005) focus on the UK and use panel data on 50 manufacturing industries over the years 1982-1996 and assess the impact of offshoring on three different labour types. They find that offshoring has negatively affected labour demand of the lowest skilled workers only, which implies a shift in relative demand away from those workers to the other two labour types. Ekholm and Hakkala (2005) also distinguish between three types of labour but instead find that in Sweden, offshoring reduced medium skilled labour demand, over the years 1995-2000. They include both manufacturing and services industries. When they split their sample of host countries they find that their result is mainly driven by offshoring to low-wage countries.

While these three studies used a cost share for a labour type to capture its labour demand, other papers use an employment share, which is justified when the domestic labour market has wage rigidities. This is done by Strauss-Kahn (2004) for France and by Hertveldt and Michel (2013) for Belgium and they also find negative effects on relative employment of low skilled labour. Foster-McGregor et al. (2013) take a wider view and assess the effects of offshoring on a sample of 40 countries over the time period 1995-2009. They therefore use cost shares instead of employment shares. Their results show that demand of all three labour types are negatively affected by offshoring, but low and medium skilled labour are affected more heavily than high skilled labour demand.

The results obtained by these papers are thus very similar and suggest that offshoring has increased the wage and/or employment gap between lower and higher skilled labour. Furthermore, it seems that older papers find the largest negative effect on the lowest skill type, while relative demand for medium skilled labour is equally or even more harmed than low skilled labour in papers that cover more recent time periods. However, all studies discussed above did not allow for the potential positive effects to play a role, so from a theoretical point of view, the results are as would be expected. There are only very few papers that do allow for positive effects induced by cost savings from offshoring, by estimating an unconditional model in addition to a conditional one, meaning that the results are not based on a given level of industry output. Existing studies with an unconditional model incorporated in their analysis are mainly focused on the effects of offshoring on the elasticity of labour demand (e.g. Hijzen and Swaim, 2010) or on aggregate employment (e.g. Cappariello, 2010). The latter finds that the negative effect on Italian aggregate unemployment resulting from manufacturing offshoring is smaller in absolute size and less significant in the unconditional model compared to the conditional model. I am however not aware of such a study that examines the skill structure of labour demand.

3. Theoretical framework

In this section, the theoretical framework on which the rest of this analysis is based is described. First, it is explained why offshoring occurs. After that, a theory that links offshoring with labour demand is discussed.

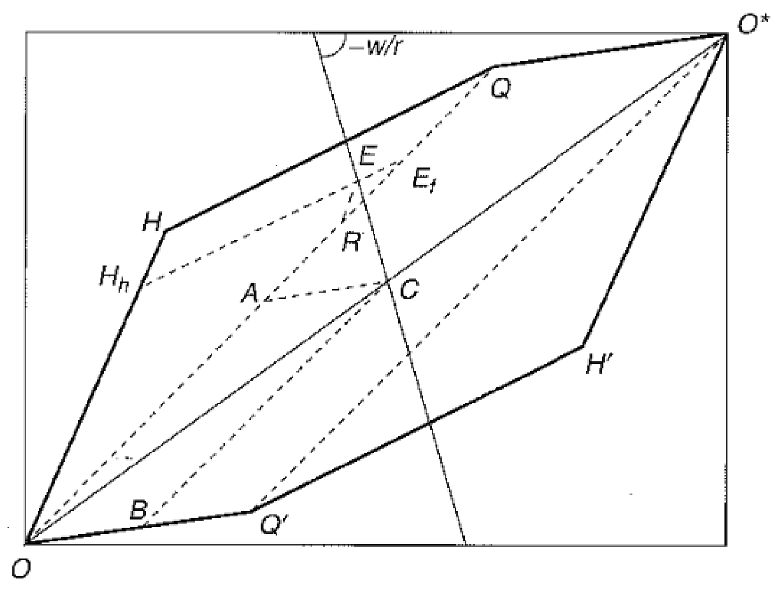
3.1. Trade in intermediate goods

International trade arises when one country has a comparative advantage over another country in producing a certain good. This principle of comparative advantage, developed by David Ricardo, can explain why countries can benefit from specialisation. A theorem developed by Heckscher and Ohlin further explains why comparative advantages exist: they emerge from relative factor abundance. If one country has a higher capital-labour ratio (K/L) than another country, then its wage-rent ratio (w/r) will be higher compared to the other country, vice versa (under the H-O model assumptions of identical and homothetic consumer preferences across countries). Countries that are relatively capital abundant will therefore export goods that are capital intensive and import goods that are labour intensive. Labour abundant countries will on the other hand export labour intensive goods and import capital intensive ones. (Bowen et al., 2012)

However, in the above described framework, all tasks required to finish a good are taken care of by the same country, while it is empirically observed that in recent years trade in intermediate goods is occurring. Therefore, to be able to theoretically explain the period of the "second great unbundling", as Baldwin (2006) refers to this new phase of globalisation, production must be considered at a more disaggregated level. Due to large reductions in international communication and transportation costs, firms can offshore stages of production that were previously considered non-tradable (Baldwin, 2006). Due to that, a country can also have a comparative advantage over another one in only one part of the production process of a good.

Bowen et al. (2012) describe the framework developed by Helpman and Krugman (1985), which explains how differences in countries' factor endowments affect whether firms undertake different stages of production in different countries. Consider Figure 1, which displays an Edgeworth-Bowley box, where the size of the box indicates the world endowment, i.e. the world supply of labour and capital. The coordinates of point *E* measured with respect to origin *O* give the endowment point of the home country, while its coordinates measured with respect to *O** denote the endowment point of the foreign country. There are two goods that can be produced, being a homogeneous good and a differentiated good. The homogeneous good is produced with factor use given by the coordinates of point *Q'* with respect to origin *O*. The coordinates of point *Q* with *O* as origin denote the amount of capital and labour used in the production of the differentiated good. The vector *OQ* represents the world output of the differentiated good. The coordinates of *H* show the factor use in the production of headquarter services used in the production of this good. By subtracting the coordinates of *Q* from that of *H*, the factor use of manufacturing is obtained. Since *OH* is steeper than *HQ*, it can be seen that manufacturing is more labour intensive than headquarter services. Note that the production process of the homogeneous good is even more labour intensive than the manufacturing stage of production of the differentiated good. Consider again endowment point *E*. Home-based firms use local capital and labour to produce OH_h units of headquarter services. Furthermore, they use the quantity H_hE of local factors and the quantity EE_f of foreign factors in the manufacturing stage of production, i.e. an amount of EE_f is offshored. Next to the offshored activities, the other country also produces *O*Q* of the homogeneous good and QE_f of the differentiated good.

Figure 1: Trade in intermediate goods



Source: Bowen, Hollander and Viaene (2012), p. 365

If endowment point *E* would be more to towards the origin *O* but still above the diagonal line between the two origins *O* and *O**, which means the disparity between the countries' endowments is larger and the home country is still relatively capital abundant, then it is possible that the home firms will offshore all its manufacturing activities to the foreign country. In that case, home firms completely specialize in headquarter services and imports both the final differentiated good and the homogeneous good. Note that the imported final differentiated goods can still be considered as imports of intermediate inputs, as they still require domestic labour for ‘headquarter services’. Therefore, theories of offshoring will still apply in this case.

3.2. Offshoring, unemployment and wages

From the above it seems straightforward to draw the conclusion that if low skilled labour jobs are offshored away, relative wages of this labour type must fall and/or unemployment is bound to increase. However, from a general equilibrium perspective, this is by no means clear. Trade theorists have long seen trade in intermediate goods as if it were the same as trade in final goods (Baldwin, 2006); the usual gains from trade applied, but because of trade in intermediate goods, more final goods could be produced with a given amount of production factors. This implies that offshoring has the same impact as technological progress in final goods sectors. However, how this affects labour markets was until recently not clear (Mankiw and Swagel, 2006).

Grossman and Rossi-Hansberg (2008) therefore established a new paradigm to fully assess the effects of offshoring, which is explained in the remainder of this section. In their widely cited paper, they elaborate on the general equilibrium effects of offshoring, or “trade in tasks” as they call it, in a Heckscher-Ohlin framework. They thus extend the traditional H-O framework by modelling production as a process that involves a large number of tasks. A task requires the input of one factor of production; L-tasks can be performed by low skilled labour, whereas H-tasks require high skilled labour. There may be other tasks as well, for instance tasks that require medium skilled labour or capital. Firms in the home country can produce two goods, X and Y, which are both produced with constant returns to scale and with a continuum of both tasks. Some tasks are more difficult to offshore than others, and tasks are ordered so that the costs of offshoring are increasing. It is assumed that only L-tasks can be offshored, as it is prohibitively costly to offshore H-tasks. This assumption is highly likely to be in line with this paper, as manufacturing offshoring typically targets less skilled labour in developed countries (Bardhan, Jaffee and Kroll, 2013). Sector X is relatively skill intensive compared to sector Y. This means that, even though a certain task requires the same amount of domestic labour of a certain type across sectors, sector X's share of the amount of H labour it needs to produce H-tasks to the amount of L labour it needs to produce L-tasks is higher than this share in the Y sector. The costs of offshoring a specific L-task are equal across industries. The authors allow for substitution between L- and H-tasks, meaning that a firm can achieve a given level of output by either conducting the L-tasks repeatedly and the H-tasks less often, or the L-tasks less often and the H-tasks more frequently.

If the overall costs of offshoring decrease, for instance due to a decrease in the transport or communication costs, the possibilities for offshoring rise. This can affect wages of low skilled labour at home through three channels: the productivity effect, the relative wage effect and the labour supply effect. Note that, as is common, full employment is assumed in this model, implying that offshoring only affects labour demand through wage changes. If labour market rigidities, such as a minimum wage, were assumed, the amount of labour employed can fall in addition to, or instead of (if the wage constraint already binds), a fall in wages (Bardhan et al.). As I am interested in the change in labour demand, it must be noted that there is another effect of an increase in offshoring, as noted in another paper of Grossman and Rossi-Hansberg (2006), which is very straightforward. As more tasks that were formerly performed by lows skilled workers are moved abroad, there is a reduction in the amount of domestically low skilled labour employed. This is called the substitution effect.

The productivity effect refers to the cost savings that are generated for both industries, due to the decreased costs of producing L-tasks. Costs decrease for two reasons. Firstly, it is profitable for firms to move more tasks abroad, where they are performed more cheaply. Secondly, firms save on tasks that were already offshored. The envelop theorem (the equation on which it can be applied is not shown here) however predicts that the first source of cost savings is negligible with a small reduction in the offshoring costs, implying that there should already be some trade in tasks for the productivity effect to be at play. These cost savings are largest for the industry that is low skilled labour intensive, as the firm's savings are proportional to the share of L-tasks in its total costs. These lower costs work as an incentive to expand output in both industries, but more so for the low skilled intensive industry. Therefore, demand for low skilled labour increases. The increase in output more than offsets the initial fall in labour demand caused by the substitution effect, meaning that the amount of low skilled labour employed is back at its initial level (full employment), but now earning a higher wage (Grossman and Rossi-Hansberg, 2006). The wage of high skilled labour does not change. Hence, the productivity effect predicts that the relative labour demand for low skilled labour increases. The authors show that this productivity effect is analogous to the effect of factor biased technological change.

From the productivity effect it is clear that output in both industries increases. As low skilled labour has to remain fully employed it must be true that, at constant relative goods prices, output in the low skilled intensive industry increases more than output in the high skilled intensive industry. Note that a rise in offshoring has the same impact on sector outputs as an increase in the endowment of low skilled labour, for which the Rybczynski theorem predicts that its effect on output is larger in the low skilled intensive industry (Feenstra, 2010). Therefore, the relative price of the low skilled intensive good decreases. This in turn increases the wage of high skilled labour, whereas it decreases the wage of low skilled labour, according to the Stolper-Samuelson theory. This implies that relative price effect induces a decrease in the relative demand for low skilled labour. It is important to note that the relative price effects only holds if the expansion in output affects world prices, which is generally only the case in large countries.

The effect of offshoring on relative wages depends on the relative strengths of these two opposing forces. As outlined by Grossman and Rossi-Hansberg (2006), if the demands for the goods are inelastic, and if the home country is sufficiently large, the change in relative price due to the change in relative output will be large. Furthermore, if the two industries do not differ much in their factor intensities, the relative wage decrease of low skilled labour due to the relative price change will be large. These circumstances increase the likelihood that the relative price effect dominates the productivity effect, implying that the relative labour demand for low skilled labour to high skilled labour decreases. However, the opposite is also true, in which case the productivity effect outweighs the relative price effect, and thus relative demand for high skilled labour increases.

In a Heckscher-Ohlin model it is assumed that countries are not completely specialised in producing goods, meaning that changes in factor supplies can affect the composition of output in each country, without affecting factor prices. In a framework in which countries do specialise in producing one or more goods, i.e. there are more factors of production than tradable goods produced by the country, there is an effect of labour supply on factor prices, referred to as the labour supply effect. The reason for this effect is easiest to see in a setting in which the offshoring country produces only one good. Consider a country that produces one good and takes world prices as given (small country assumption). The substitution effect frees up domestic low skilled labour that formerly performed the now offshored L-tasks, resulting in an effective increase in low skilled labour supply. However, with only one sector in the country, this labour cannot be reabsorbed in the labour market through Rybczynski-like reallocations. It instead leads to a decline in the wages for low skilled labour, as all domestic low skilled labour has to be employed while performing less tasks. Hence, relative wages for low skilled labour fall. Going back to the case of imperfect specialisation, the labour supply effect is large when H-tasks substitute poorly for L-tasks, and when the initial amount of offshoring is small. In that case, the negative labour supply effect is more likely to dominate the positive productivity effect.

The net effect on relative demand for low skilled labour thus depends on a number of factors. First of all, if a country is not large enough, there will be no relative price effect at play. In that case, whether the labour supply effect dominates the productivity effect depends on, amongst others, the elasticity of substitution between L- and H-tasks. If the relative wage effect is present, relative demand of low skilled labour will only increase if the positive productivity effect is larger than the negative relative price and labour supply effect together. The net effect on relative labour demand is thus ambiguous from a theoretical perspective, and it should therefore be empirically explored.

4. Methodology

This section describes the now standard approach in studying the impact of offshoring on labour demand, which therefore serves as the methodology for this paper. The model, firstly introduced in the context of trade and demand for labour by Berman, Bound and Griliches (1994), aims to explain the relative demand for labour by estimating a translog cost function. It does so in a similar way as factor-biased technological change (FBTC) effects on relative labour demand have been studied (Ekholm & Hakkala, 2005). The underlying reasoning is that technological change and offshoring affect productivity, and their effect is not necessarily the same across factor inputs. The advancements of for instance computer technologies can make the work of the unskilled obsolete. Offshoring, which is driven by other forms of technological change, could have the same effect on domestic unskilled workers. The methodology follows Foster-McGregor et al. (2013) and therefore only the basic steps of the model will be explained. Consider a firm's output function

$$Y = f(L, M, H, K, II) \tag{1}$$

where *Y* denotes gross output, *L* is low skilled labour, *M* is medium skilled labour, *H* is high-skilled labour, *K* denotes the capital stock and *II* are intermediate inputs. It is assumed that the production function *f* is increasing and concave in all its parameters, with constant returns to scale. Capital is considered to be a fixed input, as is common in the literature, whereas labour and material inputs are flexible. Firms minimise costs by choosing the optimal vector of inputs. Hence, the cost function is equal to

$$C(w_L, w_M, w_H, w_{II}, K, Y, z) = \min_{L,M,H,II} w_L L + w_M M + w_H H + w_{II} II \ , \tag{2}$$
$$s.t. f(L, M, H, K, II) \geq Y$$

with *z* referring to factor biased technological change (FBTC), and *w* to factor prices, i.e. wages for different skill types of labour and prices of material inputs. It is assumed that equation (2) can be approximated by a second order flexible functional form such as the translog. By taking the first derivatives of the translog cost function with respect to the log of wages and prices of material inputs, a labour demand function is obtained, according to Shephard's lemma. To see why, note that $\frac{\partial lnC}{\partial lnw_f} = \left(\frac{w_f}{C}\right)\left(\frac{\partial C}{\partial w_f}\right)$, with w_f denoting the wage or price of input *f*, where $\frac{\partial C}{\partial w_f}$ equals the demand for input *f*. Since $\left(\frac{w_f}{C}\right)\left(\frac{\partial C}{\partial w_f}\right) = \frac{w_f x_f^*}{C}$, with x_f referring to the quantity of input *f*, the dependent variable equals the payments to factor *f* relative to total variable costs, which is denoted by s_f. For instance, the cost share of factor L is $s_L = \frac{w_L L^*}{w_L L^* + w_M M^* + w_H H^* + w_{II} II^*,}$. By taking differences between two periods (i.e. first differences), the equation that will be estimated is obtained. The regression equation for industry *i* in country *c* at time *t* is:

$$\Delta s_{f,ict} = \alpha_{0f,ic} + \sum_{j \in M} \gamma_{fj} \Delta ln\, w_{j,ict} + \phi_{Kf} \Delta\, ln\, K_{ict} + \phi_{Yf} \Delta\, ln\, Y_{ict} + \delta_{Of} \Delta O_{ict} + \Delta u_{f,ict} \ , \tag{3}$$

with $f \in M = \{L, M, H, II\}$. O denotes offshoring, which is one of the two sources of FBTC. Due to the widely recognized importance of the diffusion in technological advancements that can explain the shifts in labour demand, it is necessary to include a second source of FBTC (Crinò, 2009), to make sure that the offshoring variable does not pick up the effect of technological change in an industry per se. To control for the technological change in industries due to the adoption of better technologies (Hijzen et al., 2005) a full set of industry-country linear time trends is included, as is also done by Foster-McGregor et al. (2013). The constant α_0 captures this time trend in levels, which also controls for other unobserved developments in an industry in a country. Taking the first differences is done to control for unobserved industry-country specific time-invariant effects. At the same time, this solves potential serial correlation issues. For this reason, the regression equation only contains a time-varying error $u_{f,ict}$.

Foster-McGregor et al. (2013), and most other empirical papers, only estimate the regression above, which is called a conditional demand function as it derives the cost-minimising level of an input for a given level of output. The factor demand approach is based on the representative firm theory, i.e. it is assumed that all firms share the same technology and produce on the same scale (Hijzen, 2005). This implies that it represents a single sector setting. However, as this analysis is performed at the industry level, and industries are not supposed to be identical, a model that allows for differences between industries would be more appropriate. As explained before, theory predicts potentially different results in a multi-sector setting. More specifically, the previously discussed productivity and relative price effect, which arise due to respectively an incentive to increase output and an actual increase in output, are thus not able to play a role in this regression. Therefore, in addition to estimating equation (3), an unconditional labour demand function will be estimated in which the output variable is removed, which is in accordance with Hijzen and Swaim (2010).

$$\Delta s_{f,ict} = \alpha_{0f,ic} + \sum_{j=1}^{M} \gamma_{fj} \Delta ln\, w_{j,ict} + \phi_{Kf} \Delta\, ln\, K_{ict} + \delta_{Of} \Delta O_{ict} + \Delta u_{f,ict} \tag{4}$$

As is standard in the case of translog cost functions, cross-equation restrictions have to be taken into account in the analysis (Crinò, 2009), something which has been omitted by Foster-McGregor et al. (2013). Symmetry implies that $\gamma_{fj} = \gamma_{jf}$. Before this restriction is imposed in the regression equations, its validity will be tested by performing a Wald test, following Hijzen et al. (2005). Furthermore, constant returns to scale requires that

$$\sum_{f=1}^{M} \gamma_{fj} = \sum_{f=1}^{M} \phi_{Kf} = \sum_{f=1}^{M} \phi_{Yf} = \sum_{f=1}^{M} \delta_{Of} = 0 \tag{5}$$

which is also known as the linear homogeneity constraint. This constraint holds automatically, as the dependent variables are shares that add up to one.

Since the data that I use has more than two types of factors of production (namely low, medium and high skilled labour and materials), the analysis requires estimating more than one regression. One option is to simply estimate these regressions separately by using OLS. However, if the errors correlate across the equations, more efficient results are obtained by using Zellner's (1962) seemingly unrelated regression (SUR) method. In the above described model it is highly likely that the errors of the equations are correlated, since the right-hand sides of the equations are identical and because there are cross-equation restrictions (Hijzen et al., 2005), as described above. Therefore, SUR will be the appropriate estimation technique. Since the dependent variables add up to one if all four equations are estimated, which causes perfect multicollinearity, I am forced to omit one of the equations. I will drop the equation for the share of material costs in total variable costs, as the effect of offshoring on the relative demand of this factor is of the least interest for this analysis. The estimates are however not invariant to which equation is deleted. Fortunately, invariance can be obtained by using the iterative seemingly unrelated regression (ISUR) estimation technique. It iterates Zellner's method over the estimated residual covariance matrix and the parameter estimates, until the parameters converge.

It is important to note that this model cannot distinguish between the different channels through which labour demand adjusts (Hijzen, 2005). The labour cost share, which is the dependent variable, is a function of both wages and employment. Hijzen explains that labour demand shocks are not observed in practice, but instead only the change in relative labour demand after wages and employment have adjusted is observed. Therefore, it is not possible to see whether relative labour demand changed as a result of changes in factor prices (w_f) or changes in factor quantities (x_f), or a combination of the two. For this reason, it depends on labour market conditions in the country that is analysed how the results of offshoring are interpreted. For countries with flexible labour markets, such as the UK and the USA, an increase in the relative demand for skilled labour works mostly through adjustments in wages. In economies with rigid labour markets (e.g. high minimum wage, strong unions), such as most western European countries except the UK, such an increase will be interpreted as an increase in the relative unemployment level of unskilled labour. As mentioned in section 2, some papers that have examined only one country have replaced cost shares with employment shares, when the country of interest has rigid labour markets (e.g. Strauss-Kahn (2004) for France and Hertveldt & Michel (2013) for Belgium). Since this paper analyses a panel of countries with both types of labour markets, I stick to using cost shares.

In addition to the regression results, elasticities of factor demand will be reported. This is in line with almost all studies that model factor demand. As the main interest in this paper lies in the outcomes of the offshoring variables, only the elasticity of factor demand f with respect to a change in offshoring is reported and is calculated as

$$\varepsilon_{fO} = \frac{\delta_{Of}}{s_f}. \tag{6}$$

The elasticities are not constant, but they differ at every data point. It is common practice to calculate them for the mean, so here they will be computed for the average cost shares per labour type across country-industries and time.

5. Data

This section describes the data sources used for the empirical analysis, followed by an explanation of the construction of the offshoring measures. In the end of this section an overview of the summary statistics is provided.

5.1. Sources

The only data source for this paper is the World Input-Output Database (WIOD)[1]. This database provides world input-output tables (WIOT's), containing data on trade, and socio economic accounts, including data on labour variables, capital and output. The WIOD covers 40 countries

[1] Available at www.wiod.org.

subdivided into 35 industries, mostly at the two digit ISIC rev. 3 level or groups thereof, over the period 1995-2011. There is a more recent version of the WIOT's, covering the years 2000-2014, but the socio economic accounts for this time period are not available yet. Therefore, the earlier dataset is used. World input-output tables are constructed by connecting national input-output tables based on bilateral international trade flows and are displayed in an industry by industry format. The columns show the users, which are split into use of intermediate products by country-industries, and use of final products by countries. What makes the world input-output tables distinct from national ones, is that imports are broken down according to the country and industry of origin, in other words the producers, which are indicated by the rows. All values in the tables are expressed in millions of US dollars and reflect all costs borne by the producer. (Timmer, Dietzenbacher, Los, Stehrer & de Vries, 2015).

Since I am interested in the effects of offshoring manufacturing activities from developed countries to China, I do not use the full WIOT. Naturally, only data with China as the producer country will be used. The data on user countries will be reduced to 19 high income countries[2]. The choice of these 19 countries is in imitation of Foster-McGregor et al. (2013), who split their sample of countries by development level as a robustness check, and based their country classification on the 1995 World Development Report (World Bank, 1995). Furthermore, the analysis focuses on manufacturing industries only. For a list of all 14 manufacturing industries, see Appendix A. Depending on the measure for offshoring, the user and/or the producer country-industries will be restricted to only the manufacturing industries. This will be explained later in this section. The time period will be limited to the years 1995-2009, as the socio economic accounts lack most of the data for the years 2010 and 2011. The total number of observations is therefore 3990 (15 years times 19 countries times 14 industries).

All data on the offshoring measures will be retrieved from the world input-output tables from the WIOD. This also includes data on an industry's value added, which is required for these measures. The labour variables are collected from the socio economic accounts, which are also available from the WIOD and are thus provided at the same industry level as the trade data. Data on labour compensation and hours worked is split into three different labour types, namely low

[2] The high income countries are: Australia, Austria, Belgium, Canada, Cyprus, Denmark, Germany, Finland, France, Ireland, Italy, Japan, Luxembourg, the Netherlands, Spain, Sweden, Taiwan, the United Kingdom and the United States.

skilled, medium skilled and high skilled labour. Labour skill types are classified based on educational attainment levels. Each labour type's 'labour compensation as a share of total labour compensation' is given. Multiplying this with 'total labour compensation' will give each labour type's total labour compensation. This is then divided by total variable costs, which is calculated as the sum of 'total labour compensation' and 'intermediate inputs at current purchasers' prices', to get the independent variable, which is the share of each labour type's labour compensation to total costs. To compute the wages for the different labour types, first the total hours worked by each labour type is calculated by multiplying 'hours worked by persons engaged per labour type as a share of total hours worked' with 'total hours worked by persons engaged'. Then, total labour compensation of a labour type, calculated before, is divided by total hours worked by the labour type. This gives the hourly wage of this labour type. Data on intermediate inputs' prices, real fixed capital stock and gross output is directly available from the socio economic accounts.

There are only a few observations that contain missing values for some of the socio economic account variables. Furthermore, there are a few observations with values of zero for value added, which results in missing values for the offshoring measures. However, since these observations are exactly the same ones as the ones that lack data on labour variables, and therefore their values for the dependent variables are missing, there is no need to slightly increase the zero values for value added. This results in only 35 observations being omitted from the analysis. The panel dataset therefore remains highly balanced.

5.2. Offshoring measures

As offshoring cannot be directly observed at the industry level, adequate proxies are required. The majority of the existing literature uses imported intermediate inputs as the base for its proxy, which I follow. Furthermore, in accordance with other literature, I make a distinction between a narrow and a broad measure for offshoring, which have been introduced by Feenstra and Hanson (1999). Suppose industry i (the user) in country c offshores part of its production to industry j (the producer) abroad, in the case of this analysis only China, where i can be equal to j. The narrow measure for offshoring of industry i in country c only measures inputs that are produced by the same industry ($i=j$). Broad offshoring includes all offshored inputs from outside industry i that are used by industry i in country c ($i \neq j$). This means that inputs produced by each industry in

China (so including non-manufacturing industries) except by industry *i* that are used by industry *i*, which is one of the manufacturing industries, are summed.

To normalize the measure of an industry's imported inputs, it can be divided by the industry's total output (e.g. Schwörer, 2013), the industry's total expenditures on non-energy intermediates (e.g. Feenstra & Hanson, 1999), or the industry's value added (e.g. Foster-McGregor et al., 2013 and Hijzen et al., 2005). Continuing following Foster-McGregor et al., the measure for imported intermediate inputs will be expressed relative to each industry's value added. Narrow offshoring will thus be calculated as

$$O_{ict}^{N} = \frac{III_{i=j,ct}}{VA_{ict}},$$

where III_{ij} denotes imported intermediate inputs by industry *i* from industry *j* and VA denotes value added. Broad offshoring will be calculated as

$$O_{ict}^{B} = \frac{\sum_{j=1}^{J} III_{i\neq j,ct}}{VA_{ict}},$$

Broad offshoring includes activities that are offshored to other industries, so it is less likely that these could have been made within the firm within the country compared to narrow offshored activities (Feenstra & Hanson, 1999). However, they could as well have been domestically outsourced, i.e. made by another industry within the same country. Offshoring production that was formerly domestically outsourced to another industry could therefore affect labour demand in this 'other' industry. Hence, to be able to capture the effect of broad offshoring on labour demand in another industry, a slightly different measure for broad offshoring is required. I am aware of the fact that this effect should not be attributed to the term offshoring if one considers offshoring as the relocation of production that was formerly made domestically within the *firm*. However, when changing this definition slightly this to stating that the offshored good was formerly made within the *country*, the existing literature on offshoring seems to not capture all effects of offshoring on labour demand, which could lead to understating the total effect. In the context of globalisation, in which this study (and as it seems most existing literature on offshoring) is written, the interest seems to lie in the effects of the movement of production processes from home to abroad. Therefore, it seems justifiable to broaden the definition of offshoring.

As an extension to the existing literature, I therefore propose an additional measure for broad offshoring when its effect is assessed on an economic outcome variable at the industry level in the country that offshores, such as labour demand, and when using a looser definition of offshoring is in line with the purpose of the study. If for example the Dutch metal industry imports inputs from a Chinese machinery industry, it could be that not Dutch labour demand in the metal industry is affected, but Dutch labour demand in the machinery industry, as that industry could have been a former supplier. Therefore, continuing with the example, I will measure offshoring of the Dutch metal industry as the inputs that are produced by the Chinese metal industry and used by all Dutch industries (including non-manufacturing industries), except the metal industry itself. In fact, this is equal to what can be called broad inshoring of the Chinese metal industry. Inshoring can be seen as the opposite of offshoring, as the good that is offshored by the using country serves as the inshored good from the point of view of the producer country. Labour demand in industry *i* in for instance the Netherlands will be regressed on inshoring from the same industry *i* in China. Existing studies that focus on the term inshoring always estimate the effect of inshoring on economic variable outcomes in the country that inshores. This is not surprising, as the term inshoring is from the point of view of the producer. As in this analysis the dependent variable is from the point of view of the user country, using the term inshoring will cause confusion. Therefore, this measure will be referred to as the alternative broad offshoring measure.

The key contribution of this analysis to the existing literature is the idea that a measure for inshoring enables one to estimate the impact of offshoring activities to another industry on domestic labour demand in this other industry. Intuitively, an effect will be found when the activity that is offshored was formerly outsourced domestically (to the same industry to which it is offshored). The alternative measure for broad offshoring for industry i in country c is be calculated as

$$O_{ict}^{B*} = \frac{\sum_{j=1}^{J} EII_{i \neq j,ct}}{VA_{j=i,ct}},$$

where EII_{ij} denotes the exported intermediate inputs from industry i in China to industry j in country c. $VA_{j=i}$ denotes the value added of industry j that is equal to industry i, so for the above example it is the value added of the Dutch metal industry.

Note that to the extent that there are inter-industry linkages between Dutch industries and the Dutch metal industry, the alternative broad offshoring measure also captures indirect effects of offshoring on subcontractors in that metal industry. There might be an indirect substitution effect, when offshoring affects employment of subcontractors (Cappariello, 2010). The increase in output that follows from the productivity effect might however be beneficial to other sectors in the domestic economy, as it may lead to increased demand for intermediate goods which production remained domestic (Arndt, 1997). The relative price effect can of course fade out this latter effect. The idea behind these indirect effects and the effect that I try to capture with the alternative broad offshoring measure are the same, namely that offshoring can have an effect on labour demand in other industries than the one that offshores. By far not all the indirect effects will be captured though, as the Dutch metal industry will not be the only subcontractor of the industry that offshores and the offshoring industry does not only offshore to the Chinese metal industry. Another measure would be needed for that, which is beyond the scope of this paper. In fact, even though the economic theory is based on a multi-sector model, almost all empirical papers ignore the interdependencies between sectors and thus do not account for inter-industry spillover effects. This is probably due to the complex implementation in empirical research. The only empirical papers that accounted for inter-industry spillover effects are, to the best of my knowledge, Cappariello (2010) and Egger and Egger (2005).

In accordance with the existing literature on the effect of offshoring on labour demand, the previous measures are restricted to trade in intermediate inputs and leave out trade in final goods. I propose a second additional measure of offshoring, in which final goods trade is included. There are two reasons for this. The first and most evident one is that looking only at data on intermediate goods trade ignores the possibility that the final stages of production, such as assembly, are offshored. This seems an important limitation especially for this analysis, as China is known for its large role in assembly activities. This shortcoming of using input-output tables with only data on intermediate goods in analysing the effects of offshoring is also stressed by Hijzen (2005). The second reason is that it is possible that a firm offshores all its production tasks, as has also been noted in the theoretical section. Such offshoring will also end up in final goods trade data, even though at least some labour is required for services that can only be carried out domestically. However, data on final goods naturally also contains goods that are entirely made abroad and that even have not been formerly made domestically. In other words, not only the effects of offshoring, but also of import competition will be measured. This is a shortcoming of using final goods data, so the results must be interpreted with caution. Final goods trade has to be incorporated in a measure for offshoring in a similar way as the alternative broad offshoring measure has been structured, as in the data the use of final goods are categorized by the end user (consumers, governments or firms) and not by industries. The measure for offshoring final inputs for industry *i* in country *c* includes the final goods imports coming from industry *i* in China which are exported to all end users *h* in country *c*, and is thus calculated as:

$$O_{ict}^{FI} = \frac{\sum_{h=1}^{H} EFG_{ih,ct}}{VA_{ict}},$$

where EFG_{ih} denotes exported final goods from industry *i* in China to end user *h* in country *c*. VA_i denotes the value added of industry *i* in country *c*.

5.3. Summary statistics

An overview of the summary statistics of all variables' growth rates is provided in Table 1. As can be seen, the cost share of low skilled labour has declined on average during the years 1995-2009, while the medium and high skilled labour cost share increased, the latter on average more than the former. Hence, the gap between lower and higher skilled workers widened over these years. The data show that this is due to an increased employment gap rather than a wage gap, as the wages of the three labour types increases on average by the same amount. The offshoring intensities have also grown over this time period.

Table 1: Summary statistics

	Observations	Mean	Standard deviation	Minimum	Maximum
Cost shares					
Δs_L	3,690	-0.0268	0.281	-0.967	11.38
Δs_M	3,690	0.00595	0.132	-0.489	3.811
Δs_H	3,690	0.0366	0.171	-0.588	4.276
Δs_{II}	3,690	0.00106	0.0247	-0.376	0.322
Input quantities					
ΔL	3,693	-0.0343	0.348	-1	15.99
ΔM	3,693	-0.00454	0.104	-1	2.200
ΔH	3,693	0.0273	0.134	-1	2.482
ΔII	3,693	0.0291	0.128	-1	2.363
Flexible factor prices					
Δw_L	3,690	0.0310	0.0901	-0.565	1.257
Δw_M	3,690	0.0326	0.0709	-0.468	0.938
Δw_H	3,690	0.0306	0.0859	-0.457	0.992
Δw_{II}	3,724	0.0153	0.0846	-0.433	1.562
Fixed input and output quantities					
ΔK	3,374	0.0243	0.0721	-0.758	2.441
ΔY	3,693	0.0241	0.111	-1	1.436
Offshoring					
ΔO^N	3,690	1.226	29.02	-0.999	1,565
ΔO^B	3,690	0.185	0.431	-0.959	8.106
ΔO^{B*}	3,690	0.283	3.754	-0.934	224.0
ΔO^{FI}	3,690	0.213	1.465	-0.992	65.646

6. Expectations and Hypotheses

In this section the expectations of the regression coefficients are discussed, based on economic theory. From these expectations, hypotheses are derived if possible.

6.1. Offshoring variables

The expected effects of offshoring can be derived from the theory discussed in Section 2. First of all, it is however important to note that the offshoring variables, as outlined above, are mere proxies for offshoring. By using trade in intermediate goods at the industry level, it cannot be ruled out that some inputs were never made domestically. This means that while theoretical model assumes that any increase in offshoring induces changes in labour demand, this is not necessarily the case in the empirical model.

The effects of the offshoring measures are expected to be different in the conditional and the unconditional model. In the former, only the substitution effect and the subsequent labour supply effect can play a role, as output is not allowed to change. The substitution effect and the labour supply effect both work in the same direction and affect labour demand that was used intensively in the offshored tasks negatively. A negative coefficient will therefore be found on the cost share of the labour type that has been offshored away. Assuming that offshored tasks are tasks that are made with relatively unskilled labour (without this assumption no expectations can be formed at all), the relative demand for low skilled labour is expected to decrease. In the unconditional model, the productivity effect and the relative price effect are additional effects that are at play, as the results are not conditional on output. While the productivity effect has a positive effect on relative demand of the labour type that is offshored away, the relative price effect has a negative effect. According to the theoretical model, the positive productivity effect will dominate the negative substitution effect. If the negative coefficient is on the same cost share as in the conditional model, which is assumed to be on the low labour cost share, this must therefore be caused by the labour supply effect and the relative price effect. If the negative coefficient in the conditional model turns into a positive one, it implies that the productivity effect is larger than the other effects together. All in all, in the unconditional model the net effects of an increase in offshoring on the relative labour demand of the different labour types are ambiguous.

Note that if only the unconditional model would be estimated, no conclusions could be drawn as to which effect dominates the other. This is because one should first know which labour type is initially substituted for offshoring, which can be inferred from the outcomes of the conditional model. The effects in the unconditional model can reverse the relative demand for the labour type that is substituted for offshoring, which may make it seem that another labour type is used intensively in the tasks that are offshored. Also note that in the theoretical model there were two types of labour, whereas the data used here distinguishes between three types of labour. Therefore, the effect on the middle one, medium skilled labour, remains ambiguous, but if we assume that low skilled labour is offshored away, it is expected that its coefficient lies in between the coefficients of low and high skilled labour.

Furthermore, it is important to note that, as the dependent variables do not only include payments to labour but also to material inputs, it is possible that all coefficients of an offshoring variable on the labour cost shares have the same sign. This is the case when the change in absolute payments to material inputs is equal to the change in absolute payments to the three labour inputs together. More specifically, as an increase in offshoring will increase the payments to material inputs, it is possible that the signs of the coefficients of offshoring on the labour cost shares are all negative. This means that materials substitute for all types of labour. The change in labour demand of a certain type relative to the other labour types can still be inferred from the regression output though, by comparing the sizes of the coefficients. In case of all negative signs in the conditional model, the absolute value of the coefficient is expected to be largest for the low skilled labour cost share, followed by the medium skilled cost share and the high skilled cost share.

As the offshoring variables are different proxies for offshoring, the circumstances under which the effects are at play differ among them. The narrow measure for offshoring is commonly said to be more closely related to offshoring than the broad measure (Feenstra & Hanson, 1999), as by definition offshoring represents the transfer abroad of production activities that were formerly made by the company within the country, and the closer the inputs are to final outputs, the more likely it is that domestic labour within the firm could have produced those inputs (Hummels, Jorgensen, Munch and Xiang, 2014). Offshoring an activity to a firm in another industry is expected to have a smaller effect on labour demand in the industry to which the firm belongs that offshores, as this activity was less likely made by the industry itself beforehand, i.e. the substitution effect and hence the subsequent other effects are less likely to be at play. For the alternative broad offshoring measure the substitution effect and the labour supply effect are at play to the extent that the offshored tasks were formerly outsourced domestically. Another condition is that it must be offshored to the same industry as to which it was formerly outsourced. If part of these tasks remained to be outsourced domestically, the productivity effect, and hence the subsequent relative price effect can work. Furthermore, as mentioned in section 5, the alternative measure for broad offshoring captures some indirect effects of offshoring if there are inter-industry linkages. If all the formerly domestically outsourced tasks are moved abroad, and if there are no inter-industry linkages, there is only a substitution and a labour supply effect. Regarding the final goods offshoring measure, the substitution and hence all other effects are only at play if the industry to which the final stage of production is offshored is the same is the same industry that formerly carried it out domestically.

6.2. Factor price variables

The coefficients of the factor prices (γ_{fj}) depend on whether the different types of labour and material inputs are substitutes for or complements to each other. This rate at which inputs can be substituted for each other while output remains the same is called the marginal rate of technical substitution (MRTS) and allows producers to react to changes in relative input prices. Assume that there are two inputs, then graphically, the MRTS is the slope of a firm's isoquant curve, which shows the possible combinations of the inputs that are needed to produce a certain amount of output. A profit maximising firm chooses the quantity of inputs where the MRTS is equal to the slope of the isocost line, which shows the price ratio of the two inputs. If the isoquant curve is L-shaped, it is impossible to substitute one input for another and hence they are perfect complements. On the contrary, if the isoquant curve is a straight line with slope -1, the inputs are perfect substitutes. When the isoquant is convex inputs are imperfect substitutes and the MRTS changes along the isoquant. The MRTS describes the firms' technology. Wolcowitz (2014) explains that a change in relative factor prices affects relative factor demand through a substitution effect and an output effect, and the analysis generalises to more than two inputs.

If for instance the wage for low skilled labour decreases, the relative price of low skilled labour decreases, keeping the price of the other input constant. As this type of labour becomes cheaper compared to the other factor, the isocost line rotates and the firm chooses a different input mix, even if it would produce the same amount of output. More specifically, if the inputs are imperfect substitutes, the use of low skilled labour increases and demand for the other inputs decrease. This is the substitution effect. In case of perfect substitutes, the substitution effect is very large, while if the inputs are perfect substitutes, the input mix does not change, meaning that there is no substitution effect (Borjas, 2013). As mentioned, there is a second effect. As the costs of producing any amount of output reduces, the isocost line shifts outward. Therefore, the firm will increase its output in order to maximize profits and hence demand more factors of production. Since constant returns to scale are assumed, the production function must be homogenous, and therefore also homothetic, i.e. the expansion path (which connects the points of the optimal input mix for different output quantities) of the firm is a straight line through the origin (Rasmussen, 2012). For these type of functions, the MRTS does not change along any ray through the origin. Hence, it is expected that the output effect will not change the relative demand for the factors of production, given the new relative factor prices. Therefore, not only the sign but also the size of the coefficients of a factor price are expected to be the same in the conditional and the unconditional model.

The own-price and the cross-price coefficients are however hard to interpret. This is probably the reason as to why other empirical literature does not comment on the results of these coefficients whatsoever. The difficulty lies in the fact that the dependent variables, the cost shares, are not in real terms but in nominal terms. From the micro economic theory described above, we know that an increase in an inputs' price causes a substitution away from this input in real terms (Cronin, Gold, Herbert and Lewitzky, 1993), due to the negative relationship between price and quantity demanded. However, how the nominal payments to this input change depends its price elasticity of demand. Instead of interpreting the obtained coefficients, the existing literature directly estimates these elasticities. By examining the formulas of the elasticities however, the interpretation of the coefficients can be derived, which is to the best of my knowledge not done before. To see the dependence between the two, consider the formula for the own-price elasticity:

$$\eta_{fj} = \frac{\gamma_{fj}}{s_f} + s_j - 1 \text{ }, with\ f = j$$

As mentioned, the own-price elasticity is always negative and the cost share is by definition positive. By rearranging the terms, we get that $\gamma_{fj} = (\eta_{fj} - s_j + 1)s_f$. So, if $\eta_{fj} > s_j - 1$, the coefficient will be positive. This outcome can thus be obtained only when input demand is inelastic (η_{fj} is between -1 and 0) and it must be even more inelastic when the cost share is high. The coefficient is negative if $\eta_{fj} < s_j - 1$. Hence, even with an inelastic input demand, a negative coefficient can be obtained, which might be counterintuitive. This becomes more likely when the cost share is high. If input demand is elastic ($\eta_{fj} < -1$), the coefficient must be negative. Due to the above, even if an inelastic input demand is assumed, no expectations can be formed about the sign of the own-price coefficient.

Also the cross-price coefficient depends on its cross-price elasticities, which give the answer as to whether inputs are substitutes or complements to other input's price changes. Calculating cross-price elasticities of factor demand from a translog cost function is done with the following formula:

$$\eta_{fj} = \frac{\gamma_{fj}}{s_f} + s_j, with\ f \neq j$$

By rearranging the equation, it can be seen that if $\gamma_{fj} > 0$, it must be true that $\eta_{fj} > s_j$, and since the cost shares are by definition larger than zero, we get that the elasticity is positive. A positive cross-price elasticity means that if the price of one input goes up, the quantity demanded for the other input goes up, and hence these two inputs are substitutes. However, if $\gamma_{fj} < 0$, this means that $\eta_{fj} < s_j$, and the sign of the elasticity becomes ambiguous. Therefore, not only is the expected sign of the coefficient of the factor price variable ambiguous, if the estimated coefficient is negative it is not possible to conclude whether the inputs are substitutes or complements. Only if it is positive, it can be said with certainty that the inputs are substitutes. For these reasons no expectations can be formed about the cross-price coefficients either. As the factor price coefficients are not of particular interest for this paper, their elasticities will not be calculated.

6.3. Capital and output variables

As briefly mentioned in a footnote in Hijzen et al. (2005), if there are constant returns to scale, the coefficients of the capital stock and output should mirror each other. This can be explained as follows. With constant returns to scale, the optimal input mix of production should not change, given variable input prices, as the production function is homogeneous and therefore homothetic. To keep the relative demand of a production factor unchanged, the coefficients of the capital stock and output on this factor must cancel out. Hence, the coefficients must be opposite in sign, as well as equal in absolute size.

6.4. Hypotheses

The expected signs of the offshoring variables for the conditional and the unconditional model are summarised in Table 2 and Table 3 respectively.

Table 2: Expected signs conditional model

Conditional model	Δs_L	Δs_M	Δs_H
ΔO^N	-	-/+	+
ΔO^B	-	-/+	+
ΔO^{B*}	-	-/+	+
ΔO^{FI}	-	-/+	+

Table 3: Expected signs unconditional model

Unconditional model	Δs_L	Δs_M	Δs_H
ΔO^N	-/+	-/+	-/+
ΔO^B	-/+	-/+	-/+
ΔO^{B*}	-/+	-/+	-/+
ΔO^{FI}	-/+	-/+	-/+

7. Results

This section presents the regression output and the interpretation of the results. I begin by estimating the conditional labour demand function and by including the narrow offshoring measure only, as that measure is closest to the essence of offshoring according to Feenstra and Hanson (1999). In addition to the regression output, estimated elasticities will be reported. This is repeated when broad offshoring is included in the regression, followed by the proposed alternative measures for broad offshoring and for final goods offshoring. Finally, the unconditional demand function is estimated, with all offshoring measures directly included.

7.1. Conditional model

7.1.1. Narrow offshoring

Appendix B shows the results of equation (3) for each labour type, which is estimated with an iterated SUR model including the narrow offshoring measure only. Using the iterated SUR instead of non-iterated SUR model ensures that the results are invariant to the equation dropped. This also allows showing the outcomes of the material input cost share, which are obtained by estimating again the system of equations and now dropping one of the labour cost share regression equations. By doing that, it can be seen that the coefficients of each variable add up to zero. As can be observed, the symmetry restrictions are not yet imposed. A Wald test of symmetry shows that the null hypothesis of equal coefficients of factor j's wage effect on factor f's cost share and factor f's wage effect of the cost share of factor j can be rejected at a 1% significance level in four out of the six cases ($\gamma_{LM} = \gamma_{ML}$, p=0.152; $\gamma_{LH} = \gamma_{HL}$, p=0.001; $\gamma_{MH} = \gamma_{HM}$, p=0.009; $\gamma_{LII} = \gamma_{IIL}$, p=0.000; $\gamma_{MII} = \gamma_{IIM}$, p=0.000 and $\gamma_{HII} = \gamma_{IIH}$, p=0.849). However, due to the fact that the model is a second-order approximation of an unknown cost function, it is not possible to rule out misspecification issues, which typically prevents such a model from exact alignment with the theoretical restrictions (Manera and Sitzia, 2000). In fact, in most factor demand studies symmetry constraints are not satisfied, but they are imposed anyway (Manera & Sitzia). As I do not make deviations from the existing literature in this respect, in the rest of the analysis the symmetry restrictions will be imposed.

Table 4 shows the results when the same model is estimated again, but now with the symmetry restrictions imposed. Due to the symmetry restrictions it is not possible anymore to show the results of all four cost equations together. This is because not all restrictions can be imposed simultaneously and therefore now the coefficients of the restricted parameters are dependent on which equation is dropped. As mentioned before, the material input cost share will be omitted. The coefficients of all variables do not change in sign and significance and only very slightly in size, compared to the regression output without the symmetry restrictions.

Table 4: ISUR output with narrow offshoring included and with symmetry restrictions imposed

	(1) Δs_L	(2) Δs_M	(3) Δs_H
Δlnw_L	0.0523***	-0.0158***	-0.0129***
	(0.00127)	(0.00116)	(0.000906)
Δlnw_M	-0.0158***	0.0761***	-0.0188***
	(0.00116)	(0.00226)	(0.00147)
Δlnw_H	-0.0129***	-0.0188***	0.0450***
	(0.000906)	(0.00147)	(0.00137)
Δlnw_{II}	0.00969***	0.00775***	0.00178
	(0.00145)	(0.00172)	(0.00133)
ΔlnK	0.00675***	0.0204***	0.00592***
	(0.00186)	(0.00221)	(0.00171)
ΔlnY	-0.0293***	-0.0517***	-0.0283***
	(0.00124)	(0.00147)	(0.00114)
ΔO^N	-0.0494***	-0.0636***	-0.0104
	(0.0141)	(0.0168)	(0.0130)
Constant	-0.00271***	-0.000619***	0.00170***
	(0.000125)	(0.000150)	(0.000115)
Observations	3,370	3,370	3,370
R-squared	0.405	0.371	0.284

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results in Table 4 show that all coefficients, except two, are significant at a 1% significance level. The own-wage coefficients are positive, meaning that input demand is inelastic, i.e. that input quantity demanded changes less than proportional to a change in its price. The cross-wage coefficients are all negative. As explained in Section 6, from this result it cannot be derived whether the different types of labour substitute for or complements to each other. The price of intermediate inputs positively affects all labour cost shares, but not significantly on high skilled cost share. This implies that intermediate inputs act as substitutes for low and medium skilled workers. Capital turns out to have a positive effect on all labour shares, while output negatively affects them. This is in line with the assumption of constant returns to scale. The absolute sizes of the coefficients are not exactly equal though.

All coefficients of the narrow offshoring measure have a negative sign, meaning that narrow offshoring reduces demand for all labour types, in favour of material inputs. However, its effect is strongly significant for the cost shares of low and medium skilled labour, while it is not significant for the high skilled labour cost share. Furthermore, the absolute values of the coefficients are smallest for the high cost share. This is in line with the expectations that the substitution effect and the labour supply effect lower the demand for lower skilled labour relative to higher skilled labour. Remarkably, it turns out that the effect of offshoring is larger in size on medium than on low skilled labour demand, although this difference is small. This seems to suggest that firms offshore more tasks that require medium skilled labour than tasks that are produced with low skilled labour. The constant, which is the time trend that aims to capture factor biased technological change, has a significant negative coefficient on low and medium skilled labour demand, while it is positive and highly significant for high skilled labour demand. This implies that technological change works to the disadvantage of low skilled labour demand and, to a smaller extent also medium skilled labour demand, which is in line with the expectations. The results confirm the idea that both offshoring and technological change have a skill biased effect on relative demand for labour in favour of the high skilled. The signs of all variables are completely in line with the results of Hijzen et al. (2005). Compared to the main results found by Foster-McGregor et al. (2013), the signs of the non-offshoring coefficients are partly different, but those of offshoring are the same.

A Breusch-Pagan test ensures that it is more efficient to estimate the equations jointly with SUR than separately by using OLS; the null hypothesis of independence between the residual vectors of the different regression equations can be rejected at the 1% significance level (p=0.000).

By estimating the translog cost function on the full sample of manufacturing industries it is implicitly assumed that the same cost function applies across all manufacturing industries. This means that so far, potential heterogeneity in demand across different industries has been ignored. It might be more realistic to allow industries to have a different cost functions. Even though manufacturing industries are already a subsample of the full sample of industries, it could still be that in one manufacturing industry offshoring acts as a substitute to a certain type of domestic labour, whereas in another it serves as a complement, or as also as a substitute but to another extent. To address this issue, industries are split into low-, medium- and high-tech manufacturing industries, as is done by Foster-McGregor et al. (2013). The allocation of the industries to these categories, which is also taken from Foster-McGregor et al., is shown in the third column of Appendix A. Table 5 provides the coefficients of narrow offshoring split by industry type.

The results show that the significant negative effect of narrow offshoring on low and medium skilled labour demand are caused by offshoring in low- and medium-tech industries. This is in line with the theory, which predicts that the effect of offshoring is more pronounced in the unskilled labour intensive industries. More surprising is that not the low- but the medium-tech industries are mainly responsible for this decline, as appears from the larger size of the coefficients in the regressions with the latter industries included. This suggests that firms in this sector substitute more labour for imported intermediate inputs than firms in other sectors. The coefficient on high skilled labour in the medium-tech sector is significant at a 10% significance level, but its size remains smaller than the coefficient on the other cost shares. Offshoring from high-tech manufacturing industries does not affect relative labour demand significantly for any labour type. The constant is largely the same across industry types.

Table 5: ISUR output of narrow offshoring measure by industry type

	(1)	(2)	(3)
	Δs_L	Δs_M	Δs_H
Low tech			
ΔO^N	-0.0529***	-0.0706***	-0.0102
	(0.0147)	(0.0195)	(0.0148)
Constant	-0.00326***	-0.000672***	0.00167***
	(0.000159)	(0.000214)	(0.000160)
Observations	1,444	1,444	1,444
R-squared	0.491	0.391	0.324
Medium tech			
ΔO^N	-0.452**	-0.719***	-0.323*
	(0.192)	(0.230)	(0.177)
Constant	-0.00223***	-0.000620**	0.00158***
	(0.000245)	(0.000297)	(0.000227)
Observations	954	954	954
R-squared	0.325	0.308	0.213
High tech			
ΔO^N	-0.0229	-0.0105	0.0104
	(0.0284)	(0.0294)	(0.0241)
Constant	-0.00219***	-0.000128	0.00216***
	(0.000293)	(0.000309)	(0.000250)
Observations	972	972	972
R-squared	0.435	0.463	0.342

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Next I turn to the estimated elasticities, which allow for a more precise interpretation of the above obtained results. The elasticities are evaluated at the mean cost shares per labour type, which are averaged across all countries, industries (or industry types) and years and are reported in Appendix C. Additionally, average cost shares split by industry type are reported. As can be seen in the Appendix, the material costs make up the largest part of the total variable cost share and the cost shares are very similar across industry types. The reason for the latter can be found by looking at the raw data, where the values for 'labour compensation as a share of total labour compensation' are in some cases exactly the same for each industry in a country in a year. This is of course a limitation of the dataset. The elasticities of the cost shares with respect to narrow offshoring, which are calculated according to equation (6), are displayed in Table 6. These elasticities are based on the narrow offshoring coefficients from Table 4 and Table 5.

Table 6: Estimated elasticities of narrow offshoring measure

	(1)	(2)	(3)
	s_L	s_M	s_H
All industries	-0.756***	-0.531***	-0.182
	(0.216)	(0.140)	(0.227)
Low tech	-0.808***	-0.590***	-0.178
	(0.224)	(0.163)	(0.259)
Medium tech	-6.905**	-6.008***	-5.646*
	(2.933)	(1.921)	(3.091)
High tech	-0.350	-0.087	0.182
	(0.434)	(0.245)	(0.420)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The elasticity of for instance the low skilled labour cost share with respect to a change in narrow offshoring across all industries is 0.756, meaning that a 1% increase in narrow offshoring results in a 0.765% decrease in the relative demand for low skilled labour, keeping output and all other inputs constant. Despite the fact that the coefficients of narrow offshoring in the regression were largest for medium skilled labour, when considering elasticities this is no longer the case. This is in line with part of the results of Foster-McGregor et al. (2013), and this is caused by the relatively high cost shares of medium skilled labour, which dampen the estimated elasticities of this labour type to some extent. Therefore, it appears that not medium but low skilled labour demand is hardest hit by narrow offshoring.

7.1.2. Narrow and broad offshoring

In this subsection the same ISUR is estimated, but now the broad measure for offshoring is included in addition to the narrow one. The results are shown below in Table 7. When comparing the results from the regression output with and without the broad offshoring measure, it can be observed that none of the coefficients changes in sign or significance, and only very slightly in size. This implies that the variables are not correlated with the broad offshoring variable. The coefficient of broad offshoring itself shows a somewhat similar pattern as that of narrow offshoring, as could have been expected. Broad offshoring has a larger negative effect on the low skilled labour cost share than narrow offshoring, and this effect is highly significant. Hence, it seems to be the case that core tasks that are offshored require relatively more medium skilled labour, while non-core tasks that are offshored require relatively more low skilled labour. This is however not logical, as with certain costs for offshoring, it would be earlier profitable to offshore tasks that are made in-house relatively inefficient (non-core tasks), so the opposite would be expected. Another underlying reason for this result could be that tasks that require medium skilled labour are already outsourced domestically before they were offshored, although this would also be more likely for low skilled labour. The effect of broad offshoring on the cost share of high skilled labour is positive, which means that labour demand for high skilled labour increases as broad offshoring increases. However, the effect is not statistically significant.

Table 7: ISUR output with narrow and broad offshoring measures included

	(1) Δs_L	(2) Δs_M	(3) Δs_H
$\Delta \ln w_L$	0.0530***	-0.0160***	-0.0132***
	(0.00127)	(0.00116)	(0.000906)
$\Delta \ln w_M$	-0.0160***	0.0761***	-0.0187***
	(0.00116)	(0.00226)	(0.00147)
$\Delta \ln w_H$	-0.0132***	-0.0187***	0.0451***
	(0.000906)	(0.00147)	(0.00137)
$\Delta \ln w_{II}$	0.00943***	0.00768***	0.00181
	(0.00144)	(0.00172)	(0.00133)
$\Delta \ln K$	0.00694***	0.0205***	0.00591***
	(0.00185)	(0.00221)	(0.00171)
$\Delta \ln Y$	-0.0286***	-0.0515***	-0.0284***
	(0.00123)	(0.00148)	(0.00115)
ΔO^N	-0.0435***	-0.0620***	-0.0111
	(0.0140)	(0.0168)	(0.0130)
ΔO^B	-0.0865***	-0.0220	0.00977
	(0.0117)	(0.0140)	(0.0109)
Constant	-0.00262***	-0.000592***	0.00169***
	(0.000125)	(0.000151)	(0.000116)
Observations	3,370	3,370	3,370
R-squared	0.415	0.372	0.284

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To provide a more detailed look into the results, the industries are again split into low-, medium- and high-tech manufacturing industries. Table 8 displays the coefficients of the offshoring measures only. The constant gives rather similar results as in Table 5, which is why it is omitted.

Table 8: ISUR output of narrow and broad offshoring by industry type

	(1) Δs_L	(2) Δs_M	(3) Δs_H
Low tech			
ΔO^N	-0.0471***	-0.0634***	-0.00793
	(0.0147)	(0.0196)	(0.0149)
ΔO^B	-0.143***	-0.179***	-0.0537
	(0.0389)	(0.0518)	(0.0394)
Observations	1,444	1,444	1,444
R-squared	0.495	0.396	0.324
Medium tech			
ΔO^N	-0.349*	-0.735***	-0.360**
	(0.191)	(0.231)	(0.178)
ΔO^B	-0.0682***	0.0111	0.0254**
	(0.0139)	(0.0168)	(0.0130)
Observations	954	954	954
R-squared	0.342	0.308	0.215
High tech			
ΔO^N	-0.0130	0.00123	0.0147
	(0.0285)	(0.0295)	(0.0242)
ΔO^B	-0.0971***	-0.116***	-0.0422
	(0.0362)	(0.0375)	(0.0308)
Observations	972	972	972
R-squared	0.439	0.468	0.343

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Remarkably, it can be observed that the insignificant coefficient of broad offshoring on medium skilled labour demand is solely driven by medium-tech industries. Such a result in this type of industry makes more sense, as in medium-tech sectors, the core activities are likely to require medium skilled labour, whereas non-core activities thus require low or high skilled labour. Broad offshoring in the medium-tech sector is therefore likely to harm low skilled labour more than in other industry types. Low-tech industries that offshore non-core activities reduce relative demand for medium skilled labour more than for low skilled labour, although the difference is small. This brings me to another striking result, namely that offshoring does seem to affect labour demand in the high-tech manufacturing sector; the coefficients of broad offshoring on low and medium skilled labour demand are significant at a 1% significance level. The narrow offshoring measures in this sector being still insignificant suggests that in high-tech industries, offshoring activities to the same high-tech industry does not substitute for low and medium skilled labour, but offshoring them to other industry types does. The results also show that the larger coefficient of broad offshoring compared to narrow offshoring on low skilled labour demand as found in Table 7 is driven by the low- and high-tech industries. Lastly, high skilled labour demand in the medium-tech sector is negatively affected by narrow offshoring, but positively by broad offshoring, both at a significance level of 5%.

The estimated elasticities derived from the coefficients of offshoring in Table 7 and Table 8 are shown in Appendix D. Now it becomes clear that in each industry type, broad offshoring affects mostly low skilled labour, followed by medium and high skilled labour. This is thus also the case in low- and high-tech industries, where regression coefficients suggested otherwise. Due to the marginal changes in the narrow offshoring coefficients when broad offshoring was included, the pattern in the elasticities of narrow offshoring in the medium-tech industry change; medium and high skilled labour are substituted to a larger extent for imported intermediate inputs from the same industry than low skilled labour. This contradicts with the expectations. The pattern for narrow offshoring elasticities when considering all industries together remains the same, though.

7.1.3. Narrow, broad and alternative broad offshoring

Until now only changes in labour of the industry that offshores were assessed. However, if these activities were formerly already outsourced domestically to another industry, labour demand in that industry is expected to change. This effect can be captured by including an alternative measure for broad offshoring in the regression, which is outlined in the data section. Including both broad offshoring measures in the regression might lead to multicollinearity, as the measures are constructed with exactly the same data. Therefore, I estimate a regression with only the alternative broad offshoring measure (see Appendix E) as well as a regression with both broad offshoring measures, shown in Table 9, which allows for a comparison of the results. By comparing the results of the broad offshoring in Table 7 (and also Table 8) with those in Table 9 shows that they are very similar. Furthermore, the results of the alternative broad offshoring measure in Appendix E and those in Table 9 (for all industries) are also very much alike. I therefore continue with the model with both broad offshoring measures included.

The regression results for the non-offshoring variables and the constant are very similar to the ones obtained in the previous regressions. For that reason, the complete regression output is shown in Appendix F. The results for the offshoring variables split by industry type are also shown in Table 9. Note that the interpretation of the industry type differs between the broad and the alternative broad offshoring measure. In the former, for instance low-tech industries refer to the user industry that offshores, whereas in the latter, it refers to the industry that has produced the inputs. It is however not necessarily the case that for instance the low-tech industry produces inputs that require low skilled labour only.

Table 9: ISUR output of narrow, broad and alternative broad offshoring measures

	(1) Δs_L	(2) Δs_M	(3) Δs_H
All industries			
ΔO^N	-0.0347**	-0.0724***	-0.0144
	(0.0147)	(0.0176)	(0.0137)
ΔO^B	-0.0849***	-0.0238*	0.00915
	(0.0118)	(0.0141)	(0.0109)
ΔO^{B*}	-0.00691*	0.00823*	0.00266
	(0.00357)	(0.00427)	(0.00331)
Observations	3,370	3,370	3,370
R-squared	0.415	0.373	0.284
Low tech			
ΔO^N	-0.0519***	-0.0780***	-0.0122
	(0.0160)	(0.0213)	(0.0162)
ΔO^B	-0.148***	-0.191***	-0.0575
	(0.0393)	(0.0523)	(0.0398)
ΔO^{B*}	0.00472	0.0145*	0.00430
	(0.00635)	(0.00846)	(0.00644)
Observations	1,444	1,444	1,444
R-squared	0.496	0.397	0.325
Medium tech			
ΔO^N	-0.373*	-0.655**	-0.212
	(0.216)	(0.262)	(0.201)
ΔO^B	-0.0685***	0.0121	0.0272**
	(0.0140)	(0.0169)	(0.0130)
ΔO^{B*}	0.00472	-0.0155	-0.0290
	(0.0196)	(0.0237)	(0.0182)
Observations	954	954	954
R-squared	0.342	0.308	0.217
High tech			
ΔO^N	0.00619	-0.0139	0.00715
	(0.0295)	(0.0305)	(0.0251)
ΔO^B	-0.0890**	-0.122***	-0.0454
	(0.0362)	(0.0376)	(0.0309)
ΔO^{B*}	-0.0114**	0.00896*	0.00448
	(0.00464)	(0.00481)	(0.00396)
Observations	972	972	972
R-squared	0.443	0.470	0.344

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To start with, not only the coefficients for broad but also for narrow offshoring have remained almost completely the same, except for the coefficient of narrow offshoring on high skilled labour in the medium-tech sector, which is not significant anymore. Apparently, it was taking up part of the effect of alternative broad offshoring. More interesting are the results for the alternative broad offshoring measure. Considering all industries together, the alternative broad offshoring measure has a negative effect on the demand for low skilled labour and a positive effect on medium skilled labour demand, although these effects are only significant at a 10% significance level. This indicates that tasks that were formerly outsourced domestically and now moved abroad substitute for low skilled labour, whereas they complement to medium skilled labour. The previously made suggestion that the insignificant coefficient of broad offshoring on medium skilled labour found in Table 7 was because tasks that require medium skilled labour were already outsourced domestically turns out to be incorrect. Nevertheless, allowing for an additional measure for broad offshoring suggests that the widening wage and/or employment gap between low and higher skilled labour can be accounted to offshoring to an even larger extent.

The effect on low skilled labour demand is entirely driven by the high-tech manufacturing sector and the effect on medium skilled labour demand by the low- and high-tech industries. The overall result in the low-tech sector is however not as would be expected; all coefficients are positive, and the one on medium skilled labour demand is largest and is the only one that is significant. For the medium-tech sector, all coefficients are insignificant. Insignificant coefficients for each labour cost share for an industry type suggests that either production that is outsourced domestically is not moved abroad, and therefore does not substitute for or complement to labour demand, or production that is offshored was not outsourced domestically in the first place, at least not in the time period 1995-2009.

The estimated elasticities that are computed by using the coefficients from Table 9 are provided in Appendix G. The overall pattern of the effects of the alternative broad offshoring measure does not change when considering elasticities. What does change are the elasticities of narrow offshoring, which have become larger in absolute size for medium skilled labour demand than low skilled labour demand, although the difference is small. While the narrow offshoring elasticity in the medium-tech sector has again its expected outcome, as the largest negative elasticity is found on the low skilled cost share, followed by the medium and high skilled cost share, now the narrow offshoring elasticities in the high-tech sector are not in line with the expectations. Even though the latter are all insignificant, they seem to drive the results when all industries are assessed together.

7.1.4. Narrow, broad, alternative broad offshoring and offshoring of final inputs

Finally, the effects of offshoring the final stages of production are assessed by including the measure containing trade in final goods in addition the measures with trade in intermediate goods. Again, the complete regression output is provided in Appendix H, as the non-offshoring measures have not changed markedly. In Table 10 the coefficients of the alternative broad offshoring measure for intermediate inputs (O^{B*}) and the measure for offshoring of final inputs (O^{FI}) are be provided, for all industries together and for each industry type separately. As this type of offshoring is measured in the same way as the alternative broad offshoring measure, the industry type again refers to the producing industry. The coefficients for narrow and broad offshoring are not shown as they are very similar to the ones obtained in Table 9.

The coefficients of the alternative broad offshoring measure do not change in sign and only some of them become somewhat more statistically significant. The results for offshoring of final goods on relative domestic labour demand are rather unexpected. Looking at all industries together, results suggest that medium and high skilled labour demand are negatively affected by this type of offshoring, and even most significantly for high skilled labour demand. On the contrary, the coefficient on low skilled labour demand has a positive sign, although it is not significant. The pattern that low skilled labour benefits from offshoring relative to medium and high skilled labour is obtained in all industry groups. As only the negative substitution and labour supply effect are at work, such results cannot be obtained when assembly activities, which requires mainly low skilled labour, takes up the largest part of offshored final tasks. This suggests that the measure for final inputs offshoring does not only adequately capture offshored final tasks. The result might be biased as the measure also captures the effects of import competition, a limitation that has been mentioned before. A noteworthy aspect of the results that strengthens this concern is that all labour cost shares in the low and medium tech sector are negatively affected by the final offshoring measure. Although such a result has been obtained with other types of offshoring as well, in the final inputs measure this is more likely, as this measure contains not only offshored final stages of production, but also final goods that have been produced without, or at least not with a sufficiently compensating amount of, domestic labour.

Table 10: ISUR output of alternative broad offshoring measure and final inputs offshoring measure

	(1) Δs_L	(2) Δs_M	(3) Δs_H
All industries			
ΔO^{B*}	-0.00716*	0.0123**	0.00788**
	(0.00400)	(0.00478)	(0.00370)
ΔO^{FI}	0.000208	-0.00349*	-0.00448***
	(0.00155)	(0.00186)	(0.00144)
Observations	3,370	3,370	3,370
R-squared	0.415	0.373	0.287
Low tech			
ΔO^{B*}	0.00837	0.0236***	0.0121*
	(0.00681)	(0.00906)	(0.00689)
ΔO^{FI}	-0.00244	-0.00606***	-0.00522***
	(0.00166)	(0.00221)	(0.00168)
Observations	1,444	1,444	1,444
R-squared	0.496	0.400	0.329
Medium tech			
ΔO^{B*}	0.00820	-0.00789	-0.0220
	(0.0197)	(0.0239)	(0.0183)
ΔO^{FI}	-0.0221	-0.0487**	-0.0445***
	(0.0178)	(0.0215)	(0.0165)
Observations	954	954	954
R-squared	0.343	0.312	0.223
High tech			
ΔO^{B*}	-0.0215***	0.00791	0.00729
	(0.00578)	(0.00602)	(0.00495)
ΔO^{FI}	0.00929***	0.000966	-0.00257
	(0.00317)	(0.00331)	(0.00273)
Observations	972	972	972
R-squared	0.447	0.470	0.345

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The above described pattern of the effects of final goods offshoring on relative labour demand does not change when considering the corresponding elasticities, which are provided in Appendix I.

7.2. Unconditional model

To allow for the productivity and the subsequent relative price effect of offshoring, the unconditional labour demand function is estimated, with all four measures of offshoring included. The complete regression output is provided in Appendix J. The coefficients of the wage variables do not change in sign and only very slightly in size, which is according to the expectations, as the output effect should not play a role in the input mix when there are constant returns to scale. However, the coefficients of the price of intermediate inputs do change; they all become negative. This change in sign thus contradicts with what would be expected based on microeconomic theory. The results of the offshoring measures for all industries together and split by industry type are provided in Table 11.

The results for all industries together will be compared with the output of the conditional model (Appendix H), and the results split by industry type with Table 9 and Table 10. As explained before, the expected results of the offshoring measures on labour demand of the labour types become ambiguous in the unconditional model. For all industries together, regarding narrow offshoring, the results become more pronounced, i.e. the negative effects become larger. This suggests that the positive productivity effect is more than outweighed by the negative relative price effect. This result is found in all industry types. The outcomes of broad offshoring point to the same conclusion; the effect on the low skilled cost share becomes more negative, the coefficient on the medium skilled cost share also decreases and becomes highly significant (from significant at a 10% to a 1% significance level) and the coefficient on the high skilled cost share turns from a positive to a negative sign, although it remains insignificant. This suggests that also for broad offshoring, the productivity effect does not alter the results. The change in the effect on low skilled labour demand is driven by the medium- and high-tech industries, while the change in the effect on the medium skilled cost share is caused by low- and high-tech industries. The outcomes of the alternative broad offshoring measure do not differ much between the two models. This can mean that the productivity effect and the relative price effect cancel out, or that they are not present. The latter is not unrealistic; it occurs when all formerly domestically outsourced tasks to a certain industry are moved abroad, and when there are no inter-industry linkages (at least not captured with this measure). As for final inputs offshoring, the coefficients stay all very similar in size, change sometimes in significance level and only the sign of the coefficient on the medium cost share turns from negative to positive, but it becomes insignificant (while it was significant at a 10% significance level).

Table 11: Unconditional ISUR output of all offshoring measures

	(1)	(2)	(3)
	Δs_L	Δs_M	Δs_H
All industries			
ΔO^N	-0.0678***	-0.131***	-0.0471***
	(0.0158)	(0.0204)	(0.0148)
ΔO^B	-0.106***	-0.0616***	-0.0118
	(0.0126)	(0.0163)	(0.0118)
ΔO^{B*}	-0.00530	0.0155***	0.00968**
	(0.00430)	(0.00557)	(0.00403)
ΔO^{FI}	0.00382**	0.00299	-0.000883
	(0.00166)	(0.00215)	(0.00156)
Observations	3,370	3,370	3,370
R-squared	0.323	0.149	0.154
Low tech			
ΔO^N	-0.0871***	-0.149***	-0.0514***
	(0.0170)	(0.0246)	(0.0175)
ΔO^B	-0.181***	-0.261***	-0.0950**
	(0.0422)	(0.0609)	(0.0432)
ΔO^{B*}	0.0135*	0.0339***	0.0177**
	(0.00732)	(0.0106)	(0.00751)
ΔO^{FI}	0.00191	0.00272	-0.000456
	(0.00176)	(0.00254)	(0.00181)
Observations	1,444	1,444	1,444
R-squared	0.416	0.181	0.202
Medium tech			
ΔO^N	-0.555**	-0.967***	-0.355*
	(0.227)	(0.288)	(0.212)
ΔO^B	-0.0739***	0.00347	0.0235*
	(0.0146)	(0.0185)	(0.0137)
ΔO^{B*}	0.0248	0.0221	-0.00515
	(0.0206)	(0.0262)	(0.0193)
ΔO^{FI}	-0.0149	-0.0359	-0.0373**
	(0.0186)	(0.0237)	(0.0174)
Observations	954	954	954
R-squared	0.281	0.168	0.135
High tech			
ΔO^N	-0.0249	-0.0612	-0.0202
	(0.0331)	(0.0385)	(0.0285)
ΔO^B	-0.205***	-0.298***	-0.145***
	(0.0399)	(0.0465)	(0.0344)
ΔO^{B*}	-0.0183***	0.0129*	0.0101*
	(0.00652)	(0.00759)	(0.00562)
ΔO^{FI}	0.0115***	0.00414	-0.000699
	(0.00357)	(0.00417)	(0.00310)
Observations	972	972	972
R-squared	0.296	0.155	0.153

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To see whether the relative productivity and relative price effect change the pattern of the results, the elasticities based on the unconditional model must be examined, which are shown Appendix K (only for the full sample of industries). We know from the elasticities derived from the conditional model that narrow offshoring mostly works to the disadvantage of medium skilled labour, although the difference with low skilled labour is very small, and that broad offshoring mostly harms low skilled labour. The results show that this remains the case in the unconditional model. Also the pattern of the results of the alternative broad offshoring measure and the final inputs offshoring measure stays the same.

Looking at the overall results of the unconditional model, one can conclude that offshoring reduces the demand for low and medium skilled labour. The positive coefficients on these cost shares are smaller than the negative ones and less significant. The net effect of the offshoring measures on the demand for high skilled labour also seems to be negative. Nevertheless, the negative effects on low and medium skilled labour demand are without a doubt larger than the negative effect on high skilled labour demand. The difference between low and medium skilled labour demand are less pronounced, but the results suggest that low skilled labour is somewhat more harmed by offshoring than medium skilled labour. From the above it can be concluded that offshoring increases the wage and/or employment gap between lower and higher skilled labour.

8. Robustness check

When the capital stock is added in the regression equation, this is mostly because of a lack of data on rental prices of capital at the disaggregated level of the firm or industry (e.g. Senses (2010) and Berman et al., 1994). The unconditional model as estimated in the main analysis is therefore sometimes referred to as the capital-constrained model (Hijzen & Swaim, 2010). Since I do have data on the rental price of capital, in order to check whether the results obtained with this model are robust, the capital stock is replaced by the cost of capital.

Data on the cost of capital is derived from socio economic accounts of the WIOD (Timmer et al., 2015) and is hence at exactly the same industry level as the data on the other variables. As explained in another paper on the construction of the WIOD (Erumban et al., 2011) the ‘capital compensation’ variable in the dataset is computed by multiplying capital stocks with rental prices. Therefore, the rental price can simply be estimates by dividing ‘capital compensation’ by the capital stock K. As capital is now assumed to be a variable input, there is an additional variable cost share and hence also all existing variable cost shares need to be recalculated. For instance the low skilled labour cost share is now defines as: $s_L = \frac{w_L L^*}{w_L L^* + w_M M^* + w_H H^* + w_{II} II^* + w_K K^*}$, where w_K indicates the rental price of capital. For that reason, the coefficients are expected to be smaller so that the sizes of the results are not comparable. On the other hand, if the productivity and relative price effect, which net effect turned out to be negative, were not fully captured due to the capital constraint on output, the coefficients can also become larger. Regardless of that, the pattern of the changes in relative labour demand is comparable. The equation that is deleted from the system of now five equations is still the material inputs cost share equation. Furthermore, the symmetry restrictions are directly imposed. The results are shown in Table 12.

Table 12: Unconditional ISUR output with capital included as a variable input factor

	(1) Δs_L	(2) Δs_M	(3) Δs_H	(4) Δs_K
$\Delta \ln w_L$	0.0461***	-0.0155***	-0.0125***	-0.00487***
	(0.00117)	(0.00108)	(0.000808)	(0.000324)
$\Delta \ln w_M$	-0.0155***	0.0644***	-0.0184***	-0.00999***
	(0.00108)	(0.00211)	(0.00134)	(0.000396)
$\Delta \ln w_H$	-0.0125***	-0.0184***	0.0393***	-0.00479***
	(0.000808)	(0.00134)	(0.00122)	(0.000282)
$\Delta \ln w_K$	-0.00487***	-0.00999***	-0.00479***	0.0434***
	(0.000324)	(0.000396)	(0.000282)	(0.000795)
$\Delta \ln w_{II}$	0.00140	-0.00363**	-0.00408***	-0.00853***
	(0.00135)	(0.00165)	(0.00117)	(0.00330)
ΔO^N	-0.0490***	-0.0886***	-0.0292**	-0.196***
	(0.0140)	(0.0172)	(0.0122)	(0.0343)
ΔO^B	-0.104***	-0.0747***	-0.0237**	-0.113***
	(0.0113)	(0.0138)	(0.00980)	(0.0275)
ΔO^{B*}	-0.00473	0.0145***	0.00918***	-0.0174*
	(0.00385)	(0.00472)	(0.00335)	(0.00941)
ΔO^{FI}	0.00258*	0.000945	-0.000953	0.00383
	(0.00148)	(0.00181)	(0.00129)	(0.00361)
Constant	-0.00271***	-0.00116***	0.00102***	0.000487*
	(0.000116)	(0.000144)	(0.000101)	(0.000264)
Observations	3,307	3,307	3,307	3,307
R-squared	0.358	0.289	0.234	0.497

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

By comparing these outcomes with those of the ‘capital-constrained’ model (see Appendix J), it can be seen that the offshoring variables have highly similar coefficients, even in size. This suggests either that the ‘capital-constrained’ model allows sufficiently for changes in output to capture the full productivity and relative price effects, and that the change in the effect on the material inputs cost share is completely absorbed by the change in the capital cost share, or that the net effect of the productivity and relative price effect has become bigger, but this is equally divided over all the cost shares. In either way, the results of the ‘capital-constrained’ model seem to be robust to replacing the capital stock variable with the price of capital. This is not only true for the results of the offshoring variables, but also for the coefficients of the factor price variables.

Since there is data available on the cost of capital, also the conditional model can be re-estimated with the cost of capital included instead of the capital stock. Results are reported in Appendix L and show no major changes compared to the initial conditional model (see Appendix H).

9. Conclusion and discussion

The results obtained in this analysis point towards an increased wage and/or employment gap between lower and higher skilled labour from offshoring. This finding is in line with the majority of the existing empirical literature. The alternative measure for broad offshoring that has been proposed in this paper turns out to affect relative labour demand in the same way as the widely used narrow and broad offshoring measure, although the results are less significant. This suggests that by including this additional measure, the widening gap can be attributed to offshoring to a somewhat larger extent than has been estimated before. A fourth measure containing final goods trade did not seem to not capture the effects of offshoring the final stages of production well. Results also suggest that the effect of offshoring differs among low-, medium- and high-tech industries. The above obtained results should however be interpreted with caution, as some results showed that the model could be misspecified. Other limitations of this analysis are discussed below.

One potential limitation of this paper is that the linear industry-country time trend might not adequately capture factor biased technological change. In that case (part of) the effect of technological change is subsumed in the error term. If offshoring is correlated with other sources of FBTC, this might lead to an endogenous offshoring variable as this variable is correlated with the error term. This would manifest itself in overstating the effect of offshoring on wage/employment gap, assuming that they both reduce relative unskilled labour demand. Unfortunately, the WIOD does not contain any variables that could capture FBTC. It is suggested in some papers to control for it by splitting the capital stock variable into ICT capital and non-ICT capital. However, I am not aware of any database that includes this information for the broad sample of countries and industries covered in my analysis. The EU KLEMS database[3] (O'Mahony & Timmer, 2009) does provide data on the share of ICT capital in total capital for some European countries, so the original sample could be reduced to the countries and years for which it is available. However, by roughly examining this data, it can be observed that this share is very small and does not increase over the years in manufacturing sectors. This suggests that ICT expenditures do not capture technological change in manufacturing industries well. It might be a better indicator for services industries, where the share of ICT capital is much higher and increasing over time. Other papers use for instance R&D expenditures of industries as an additional regressor to control for FBTC. However, also for such a variable there is no comparable data available for my sample.

As pointed out by Hijzen (2005), the independent wage variables are likely to be endogenous. The factor demand approach is based on the theory of the representative firm, where firms are assumed to be identical. However, industries are not supposed to be identical. While for the representative firm labour supply can be considered perfectly inelastic, it will be upward-sloping for industries. Since labour supply is considered to be increasing in wages, a change in labour demand in a certain industry can affect wages. Hence, this suggests that including wages as regressors might lead to simultaneity bias. This concern is not addressed in Foster-McGregor et al. (2013). A rather common way of solving this potential issue is by replacing the cost shares by employment shares. However, this is only justified if wage rigidities are present in all countries under study, which is not the case for this analysis. Another option would be to use an instrumental variable for wages. However, the instruments used in similar research are not available to this paper due to a lack of comparable data for the large amount of countries included. Therefore, I leave it to future research to perform such an analysis. This potential issue

[3] Available at www.euklems.net.

seems however not a major limitation, as other studies that used a translog cost function do not find different results of offshoring on relative labour demand when solving for wage endogeneity (e.g. Hertveldt & Michel, 2013 and Hijzen et al., 2005).

There are also a number of shortcomings when WIOT's, or input-output tables in general, are used for measuring offshoring. Firstly, as mentioned before, the data can include tasks that are not relocated abroad, i.e. that were not formerly carried out domestically. In that case, the intensity of offshoring will be overestimated. Secondly, the data does not include offshored products that are not re-imported, but exported directly to third markets (Hijzen, 2005). This underestimates the amount of offshoring. Thirdly, imported intermediate inputs can partly consist of tasks that are carried out domestically. More generally, it could contain tasks that are not made in China. This would cause an overestimation of the extent of offshoring to China. For example, when the offshored task is assembly production, the value of this final input will be high as it consists of all inputs required to make the final good. If however assembly is the only task that is carried out in China, the impact on domestic labour demand will be relatively low. The closer the traded intermediate input is to the end product, the more severe this limitation. So, the final inputs offshoring measure is most hurt by this limitation. It might explain why the results do not adhere to the results that would be obtained when assembly activities are offshored. This shortcoming could be solved by examining imported intermediate inputs in value added terms, which is done by Michel and Stavrevska (n.d.). They calculate the amount of value added trade between industries from WIOT's, by using matrix algebra. It is therefore beyond the scope of this paper to do that. A fourth shortcoming of the offshoring measure is that, as offshoring occurs when production abroad is cheaper, the costs of tasks that are offshored are lower than if they would have been carried out domestically, which results in an underestimation of the extent of offshoring (Hertveldt & Michel, 2013). Finally, the data is reported in nominal values, not in real values. Offshoring in real values could change without observing a change in offshoring in nominal values, due to changes in price levels (Crinò, 2009). This can lead to an under- or overestimation of the intensity of offshoring.

Not particularly a limitation, but rather an important note in case country specific policy implications will be derived from the results, is that the type of labour that is substituted for offshoring might differ across countries that are included in the analysis. This seems unlikely at first sight, as the countries are all developed countries and are expected to be in the same position in the global value chain. In the theoretical model that has been discussed it was assumed that the cost for offshoring were identical across industries. Hence, in a multi-country setting, this implies identical costs across countries as well. What the exact sources of the offshoring costs are is not elaborated on, but transportation is certainly one of them. As the sample includes countries with a variance in distance to China, the transportation costs and thus the offshoring costs are expected to differ between countries. Therefore, a reduction in the overall offshoring cost could make it profitable to offshore a certain task in for instance Taiwan whereas this is not yet the case for a European country. The above implies that the type of labour that is harmed by offshoring could differ across countries. This concern is very specific to this analysis, as it is a cross-country analysis and examines offshoring to a specific host country. Because of the above, it is not desirable to derive policy implication from the results that are targeted at specific skill groups in society. However, as the general results point to an increased gap between lower and higher skilled workers induced by offshoring to China, policy makers should take into account the trade-off between the usual gains from trade that are made possible by trade agreements with upcoming countries such as China, and worker inequality.

I recommend future research on this topic to focus on empirical research at the firm level, which thus requires obtaining firm level data, as this allows for more adequate measures of offshoring intensities. Furthermore, as most papers in this field have not distinguished between host countries, it is not yet possible to compare the results obtained in this paper, which focuses on China, with offshoring to for instance other low-wage countries. As this would be interesting, future research could focus on this.

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Appendix

A. Manufacturing industries

ISIC rev.3 code	Industry name	Industry type
15t16	Food, beverages and tobacco	Low-tech
17t18	Textiles and textile products	Low-tech
19	Leather, leather products and footwear	Low-tech
20	Wood and products of wood and cork	Low-tech
21t22	Pulp, paper, printing and publishing	Medium-tech
23	Coke, refined petroleum and nuclear fuel	Medium-tech
24	Chemicals and chemical products	High-tech
25	Rubber and plastics	Medium-tech
26	Other non-metallic mineral	Low-tech
27t28	Basic metals and fabricated metal	Low-tech
29	Machinery, not elsewhere classified	High-tech
30t33	Electrical and optical equipment	High-tech
34t35	Transport equipment	High-tech
36t37	Manufacturing, not elsewhere classified; recycling	Medium-tech

B. ISUR output with narrow offshoring included without symmetry restrictions imposed

	(1)	(2)	(3)	(4)
	Δs_L	Δs_M	Δs_H	Δs_{II}
$\Delta \ln w_L$	0.0518***	-0.0150***	-0.0111***	-0.0256***
	(0.00140)	(0.00166)	(0.00128)	(0.00280)
$\Delta \ln w_M$	-0.0104***	0.0823***	-0.0152***	-0.0567***
	(0.00271)	(0.00322)	(0.00249)	(0.00544)
$\Delta \ln w_H$	-0.0193***	-0.0253***	0.0420***	0.00259
	(0.00204)	(0.00243)	(0.00188)	(0.00411)
$\Delta \ln w_{II}$	0.00958***	0.00766***	0.00176	-0.0190***
	(0.00144)	(0.00172)	(0.00133)	(0.00290)
$\Delta \ln K$	0.00675***	0.0203***	0.00575***	-0.0328***
	(0.00186)	(0.00221)	(0.00171)	(0.00373)
$\Delta \ln Y$	-0.0291***	-0.0515***	-0.0283***	0.109***
	(0.00124)	(0.00147)	(0.00114)	(0.00249)
ΔO^N	-0.0494***	-0.0635***	-0.0102	0.123***
	(0.0141)	(0.0167)	(0.0130)	(0.0283)
Constant	-0.00268***	-0.000648***	0.00163***	0.00170***
	(0.000127)	(0.000151)	(0.000117)	(0.000255)
Observations	3,370	3,370	3,370	3,370
R-squared	0.407	0.373	0.286	0.421

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

C. Average cost shares of input factors for all industries and split by industry type

	s_L	s_M	s_H	s_{II}
All industries	0.0654459	0.1197182	0.0572626	0.7575732
Low tech	0.0697965	0.1278452	0.0584816	0.7438767
Medium tech	0.0622389	0.1144614	0.0544754	0.7688243
High tech	0.0621347	0.112811	0.0581921	0.7668622

D. Estimated elasticities derived from ISUR output with narrow and broad offshoring included

	(1)	(2)	(3)
	s_L	s_M	s_H
All industries			
ΔO^N	-0.6643231***	-0.5181854***	-0.1934151
	(0.2143022)	(0.1401836)	(0.2271025)
ΔO^B	-1.322189***	-0.1833752	0.1705347
	(0.1794331)	(0.1172834)	(0.1900219)
Low tech			
ΔO^N	-0.7201419***	-0.5297089***	-0.1384242
	(0.2242688)	(0.1635022)	(0.2601345)
ΔO^B	-2.189981***	-1.491717***	-0.9376832
	(0.5942204)	(0.4329132)	(0.6885422)
Medium tech			
ΔO^N	-5.333378*	-6.136879***	-6.293719**
	(2.913794)	(1.933695)	(3.106579)
ΔO^B	-1.042291***	0.0929107	0.4439526**
	(0.2131172)	(0.1404117)	(0.2264294)
High tech			
ΔO^N	-0.1991395	0.0102481	0.2564149
	(0.4355474)	(0.2463232)	(0.4234098)
ΔO^B	-1.484392***	-0.9668341***	-0.7364435
	(0.5524831)	(0.3129552)	(0.5376051)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

E. ISUR output with narrow and alternative broad offshoring measure included

	(1)	(2)	(3)
	Δs_L	Δs_M	Δs_H
$\Delta \ln w_L$	0.0523***	-0.0159***	-0.0129***
	(0.00127)	(0.00116)	(0.000906)
$\Delta \ln w_M$	-0.0159***	0.0762***	-0.0188***
	(0.00116)	(0.00226)	(0.00147)
$\Delta \ln w_H$	-0.0129***	-0.0188***	0.0450***
	(0.000906)	(0.00147)	(0.00137)
$\Delta \ln w_{II}$	0.00965***	0.00777***	0.00179
	(0.00145)	(0.00172)	(0.00133)

ΔlnK	0.00670***	0.0204***	0.00594***
	(0.00186)	(0.00221)	(0.00171)
ΔlnY	-0.0295***	-0.0515***	-0.0282***
	(0.00124)	(0.00148)	(0.00115)
ΔO^N	-0.0383***	-0.0735***	-0.0141
	(0.0148)	(0.0176)	(0.0137)
ΔO^{B*}	-0.00872**	0.00772*	0.00285
	(0.00358)	(0.00426)	(0.00330)
Constant	-0.00268***	-0.000648***	0.00169***
	(0.000126)	(0.000151)	(0.000116)
Observations	3,370	3,370	3,370
R-squared	0.406	0.372	0.285

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

F. ISUR output with narrow, broad and alternative broad offshoring measure included

	(1)	(2)	(3)
	Δs_L	Δs_M	Δs_H
Δlnw_L	0.0530***	-0.0161***	-0.0132***
	(0.00127)	(0.00116)	(0.000905)
Δlnw_M	-0.0161***	0.0762***	-0.0188***
	(0.00116)	(0.00226)	(0.00147)
Δlnw_H	-0.0132***	-0.0188***	0.0451***
	(0.000905)	(0.00147)	(0.00137)
Δlnw_{II}	0.00941***	0.00770***	0.00181
	(0.00143)	(0.00172)	(0.00133)
ΔlnK	0.00690***	0.0205***	0.00593***
	(0.00185)	(0.00221)	(0.00171)
ΔlnY	-0.0288***	-0.0513***	-0.0283***
	(0.00124)	(0.00148)	(0.00115)
ΔO^N	-0.0347**	-0.0724***	-0.0144
	(0.0147)	(0.0176)	(0.0137)
ΔO^B	-0.0849***	-0.0238*	0.00915
	(0.0118)	(0.0141)	(0.0109)
ΔO^{B*}	-0.00691*	0.00823*	0.00266
	(0.00357)	(0.00427)	(0.00331)
Constant	-0.00259***	-0.000619***	0.00168***
	(0.000125)	(0.000152)	(0.000117)
Observations	3,370	3,370	3,370
R-squared	0.415	0.373	0.284

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

G. Estimated elasticities derived from ISUR output with narrow, broad and alternative broad offshoring included

	(1)	(2)	(3)
	s_L	s_M	s_H
All industries			
ΔO^N	-0.5307434**	-0.6049867***	-0.2521047
	(0.2249884)	(0.1471639)	(0.2385307)
ΔO^B	-1.297719***	-0.199002*	0.1597647
	(0.1797752)	(0.117504)	(0.1904702)
ΔO^{B*}	-0.1056449*	0.0687301*	0.0463851
	(0.0544818)	(0.0356361)	(0.0577599)
Low tech			
ΔO^N	-0.7927327***	-0.6515267***	-0.2137072
	(0.244433)	(0.1780297)	(0.283504)
ΔO^B	-2.254623***	-1.598782***	-1.003824
	(0.6003437)	(0.4369387)	(0.6955798)
ΔO^{B*}	0.0721623	0.1214951*	0.0750614
	(0.097019)	(0.0706397)	(0.1124918)
Medium tech			
ΔO^N	-5.703975*	-5.472423**	-3.698437
	(3.292851)	(2.185233)	(3.506621)
ΔO^B	-1.04721***	0.1009418	0.4754055**
	(0.2139271)	(0.1409208)	(0.227008)
ΔO^{B*}	0.0720747	-0.1296431	-0.5055776
	(0.298975)	(0.1983611)	(0.3183447)
High tech			
ΔO^N	0.0946257	-0.1157869	0.1248565
	(0.4504301)	(0.2550811)	(0.4389618)
ΔO^B	-1.359692**	-1.020722***	-0.7932446
	(0.5531167)	(0.3137188)	(0.5395612)
ΔO^{B*}	-0.1738486**	0.0748514*	0.0781746
	(0.0709625)	(0.0402041)	(0.0691836)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

H. ISUR output with narrow, broad, alternative broad and final inputs offshoring measures included

	(1)	(2)	(3)
	Δs_L	Δs_M	Δs_H
Δlnw_L	0.0529***	-0.0160***	-0.0131***
	(0.00127)	(0.00116)	(0.000905)
Δlnw_M	-0.0160***	0.0762***	-0.0187***
	(0.00116)	(0.00226)	(0.00147)
Δlnw_H	-0.0131***	-0.0187***	0.0450***
	(0.000905)	(0.00147)	(0.00137)
Δlnw_{II}	0.00941***	0.00769***	0.00179

	(0.00143)	(0.00172)	(0.00133)
ΔlnK	0.00692***	0.0201***	0.00539***
	(0.00186)	(0.00222)	(0.00172)
ΔlnY	-0.0288***	-0.0516***	-0.0286***
	(0.00124)	(0.00149)	(0.00115)
ΔO^{N}	-0.0347**	-0.0723***	-0.0142
	(0.0147)	(0.0176)	(0.0136)
ΔO^{B}	-0.0849***	-0.0237*	0.00922
	(0.0118)	(0.0141)	(0.0109)
ΔO^{B*}	-0.00716*	0.0123**	0.00788**
	(0.00400)	(0.00478)	(0.00370)
ΔO^{FI}	0.000208	-0.00349*	-0.00448***
	(0.00155)	(0.00186)	(0.00144)
Constant	-0.00260***	-0.000571***	0.00175***
	(0.000127)	(0.000154)	(0.000118)
Observations	3,370	3,370	3,370
R-squared	0.415	0.373	0.287

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

I. Estimated elasticities derived from ISUR output with all offshoring measures included

	(1)	(2)	(3)
	s_L	s_M	s_H
All industries			
ΔO^{B*}	-0.1093274*	0.102687**	0.13763**
	(0.0611058)	(0.0399456)	(0.0646843)
ΔO^{FI}	0.0031739	-0.0291227*	-0.078244***
	(0.0237202)	(0.0155031)	(0.0251099)
Low tech			
ΔO^{B*}	0.1278733	0.1969235***	0.2110777*
	(0.1040715)	(0.075659)	(0.1203591)
ΔO^{FI}	-0.0373482	-0.0506067***	-0.0911739***
	(0.025366)	(0.0184563)	(0.0293426)
Medium tech			
ΔO^{B*}	0.1253456	-0.0658639	-0.383998
	(0.3017218)	(0.1998308)	(0.3203428)
ΔO^{FI}	-0.3384216	-0.407125**	-0.7772221***
	(0.2717964)	(0.1799724)	(0.2886736)
High tech			
ΔO^{B*}	-0.329025***	0.0660308	0.1273253
	(0.0883372)	(0.0502541)	(0.0865062)
ΔO^{FI}	0.1418741***	0.0080699	-0.0449481
	(0.0484432)	(0.0276265)	(0.0476406)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

J. Unconditional model

	(1)	(2)	(3)
	Δs_L	Δs_M	Δs_H
Δlnw_L	0.0524***	-0.0176***	-0.0140***
	(0.00130)	(0.00121)	(0.000921)
Δlnw_M	-0.0176***	0.0723***	-0.0208***
	(0.00121)	(0.00234)	(0.00151)
Δlnw_H	-0.0140***	-0.0208***	0.0438***
	(0.000921)	(0.00151)	(0.00139)
Δlnw_{II}	-6.92e-05	-0.00926***	-0.00763***
	(0.00148)	(0.00192)	(0.00139)
ΔlnK	-0.00720***	-0.00507**	-0.00859***
	(0.00189)	(0.00244)	(0.00177)
ΔO^N	-0.0678***	-0.131***	-0.0471***
	(0.0158)	(0.0204)	(0.0148)
ΔO^B	-0.106***	-0.0616***	-0.0118
	(0.0126)	(0.0163)	(0.0118)
ΔO^{B*}	-0.00530	0.0155***	0.00968**
	(0.00430)	(0.00557)	(0.00403)
ΔO^{FI}	0.00382**	0.00299	-0.000883
	(0.00166)	(0.00215)	(0.00156)
Constant	-0.00289***	-0.00103***	0.00149***
	(0.000137)	(0.000179)	(0.000129)
Observations	3,370	3,370	3,370
R-squared	0.323	0.149	0.154

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

K. Estimated elasticities unconditional model

	(1)	(2)	(3)
	s_L	s_M	s_H
All industries			
ΔO^N	-1.035241***	-1.097947***	-0.8223565***
	(0.2409722)	(0.1705472)	(0.2581492)
ΔO^B	-1.621121***	-0.5146851***	-0.2056154
	(0.1927683)	(0.1363107)	(0.2063671)
ΔO^{B*}	-0.0810151	0.1296675***	0.1690639**
	(0.0657391)	(0.0465269)	(0.0704256)
ΔO^{FI}	0.0584414**	0.0249555	-0.0154202
	(0.0253964)	(0.0179702)	(0.0272106)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

L. Conditional model with capital as a variable input factor

	(1)	(2)	(3)	(4)
	Δs_L	Δs_M	Δs_H	Δs_K
Δlnw_L	0.0473***	-0.0134***	-0.0114***	-0.00288***
	(0.00114)	(0.00105)	(0.000795)	(0.000320)
Δlnw_M	-0.0134***	0.0680***	-0.0164***	-0.00681***
	(0.00105)	(0.00207)	(0.00132)	(0.000375)
Δlnw_H	-0.0114***	-0.0164***	0.0403***	-0.00296***
	(0.000795)	(0.00132)	(0.00121)	(0.000276)
Δlnw_{II}	0.00755***	0.00611***	0.00156	0.00125
	(0.00131)	(0.00153)	(0.00113)	(0.00330)
Δlnw_K	-0.00288***	-0.00681***	-0.00296***	0.0466***
	(0.000320)	(0.000375)	(0.000276)	(0.000808)
ΔlnY	-0.0231***	-0.0367***	-0.0212***	-0.0368***
	(0.00113)	(0.00133)	(0.000975)	(0.00283)
ΔO^N	-0.0251*	-0.0507***	-0.00728	-0.158***
	(0.0133)	(0.0156)	(0.0114)	(0.0336)
ΔO^B	-0.0767***	-0.0310**	0.00159	-0.0691**
	(0.0107)	(0.0126)	(0.00923)	(0.0270)
ΔO^{B*}	-0.00455	0.0148***	0.00935***	-0.0172*
	(0.00363)	(0.00426)	(0.00313)	(0.00918)
ΔO^{FI}	-0.000944	-0.00462***	-0.00419***	-0.00178
	(0.00140)	(0.00165)	(0.00121)	(0.00355)
Constant	-0.00224***	-0.000444***	0.00145***	0.00123***
	(0.000111)	(0.000132)	(9.63e-05)	(0.000267)
Observations	3,307	3,307	3,307	3,307
R-squared	0.429	0.423	0.331	0.521

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1