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***INTERNATIONAL TRADE AND
REGIONAL ECONOMICS***



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ABSTRACT

Services offshoring and wages: Evidence from micro data

This paper investigates the effects of services offshoring on wages using individual-level data combined with industry information on offshoring for the United Kingdom. Our results show that services offshoring affects the real wage of low- and medium-skilled individuals negatively. By contrast, skilled workers may benefit from services offshoring in terms of higher real wages. Hence, offshoring has contributed to a widening of the wage gap between skilled and less skilled workers. This result is obtained while controlling for individual and sectoral observed and unobserved heterogeneity. In particular, our empirical model also controls for the impact of technological change and offshoring of materials.

JEL Classification: C23, F16 and J31

Keywords: individual level, services offshoring and wages

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1 Introduction

Offshoring from industrialised countries has been a topical issue, both in academic discourse and public debate for a number of years. Initially, the concern was with offshoring of manufacturing activities and the implications for domestic labour markets, in particular as regards shifts in the demand for skilled labour (see Feenstra and Hanson, 1999 for the US and Hijzen et al., 2005 for the UK). More recently, the attention has turned towards offshoring of services activities. In a much cited paper, Amiti and Wei (2005) show that services offshoring is still at relatively low levels compared to materials offshoring. However, its growth rates are much higher. In order to examine the implications of offshoring for domestic labour they estimate labour demand equations which incorporate services and materials offshoring. Using sector level data for the UK they find that employment growth is not negatively related to services offshoring.¹ Using highly disaggregated firm-level data on job creation and destruction, and firm-level data on trade in services, Hijzen et al. (2007) also fail to find any negative effects of services offshoring (measured as services imports). By contrast, they find that, on average, firms that start offshoring services experience faster employment growth than other comparable firms. Hence, the conclusion that may be drawn from the work so far is that there is little to worry about for domestic workers. However, the papers by Amiti and Wei (2005) and Hijzen et al. (2007) focus on one aspect of labour adjustment only, namely, the quantity of labour. However, an adjustment in the labour market to offshoring can go through either quantity or the price of labour, or both. In this case, concluding on the benevolent (or otherwise) effects of offshoring purely on the basis of an analysis of the quantity of labour can be misleading. Especially in a country with flexible labour markets (such as the UK) a full labour market picture of the effects of offshoring of services needs to look at the price of work as well. This is the gap we fill in this paper.

We investigate the effect of offshoring of services activities on UK wages. To do so, we use household-level panel data from the British Household Panel Survey (BHPS) and

¹In a companion paper Amiti and Wei (2007) provide evidence for the US which also shows little evidence of reductions in employment following increased levels of services offshoring.

combine these with industry-level measures of offshoring of services inputs over the period 1992 to 2004. Hence, our approach allows us to estimate the effect of increasing offshoring activities in an industry on individual wages of workers in the affected industry. The idea of assessing the labour market impact of offshoring by utilizing individual-level data has already been applied in a small number of studies, e.g., Egger et al. (2007), Geishecker and Görg (2008), Geishecker (2008) or Munch and Skaksen (2009) for Europe and most recently, building on this body of literature, Ebenstein et al. (2009) for the US. However, these studies only look at offshoring of materials, not services. An exception is Liu and Treffer (2008), who, however, limit themselves to investigating the impact of services offshoring to China and India using US data.

The present paper is the first analysis we are aware of that looks at the wage effects of services offshoring in general using individual-level data, while controlling for technological progress and materials offshoring.² This is a highly policy relevant issue and deserves of detailed inspection. In our analysis we are careful to assess the economic significance of our estimates, and compare and contrast the effects of services and materials offshoring.

The main advantage of using individual-level data is that they allow to control for observed and unobserved heterogeneity while avoiding aggregation bias that may hamper more aggregate studies. Also, utilizing micro-level data allow to clearly identify the winners and losers from offshoring. Furthermore, the combination of household-level data for wages and industry-level data for services offshoring mitigates concerns about the possible endogeneity of offshoring.³

We use two strategies to identify a link between offshoring and wages. The first follows the standard approach in the literature looking at the impact of within-industry changes in offshoring intensities on wage changes of individuals in the same industry.⁴ The second strategy is based on the idea that offshoring may not only affect wages of workers with a given skill level in the industry in which the offshoring takes place, but also in industries

²These variables have been shown to affect the relative wages of skilled workers, see, e.g., Feenstra and Hanson (1999), Hijzen et al. (2005).

³However, we also explicitly test for the exogeneity of our services offshoring variable.

⁴This is the approach of Feenstra and Hanson (1999) and is also followed in the micro level studies cited above.

that use workers with the same skill levels. This approach implicitly allows for movement of workers of a given skill level across industries.

Our results show that services offshoring affects the real wage of low- and medium-skilled individuals in the same industry negatively. By contrast, skilled workers benefit from services offshoring in their industry in terms of higher real wages. When allowing for movement of workers across industries, we find statistically significant evidence that offshoring of services in industries that use the same skills reduces wages for low- and medium-skilled workers. We cannot identify with any precision any wage effect for high skilled workers, however. These results are obtained while controlling for individual and sectoral observed and unobserved heterogeneity. In particular, our empirical model also controls for the impact of technological change and offshoring of materials. The remainder of the paper is structured as follows. Section 2 provides a brief theoretical background to motivate the empirical analysis. Section 3 introduces the data on offshoring of both services and materials, while Section 4 discusses the empirical methodology. Section 5 presents the results of the estimation based on within-industry changes; Section 6 presents the alternative empirical strategy. Some concluding remarks are in Section 7.

2 Theoretical Background

Before we proceed to the empirical analysis, which forms the core of this paper, it is useful to discuss briefly the theoretical framework which we use to motivate our empirics. This framework is provided by the recent theoretical model by Grossman and Rossi-Hansberg (2008) (GRH). In their model, a firm produces output using a continuum of production stages (which they refer to as tasks). Some of these stages are performed by low-skilled workers, while others require more skills and can only be carried out by high skilled workers. Firms can perform these production stages either at home or abroad. Offshoring is costly, and these costs apply economy-wide but differ across tasks.⁵ Carrying out production stages abroad may be advantageous due to factor cost differences, but these

⁵Kohler (2008) provides an interesting theoretical discussion which shows how results may differ if costs are assumed to be industry-specific rather than economy-wide.

potential savings have to be weighed against the costs of offshoring.

GRH focus on the offshoring of tasks performed by low-skilled workers. In their setup, there are three types of effects on wages if offshoring costs for this set of tasks decline, that is, if offshoring of production stages carried out by low-skilled workers increases. First, increased offshoring raises the productivity of low-skilled workers, and thereby generates a real wage increase for this factor. Second, there is a labour supply effect. The excess workers who have been freed up through offshoring have to be re-absorbed in the economy, which leads to a fall in the real wage for low-skilled workers. Third, in general equilibrium there is a relative price effect, whereby the price of the final good that uses offshoring declines. This will, via the familiar Stolper-Samuelson effect, also negatively affect low-skilled workers' wages. In sum, the model predicts an ambiguous effect of increased offshoring for low-skilled workers' wages, depending on the relative strength of the positive productivity and negative factor supply and relative price effects. By contrast, a fall in offshoring costs for low-skill tasks has unequivocal positive wage effects for high-skilled workers. First of all, the aforementioned labour supply effect of offshoring lowers the proportion of high-skilled workers in the remaining activities, increasing their marginal product. Second, in general equilibrium the relative price effect implies wage increases for high-skilled workers through the usual Stolper-Samuelson mechanism. One reason why services offshoring has attracted such attention is that it may lead to the relocation abroad of production stages that are performed by high skilled, not low-skilled workers. GRH cite examples of software development, radiology or preparing tax forms that has been offshored from the US to India. Hence, they expand their model to study the offshoring of such high skilled production stages. Similar to the offshoring of low-skilled tasks, they show that there is a productivity enhancing effect which benefits high skilled workers. There can also be relative price and factor supply effects, however, that harm high skilled labour. Furthermore and along the lines of the previous discussion, offshoring of such high-skill production stages generates wage increases for low skilled workers. The implication for empirical research is that the model does not predict unambiguous effects. For both low- and high-skilled workers there is the possibility of positive productivity

effects as well as adverse relative price and factor supply effects. The extent to which offshoring, on balance, harms or benefits workers' wages therefore depends on the relative strength of these effects and on whether offshored activities are low-skill or high-skill intensive.

3 Service offshoring in the UK

Before we can investigate the impact of offshoring, we need to have a good measure of the phenomenon. This is not straightforward, neither for services nor for materials. Measurement is greatly limited by data availability of coherent and comparable (across sectors and / or countries) information on such activities. Hence, trade economists usually revert to measuring trade in intermediates as a proxy. We follow this approach here. However, data on trade in intermediates are also difficult to come by. Amiti and Wei (2005) measure the importance of intermediates in a sector using data from input-output tables and combine it with data on imports (which do not distinguish final and intermediate goods) from official trade statistics.⁶ They cannot observe the actual proportion of imported inputs. The implicit assumption in this definition is that imports are used as inputs in the same proportion as domestic inputs. On the one hand this approach could be problematic if, e.g., an industry uses different types of inputs from domestic and foreign sources. On the other hand the approach allows to differentiate service imports that are more likely to be associated with offshoring, e.g., telecommunication services and other business services, from overall aggregated services imports. In the present study we apply two different measures of service offshoring, a broad measure utilising aggregate intermediate service import data and a narrow one including only intermediate imports of telecommunication, computer and other business services. The construction of narrowly defined service offshoring is similar to the method employed in Amiti and Wei (2005) and combines input output data from UK National Statistics supply and use tables with sectoral data on service imports. More specifically, we allocate overall imports of telecommunication, computer and

⁶This follows the definition of materials offshoring used by Feenstra and Hanson (1999).

other business services (SIC92 industries 64, 72, and 74) according to their typical use in manufacturing industries and set them in relation to the respective industry's output:

$$OSS_{jt}^{narrow} = \frac{\frac{BS_{jt}}{TBS_t} \times TBS_t^{Imp}}{Y_{jt}}, \quad (1)$$

where $\frac{BS_{jt}}{TBS_t}$ denotes telecommunication, computer, and other business services purchases of industry j as a share of the total supply of such services at time t and is constructed using UK National Statistics' supply and use tables.⁷ TBS_t^{Imp} denotes all imports of telecommunication, computer, and other business services at t and is derived from Eurostat's balance of payment statistics. Y_{jt} represents output of industry j in t and is directly observable in the supply and use tables.⁸ Our second measure of service offshoring is a more direct measure of imported services inputs but is also more broadly defined. Specifically, we obtain directly data on imported services inputs from national accounts' input-output supply tables provided by UK National Statistics for the years 1992 to 2004.⁹

Formally, broad service offshoring is defined as:

$$OSS_{jt}^{broad} = \frac{TS_{jt}}{Y_{jt}}, \quad (2)$$

with TS_{jt} denoting all imported services from the foreign service sector of industry j . Y_{jt} represents the production value of the domestic industry j in period t . For materials offshoring we have to draw again on international trade data as the available detailed input-output use tables do not differentiate between imported and domestically supplied

⁷UK National Statistics, Input-Output, Supply and Use Tables, August 2006

⁸Note that our denominator is industry output. Thus, it does not only consist of intermediate input purchases as in Amiti and Wei (2005) but also contains value added. This approach has the advantage that domestic outsourcing does not change the calculated offshoring measures as any corresponding increase in intermediate input purchases is mirrored by decreasing value added.

⁹UK National Statistics, Input-Output, Supply and Use Tables, August 2006. It would be interesting to investigate to which countries services are offshored. However, this is not possible to determine with the data from the supply and use tables.

materials.¹⁰ Thus, we look at aggregate imports of manufactured goods and allocate them according to their use share in domestic industries based on aggregate input-output use tables. Conceptionally, we follow Feenstra and Hanson (1999) and calculate two measures of material offshoring, which to some extent mirrors our distinction of services offshoring. The first is defined as narrow materials offshoring, which is calculated as:

$$OSM_{jt}^{narrow} = \frac{IMP_{j^*t} \times \Omega_{jj^*t}}{Y_{jt}}, \quad (3)$$

with IMP_{j^*t} denoting imported intermediate inputs from the same respective foreign industry j^* . Ω_{jj^*t} denotes the share of domestic and foreign inputs from industry j that are consumed in industry j .¹¹ Hence, this measure only considers offshoring of activities from the same industry, which may be most likely to capture what is generally meant by offshoring of manufacturing activity.

The second measure, broad materials offshoring, also considers intermediate imports from other industries and is calculated as:

$$OSM_{jt}^{broad} = \frac{\sum_{k=1}^K IMP_{k^*t} \times \Omega_{jk^*t}}{Y_{jt}}, \quad (4)$$

where k represents all industries from which industry j sources inputs (including its own). This, hence, captures all imported manufactured intermediate materials that are used in industry j . Table 1 looks at the development of the various offshoring measures, aggregated for the whole manufacturing sector over time. A few points are noteworthy. Firstly, narrowly defined services offshoring is still very low at 0.29 % of industry output in 2004. By contrast, broad services offshoring is more than ten times more important. Compared to materials offshoring, however, both types of services offshoring are still at very low levels. Services do, however, have the highest growth rates over the period 1992

¹⁰This is a common problem, e.g. US input output tables suffer from the same shortcoming. Industry-level import data was generated drawing on Eurostat's COMEXT commodity trade data base.

¹¹Note that $\sum_{j=1}^J \Omega_{jj^*t} = 1$ only if industries J contain agriculture, services, private and public consumption, inventories, capital formation, and exports.

to 2004.

4 Methodology and data

Based on these measures of offshoring we now want to assess how individual level wages are affected by offshoring activity in an industry. To do so, we estimate simple Mincerian wage equations of the form

$$\log w_{ijt} = \alpha + \beta X_{it} + \gamma Y_{jt} + \delta (R\&D/Y)_{jt} + \lambda_S OSS_{jt} + \lambda_M OSM_{jt} + T_{jt} + \mu_t + \alpha_i + \iota_j + \epsilon_{ijt}, \quad (5)$$

where w_{ijt} is the hourly wage of worker i in industry j at time t , defined as average hourly gross labour earnings including bonuses, premia, and other extra payments over the year preceding the respective interview month.¹² X_{it} is a vector of standard demographic and human capital variables which includes age, age squared, dummies for the presence of children and being married, job tenure, tenure squared, indicator variables for educational attainment, dummies for occupation using the nine main categories of the ISCO code, dummies for firm size, and regional dummies. Year effects, μ_t , and individual-specific fixed effects, α_i , are also controlled for. In addition we include industry dummies ι_j , and to control for time varying industry characteristics we also enter industry output, Y_{jt} , the ratio of industry-level R&D to output, and industry-specific time trends T_j in the model. The inclusion of R&D and industry-specific time trends controls for industry-specific technological progress. The main explanatory variables of interest are the variables for services and material offshoring, OSS_{jt} and OSM_{jt} . In the econometric estimation these are measured alternatively as narrow or broad offshoring as described above. In our main model the wage effect of offshoring is estimated conditional on individual as well as industry fixed effects. Accordingly, the parameters are identified through within-industry changes in the respective offshoring variables. Sudden changes in offshoring intensities that would result from individuals changing between industries are controlled for by the

¹²Labour earnings above the 99.5th percentile were top coded to clean up implausibly high income information. Our results are robust to this exercise.

inclusion of industry fixed effects. Since in the main model only within-industry changes of offshoring are considered the empirical model corresponds to the partial equilibrium setting discussed in Grossmann and Rossi-Hansberg (2008) in which labour is immobile between industries. In Section 6 we also estimate a model where we allow for cross industry effects of offshoring.

All the regressions are weighted using the standard sampling weights from the household data to adjust for individual sampling probabilities. In the wage equation (5), we estimate the effect of an aggregate variable (i.e. offshoring at the industry level) on wages of individual workers, so the standard errors of the estimated coefficients may be biased downwards. Accordingly, we adjust standard errors allowing for serial error correlation within individuals and contemporaneous correlation within two digit industries applying the two-way cluster robust method suggested in Cameron et al. (2011).¹³ Furthermore, to account for the small number of industries we follow Cameron et al. (2008) and make some asymptotic refinement by calculating cluster bootstrapped-t statistics. We measure wages and worker characteristics using individual-level data from the British household panel survey (BHPS) for the period 1992 - 2004. The annual survey, which started in 1991, is based on a nationally representative sample of households. Individuals are followed over time. The database provides data on wages and education levels, as well as many individual characteristics which are included in our empirical model to control for observed individual-level heterogeneity. Table 2 provides descriptive statistics for our explanatory variables. In the estimation, we restrict our sample to male prime age individuals (i.e., 18 to 65 year old) working in manufacturing. Our unbalanced sample covers 997 individuals yielding 5775 observations. In order to avoid selection bias with respect to item non-response that might be non-random each explanatory variable was supplemented with a dummy for missing values. Subsequently, missing values were recoded to zero and the generated dummies for missing values also act as regressors in the model. A particular focus of our analysis lies on skill-specific effects of offshoring. We follow the International Standard Classification of Education (ISCED) and differentiate

¹³Note that in the presence of industry switchers individuals are not nested within industries.

between high-skilled workers ($ED : High$), medium-skilled workers ($ED : Med$), and low-skilled workers ($ED : low$) according to the grouping presented in Table 3. To estimate skill-specific effects we interact the offshoring variables with dummies for the three skill categories. Fig. 1 provides some evidence on the development of the median wage rate and the 10th and 90th percentile for the three different skill groups between 1992 to 2004. Note that wages for all three groups increased over time. The trends for all three skill groups have been fairly consistent over time. There are, however, a couple of spikes in the trend for the 90th percentile for high-skilled workers in the late 1990s and 2002-2003 probably reflecting the small number of observations for high-skilled workers. In order to investigate whether some part of the wage developments may be attributed to offshoring, we now turn to econometric analysis in the next section.

5 Estimation results

We start off with considering the effect on individual wages of offshoring of services and materials narrowly defined. The results of estimating eq. 5 with the narrow offshoring measures are reported in Table 4. We report cluster bootstrap t-tests for each regression specification, following the approach described in Cameron et al. (2008). Column (I) presents a benchmark model estimated using simple OLS. Column (II) estimates the same model using individual fixed effects. In the OLS model services offshoring has no statistically discernible effect on individual wages. In the fixed effects model, service offshoring is negative and weakly statistically significant when considering the cluster bootstrapped t-statistics.^{14, 15} Column (III) shows results which also include the intensity

¹⁴One noteworthy difference between the OLS and FE results concerns the individual level controls. These are highly statistically significant in the OLS estimation, but many are insignificant in the FE model. In particular, the coefficients on the education dummies are positive and statistically significant in the OLS regression, but less significant in the FE estimation. This reflects the fact that in the FE estimation, coefficients are identified using the variation within individuals, which is low for most of the variables.

¹⁵Another noteworthy point regarding the control variables is R&D where we find statistically insignificant but negative effects in most cases in Tables 4 and 5. It is important to point out that R&D is not our only variable to capture technological progress. We also include industry-specific time trends to also control for industry-specific technology shocks. Furthermore, general time dummies also capture

of material offshoring in the industry. This is included for two reasons. First, it allows us to see whether the estimated coefficient is biased in that it just reflects an industry's propensity to offshore in general. Second, it also enables us to distinguish the relative magnitude of services and material offshoring for wage changes. The results show that, firstly, the magnitude of the coefficient on services offshoring is reduced and now becomes statistically insignificant. By contrast, material offshoring has a weakly statistically significant and negative impact on wages. A one percentage point increase in material offshoring is associated with decreases in real wages of less than one %. The estimations thus far assume that the effect of offshoring on wages is the same across education groups. This is unlikely to be a reasonable assumption. If, for example, industries offshore mainly low-skilled services and material activities abroad, then we may expect negative effects on unskilled workers if the positive productivity effect identified by Grossman and Rossi-Hansberg (2008) is dominated by the negative factor supply effects. By contrast, high-skilled workers should always benefit in this case. In order to investigate this, we report in column (IV) results of an estimation in which we interact the two offshoring variables with dummy variables for individuals in three different skill groups, namely, low, medium and high-skilled. As the results show, we now find negative coefficients of services offshoring for low- and medium-skilled workers. The coefficient for medium-skilled workers is statistically insignificant, however. High-skilled workers benefit from offshoring of services, as the statistically significant and positive coefficient indicates. For material offshoring, we also find that wages for low- and medium-skilled workers are negatively affected, although the effect is statistically insignificant for medium-skilled workers. For high-skilled workers we find a positive, albeit statistically insignificant coefficient. While the narrow definition of offshoring arguably best captures the phenomenon of relocating production stages abroad that are close to an industry's core activities, it leaves out many additional types of intermediate goods or services that are used in production. We now investigate how broadly defined offshoring (defined as all intermediate inputs, including economy wide technological progress. Jointly, all technology related control variables exert a positive wage effect in all specifications.

narrow offshoring) affects wages by estimating the same model but now using our broad offshoring measures on the right hand side. The results are reported in Table 5. The coefficients on the offshoring variables have the same signs as before, but there are some differences in statistical significance and magnitude of the point estimates. Looking at column (IV), which allows for different effects depending on educational status, shows that we find a statistically significant positive effect of services offshoring and a positive albeit insignificant effect of materials offshoring for high-skilled workers. A one percentage point increase in services offshoring implies a wage increase by about 2.5 %. Low- and medium-skilled workers are now both statistically significantly negatively affected by services offshoring. In fact, we cannot reject the hypothesis that the two coefficients are equal, hence, reductions in wages due to services offshoring are the same for low- and medium-skilled workers. We also estimate negative coefficients for material offshoring for both types of workers, though the coefficient for medium skilled workers is not estimated with precision. To sum up, our results thus far are consistent with a partial equilibrium view along the lines of Grossman and Rossi-Hansberg (2008) in which low-skill activities in services and materials production are offshored and the resulting negative labour supply effect dominates the positive productivity effect for low-skilled workers while raising wages for high-skilled workers. There is much evidence that indicates that offshoring of materials production is indeed the relocation of low-skilled activities abroad. For example, Hijzen et al. (2005) cite examples of the British firms Speedo and Dyson, both of which relocated production activities (which are mainly low skill activities) abroad. For services activities, the evidence is not as straightforward. The literature, including Grossman and Rossi-Hansberg (2008) as discussed above, presents many anecdotes of offshoring of high-skill intensive activities, such as software development or radiology. However, while there is undoubtedly offshoring of such services, many low skilled service activities are also relocated abroad. Ellram et al. (2008) present a study of eight Fortune 500 companies and their offshoring decisions.¹⁶ The study shows that all eight firms offshore some low skill

¹⁶The firms operate in manufacturing and services, specifically financial services (two firms), software, computer manufacturing, packaging, transport, manufacturing of consumer products, and manufacturing of PC hardware.

service activities, such as call centres, IT help desks, back office operations, or dealing with travel reimbursements. This is in line with Blinder's (2007) classification of occupations, where he lists telemarketers, telephone operators, customer service representatives, and travel clerks, alongside high skilled occupations such as computer programmers and mathematicians, among the twenty occupations with the highest risk of being offshored. While we do not know of any in-depths study that examines exactly what type of activity is offshored by a firm, our results are consistent with the idea that the offshoring of low skill services is an important component of offshoring activity in the UK. An important assumption implicit in our estimation thus far is that of exogeneity of regressors. This may be questionable in particular with respect to the offshoring variables. These may be endogenous due to reverse causality - industries with unskill intensive production (and low wages for unskilled workers) may also be those that are more likely to offshore. In this case our conclusions based on the estimations thus far would be problematic. We have three responses to this concern. First, given that there is substantial heterogeneity in individual wages the described scenario, that variation in individual wages causes industry-level offshoring, is unlikely. Second, we control for industry-level fixed effects which would control for time invariant characteristics, such as production technology, of the different industries. Third, we explicitly test the assumption of exogeneity of the offshoring variables using a C-test, based on a re-estimation of the equations in columns (I) to (II) using an instrumental variable GMM approach. Finding valid instruments for testing the exogeneity of the offshoring variables presents a challenge. One needs variables that are important determinants of the respective industry's offshoring activities but do not impact on industry's wages. The literature points to advances in trade liberalization, lowering of transport and communication costs as well as technological progress as important drivers of increased offshoring (see Amiti and Wei, 2005, Bartel et al., 2005). However, these factors are difficult to measure at the industry level and, thus, cannot be differentiated from common macro economic effects that impact on wages. We therefore apply a different strategy. Instead of directly including determining factors of an industry's offshoring activities as excluded instruments we use information on offshoring activities of the same

industry in a different country, namely Germany. Arguably, offshoring activities of the same industry in different countries are driven by the same global factors. This should be particularly true if countries share the same trade policy and have a similar industrial structure. We thus expect a close correlation between offshoring activities in the UK and Germany within any given manufacturing industry. At the same time, conditional on fluctuations in industry output offshoring activities of German industries are unlikely to have a direct impact on wages at the worker level in the UK. Hence, German offshoring activities should be relevant as well as valid instruments. The test statistics reported in Table 6 support our reasoning. Based on the first step F-test we find that the instruments have a high explanatory power. Also, we can clearly reject underidentification and weak identification, suggesting that our instruments are indeed relevant. We cannot reject orthogonality of our excluded instruments within reasonable confidence bands based on the Hansen J statistic, supporting our assumption of instrument validity. Furthermore, the C-test indicates that we cannot reject exogeneity of services and materials offshoring. Accordingly, the efficiency loss associated with instrumenting for services and materials offshoring cannot be justified and the fixed effects coefficients reported in Tables 4 and 5 can be considered consistent estimates of the true parameters.¹⁷

Thus far we have focussed on statistical significance. The point estimates and standard errors of the coefficients allow us to examine the direction and significance of the effects, but do not tell us much about their actual importance. To judge the economic significance of our estimates we engage in a thought experiment of implied wage changes. We do this separately for our estimates in Table 4 and Table 5. Table 7 reports the median hourly wages in British pounds for the three skill groups in 1992, the beginning of our sample period. We also report the coefficients from the estimation of the preferred specification in columns (IV) of Tables 4 and 5.

Consider the effect of narrow offshoring first. Over the full sample period, narrowly defined services offshoring increased by 0.12 percentage points, while the increase for

¹⁷All estimations and corresponding tests are carried out using the Stata add-ons `ivreg2` and `xtivreg2` provided by Baum et al. (2003, 2007).

narrow materials offshoring was 2.23 percentage points. For a high-skilled worker with an average number of working hours (1,732 per year for the UK, see OECD, 2008) this implies that the cumulative increase in wages due to services offshoring was roughly GBP 2,000. Materials offshoring has no statistically significant impact on high-skilled workers wages. Accordingly, the cumulative increase in wages due to materials offshoring is nil. For low-skilled workers, we observe a corresponding cumulative reduction in wages by GBP 619, GBP 311 of which were due to services offshoring and the remainder due to materials offshoring. The effects of offshoring for medium-skilled workers were not identified precisely enough to rule out that they are nil. The corresponding calculations for broadly defined offshoring are reported in the bottom panel of Table 7. The results are similar to those obtained from narrow offshoring, indicating wage gains for high-skilled workers of about GBP 1,278 due to services offshoring, and wage losses for medium- and low-skilled workers of about GBP 256 - 584 over the period 1992 to 2004. Given that these are effects of cumulative changes of offshoring over a twelve year period these numbers are small, but not so small as to be neglected. The economic significance calculation also shows that, even though services offshoring, especially when defined narrowly, is still at low levels it has important economic implications for workers' wages.¹⁸

6 Alternative approach

Thus far we have investigated how offshoring within an industry affects wages of workers in the same industry. Thus, the empirical approach corresponds to a partial equilibrium

¹⁸A potential question regarding our estimations is how robust this is to the definition of skills we use. As an alternative, we use a skill definition based on the Standard Occupational Classification (SOC) of individuals, information on which is in the BHPS. We classify individuals into high (SOC=1 to 3), medium (SOC=4 to 5), and low-skilled (SOC=6 to 9) occupations. For broad services offshoring and narrow materials offshoring the coefficients based on this approach are comparable to the estimates reported here in terms of signs, statistical significance, and magnitude for low- and medium-skilled workers. One notable difference is that we now do not find any statistically significant effect of services or material offshoring on high-skilled workers. Furthermore, narrow service offshoring and broad material offshoring are always rendered insignificant in this approach. Accordingly, there is some evidence that medium- and low-skilled workers are more negatively affected by offshoring than high-skilled workers. However, results are indeed sensitive to the definition of skills and offshoring. Results are not reported here to save space, but can be obtained upon request.

short-run view of the economy outlined in, e.g., Grossman and Rossi-Hansberg (2008) where employees are immobile between industries. In that case, what matters is how important offshoring is in the own industry, what happens in other industries is irrelevant. However, in the long run it is more realistic that employees can potentially move between industries. Accordingly, labour market effects of offshoring in one industry can also impact on other industries. One approach that has been used in the literature to analyse empirically such long-run effects of offshoring is the estimation of mandated wage regressions (see e.g., Feenstra and Hanson, 1999 for the US and Hijzen, 2007 for the UK). This approach is based on fairly aggregated sectoral data for long time series. Our disaggregated individual-level panel data lends itself to another approach. Instead of analysing wage effects of within-industry changes of offshoring we can construct education-specific offshoring measures and regress them on individual wages. Accordingly, we allow for cross-industry spillovers of labour demand effects of offshoring by assuming that workers are unable to change their educational attainment once they entered employment but can potentially move between industries.¹⁹ This assumption is born out by our data: while we count 1,093 occurrences of industry changes we have only 63 cases where individuals move between skill groups. To construct education-specific offshoring measures, we re-weight industry-level offshoring measures (cf. eqs 1 to 4) with respect to industry employment within a given educational group ($s = \text{high-, medium, low-skilled}$) as a share in total employment L within educational group s in 1991 (pre-sample):

$$OSS_{st}^z = \sum_{j=1}^J \frac{L_{sj}}{L_s} OSS_{jt}^z \quad (6)$$

¹⁹Our approach is similar to Ebenstein et al. (2009) and Baumgarten et al. (2010) who construct occupation-specific offshoring measures to allow for cross-industry effects of offshoring. However, in the context of the UK we find it more realistic to assume that individuals potentially can change their occupation while changing their educational attainment is more difficult.

$$OSM_{st}^z = \sum_{j=1}^J \frac{L_{sj}}{L_s} OSM_{jt}^z, \quad (7)$$

with $z = narrow, broad$. Similarly, we construct education-specific output (Y_{st}) to account for education-specific time varying industry characteristics.

We then re-estimate our empirical model in eq. 5 substituting Y_{st} , OSS_{st} and OSM_{st} for Y_{jt} , OSS_{jt} and OSM_{jt} , yielding

$$\log w_{ist} = \alpha + \beta X_{it} + \gamma Y_{st} + \delta (R\&D/Y)_{st} + \lambda_S OSS_{st}^z + \lambda_M OSM_{st}^z + T_t + \mu_t + \alpha_i + \iota_k + \epsilon_{ist}, \quad (8)$$

. When estimating the model we allow for clustered standard errors within educational groups s at time t yielding 39 clusters.²⁰ The results are reported in Table 8, where, for the sake of brevity, we only report coefficients and t-statistics for the offshoring variables interacted with education dummies.²¹

One striking point is particularly noteworthy. In the full specifications reported in Columns I and V, eight out of twelve offshoring coefficients in the two specifications are statistically insignificant. This reflects the substantially reduced variation in the offshoring variable compared to the earlier offshoring measures used above, as offshoring only varies over three education categories and time. Furthermore, when comparing the coefficients in Columns II to III and VI to VII, where we respectively excluded materials and services offshoring from the model, statistical significance of our services and materials offshoring variables changes drastically indicating multicollinearity of the two. As a consequence it is doubtful whether one can indeed separate the effects of services and materials offshoring. To reflect this we also estimate model specifications where only the sum of education-specific services and materials offshoring enters. The respective coefficients are reported in Columns IV and VIII of Table 8.

²⁰Note that since in our data individuals do not change education within a given year, individuals are nested within the education-year clusters.

²¹Results for the other variables included in the model are similar to those reported above. They can be obtained from the authors upon request.

When applying our narrow definitions of offshoring, services and material offshoring taken together exert statistically significant negative wage effects on medium- and low-skilled workers while the effect is rendered insignificant for high-skilled workers. When applying the broad offshoring definitions, high-skilled workers are found to gain from services and materials offshoring while low-skilled workers lose. For medium-skilled workers the effect of broad offshoring is rendered statistically insignificant. Similar to the within-industry discussion, our results are consistent with the wage effects postulated in Grossman and Rossi-Hansberg (2008) for offshoring of low-skill intensive activities. Accordingly, low-skilled workers experience wage cuts due to the dominance of the negative labour supply effect and, if one prescribes to the long run general equilibrium view, the negative Stolper-Samuelson type relative price effect. High-skilled workers, however, experience wage increases due to this type of offshoring, as both the labour supply as well as the relative price effect work in their favour. The implied economic significance of the estimates is, in a similar manner to Table 7 calculated in Table 9. Concentrating on the statistically significant coefficients reported in Columns IV and VIII of Table 8 we find a joint cumulated wage loss due to narrowly defined services and materials offshoring of GBP 4893 and GBP 4323 for medium- and low-skilled workers respectively. The cumulated wage loss of broadly defined services and materials offshoring is GBP 1873 for low-skilled workers while high-skilled workers gain GBP 5283. The wage effects of our education-specific offshoring variable thus follow a similar pattern as in the industry-specific partial equilibrium analysis carried out in Section 5. However, the magnitude of the effects is much higher. This may reflect that the labour supply effect highlighted by Grossman and Rossi-Hansberg (2008) is now allowed to operate across industries. If offshoring sets free workers of a given skill type, this will, *ceteris paribus*, depress the wage paid to those workers in all industries. Furthermore, the negative wage effects due to relative price changes predicted by Grossman and Rossi-Hansberg (2008) are not present in a within-industry partial equilibrium setting but may be present here.

7 Conclusion

This paper investigates the relationship between offshoring of services and individual workers' wages, using household-level panel data from the British Household Panel Survey (BHPS) combined with industry-level measures of offshoring of services activities and materials offshoring over the period 1992 to 2004. We use two different estimation strategies. One uses only within-industry changes in offshoring, while the other also considers offshoring effects across industries. Our results show that services offshoring in an industry affects the real wage of low- and medium-skilled individuals in the same industry negatively. By contrast, there is evidence that skilled workers in the industry benefit from such services offshoring in terms of higher real wages. This is consistent with the partial equilibrium view in Grossman and Rossi-Hansberg (2008) if one assumes that mainly low- and medium skilled services activities are offshored. This has positive effects for high skilled workers but may affect low skilled workers negatively, if the negative labour supply effect is not outweighed by a positive productivity effect. Once allowing for the fact that offshoring in one particular industry potentially also affects labour demand in other industries, then we cannot separately identify effects of services and materials offshoring. However, our results show some evidence for a statistically significant positive effect on high-skilled wages and negative effects for low- and medium-skilled workers for services and materials offshoring taken together.

In sum, our results suggest that offshoring of services has contributed to a widening of the wage gap between skilled and less skilled workers. However, looking at the magnitude of these effects we find that they are rather small, but not so small as to be negligible. Hence, we have identified winners and losers in terms of wage gains from services offshoring. The policy relevant question is now whether the losers should be compensated and, if this is answered in the affirmative, what form such a compensation should have. Another policy implication is that skill upgrading needs to be continued in order to allow unskilled workers to move into the 'winning' category of skilled work.

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Tables and figures

Table 1: Service and Material Offshoring Intensity in %

Year	<i>OSS</i> ^{narrow}	<i>OSM</i> ^{narrow}	<i>OSS</i> ^{broad}	<i>OSM</i> ^{broad}
1992	0.17	4.10	2.35	9.38
1993	0.21	4.28	2.42	9.41
1994	0.19	4.60	2.41	10.11
1995	0.18	4.74	2.34	10.76
1996	0.23	4.95	2.27	11.43
1997	0.21	5.24	2.37	11.95
1998	0.25	5.65	2.72	13.11
1999	0.27	5.48	3.12	12.76
2000	0.28	5.74	3.39	13.61
2001	0.28	5.70	3.55	13.55
2002	0.29	5.92	3.80	13.83
2003	0.28	6.05	3.93	14.05
2004	0.29	6.33	3.92	14.20
Absolute Change	0.12	2.23	1.57	4.81
Growth rate in %	69.78	54.35	66.58	51.32

Authors' calculations.

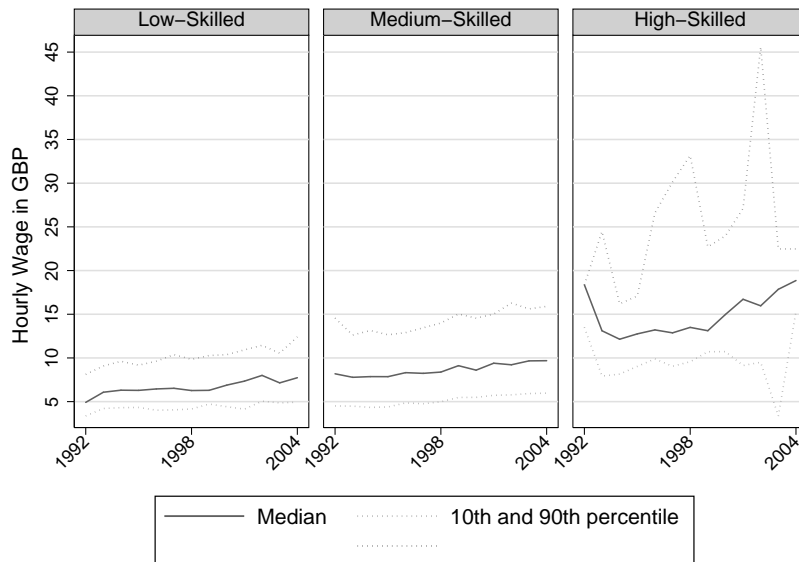
Table 2: Summary Statistics

	Mean	Standard Deviation
Hourly Wage	9.0566	4.5981
<i>Age</i> : 18 – 25	0.1118	0.3152
<i>Age</i> : 26 – 35	0.2564	0.4367
<i>Age</i> : 36 – 50	0.4257	0.4945
<i>Married</i> : <i>Dummy</i>	0.6473	0.4779
<i>Children</i> : <i>Dummy</i>	0.4452	0.4970
<i>Tenure</i>	214.9854	107.5176
<i>Tenure</i> ²	57776.74	54080.26
<i>Tenure</i> : <i>noresponse</i>	0.0978	0.2971
ISCED: high	0.0267	0.1612
ISCED: med	0.7402	0.4386
<i>FirmSize</i> : < 25	0.1824	0.3862
<i>FirmSize</i> : 25 – 100	0.2235	0.4166
<i>FirmSize</i> : 100 – 1000	0.4714	0.4992
<i>Firm</i> : <i>public</i>	0.0042	0.0648
<i>Firm</i> : <i>unknownowner</i>	0.0002	0.0123
<i>Industry</i> : <i>Output</i>	29.1356	16.6245
<i>Industry</i> : <i>R&D/Y</i>	2.1599	2.4851
Observations		5775

Table 3: Skill Grouping

High-Skilled	Second stage of tertiary education (Masters degree and higher)	years of schooling approx. $16 \leq \text{years}$
Medium-Skilled	Upper-secondary education Post-secondary but non-tertiary education First stage of tertiary education	approx. $11 \leq \text{years} < 16$
Low-Skilled	Pre-primary education Primary education Lower-secondary education	approx. $\text{years} < 11$

Figure 1: Wages by skill



Note: Authors' calculations.

Table 4: Narrow Offshoring Regression Results

	I	II	III	IV
	OLS	FE	cluster boot-t	cluster boot-t
<i>Age</i> : 18 – 25	-0.2701 [6.78]***	-0.0496 [1.28]	-0.0485 [1.25]	-0.0454 [1.16]
<i>Age</i> : 26 – 35	-0.0689 [2.81]***	0.0397 [1.24]	0.0401 [1.25]	0.0411 [1.29]
<i>Age</i> : 36 – 50	-0.0286 [1.12]	0.0521 [2.09]**	0.0523 [2.10]**	0.0524 [2.10]**
<i>Married</i> : <i>Dummy</i>	0.1093 [5.29]***	0.0234 [1.00]	0.0238 [1.02]	0.0235 [1.02]
<i>Children</i> : <i>Dummy</i>	0.0627 [4.46]***	0.0244 [1.88]*	0.0245 [1.89]*	0.0254 [1.95]*
<i>Tenure</i>	0.0008 [2.41]**	0.0008 [2.91]***	0.0008 [2.93]***	0.0008 [2.75]***
<i>Tenure</i> ²	-0.0001 [2.78]***	-0.0001 [2.31]**	-0.0001 [2.35]**	-0.0001 [2.21]**
<i>Tenure</i> : <i>noresponse</i>	0.1511 [2.39]**	0.1264 [3.06]***	0.1270 [3.07]***	0.1222 [2.92]***
<i>ISCED</i> : <i>high</i>	0.4492 [8.27]***	0.1317 [2.75]***	0.1356 [2.80]***	-0.2793 [1.88]*
<i>ISCED</i> : <i>med</i>	0.1533 [7.34]***	-0.0178 [0.55]	-0.0179 [0.55]	-0.1095 [2.00]**
<i>FirmSize</i> : < 25	-0.2272 [7.52]***	-0.0746 [2.61]***	-0.0748 [2.65]***	-0.0756 [2.71]***
<i>FirmSize</i> : 25 – 100	-0.2055 [7.48]***	-0.0377 [1.70]*	-0.0379 [1.74]*	-0.0366 [1.67]*
<i>FirmSize</i> : 100 – 1000	-0.1028 [4.52]***	-0.0033 [0.15]	-0.0033 [0.15]	-0.0034 [0.16]
<i>Firm</i> : <i>public</i>	-0.1770 [1.98]**	0.0730 [0.89]	0.0743 [0.90]	0.0685 [0.80]
<i>Firm</i> : <i>unknownowner</i>	0.1971 [6.09]***	-0.1561 [7.82]***	-0.1597 [7.76]***	-0.1648 [7.88]***
<i>Industry</i> : <i>Output</i>	0.0123 [0.80]	0.0130 [1.38]	0.0176 [1.83]*	0.0159 [1.72]*
<i>Industry</i> : <i>R&D/Y</i>	-0.0020 [0.12]	-0.0073 [0.89]	-0.0126 [1.50]	-0.0136 [1.63]**
<i>OSS</i>	-0.1437 [0.47]	-0.1510 [0.95]	-0.0886 [0.60]	
<i>OSS</i> × <i>ISCED</i> : <i>high</i>				0.5188 [2.24]**
<i>OSS</i> × <i>ISCED</i> : <i>med</i>				-0.0469 [0.30]
<i>OSS</i> × <i>ISCED</i> : <i>low</i>				-0.3014 [1.91]*
<i>OSM</i>			-0.0080 [1.87]*	
<i>OSM</i> × <i>ISCED</i> : <i>high</i>				0.0053 [0.75]
<i>OSM</i> × <i>ISCED</i> : <i>med</i>				-0.0078 [1.81]*
<i>OSM</i> × <i>ISCED</i> : <i>low</i>				-0.0162 [2.99]***
Constant	1.4834 [5.95]***			
Observations	5775	5775	5775	5775
R ²	0.49	0.83	0.83	0.83

Note: t-statistics in brackets, *** significant at 1%, ** at 5%, * at 10%.
 Default categories: *Age* : > 50, *ISCED*:low, *FirmSize* : > 1000.
 Occupation, region, industry dummies and industry time trends included.
 Cluster bootstrapped t-test with 500 repetitions.

Table 5: Broad Offshoring Regression Results

	I	II	III	IV
	OLS	FE	cluster boot-t	cluster boot-t
<i>Age</i> : 18 – 25	-0.2701 [6.77]***	-0.0492 [1.28]	-0.0484 [1.25]	-0.0467 [1.16]
<i>Age</i> : 26 – 35	-0.0690 [2.82]***	0.0396 [1.23]	0.0402 [1.25]	0.0417 [1.27]
<i>Age</i> : 36 – 50	-0.0285 [1.12]	0.0519 [2.06]**	0.0518 [2.07]**	0.0525 [2.10]**
<i>Married</i> : <i>Dummy</i>	0.1095 [5.30]***	0.0232 [0.99]	0.0233 [1.00]	0.0221 [0.95]
<i>Children</i> : <i>Dummy</i>	0.0627 [4.46]***	0.0248 [1.90]*	0.0247 [1.90]*	0.0241 [1.86]*
<i>Tenure</i>	0.0008 [2.41]**	0.0008 [2.90]***	0.0008 [2.88]***	0.0008 [2.70]***
<i>Tenure</i> ²	-0.0001 [2.79]***	-0.0001 [2.29]**	-0.0001 [2.29]**	-0.0001 [2.15]**
<i>Tenure</i> : <i>noresponse</i>	0.1507 [2.39]**	0.1248 [3.04]***	0.1243 [3.03]***	0.1204 [2.87]***
<i>ISCED</i> : <i>high</i>	0.4495 [8.27]***	0.1316 [2.74]***	0.1347 [2.85]***	-0.1642 [1.49]
<i>ISCED</i> : <i>med</i>	0.1533 [7.34]***	-0.0162 [0.50]	-0.0161 [0.50]	-0.0885 [1.45]
<i>FirmSize</i> : < 25	-0.2272 [7.49]***	-0.0744 [2.62]***	-0.0747 [2.64]***	-0.0758 [2.69]***
<i>FirmSize</i> : 25 – 100	-0.2053 [7.45]***	-0.0376 [1.70]*	-0.0378 [1.72]*	-0.0391 [1.78]*
<i>FirmSize</i> : 100 – 1000	-0.1027 [4.49]***	-0.0029 [0.13]	-0.0030 [0.14]	-0.0044 [0.21]
<i>Firm</i> : <i>public</i>	-0.1771 [1.97]**	0.0719 [0.87]	0.0729 [0.88]	0.0710 [0.86]
<i>Firm</i> : <i>unknownowner</i>	0.1906 [5.28]***	-0.1141 [4.64]***	-0.1105 [4.99]***	-0.1275 [5.47]***
<i>Industry</i> : <i>Output</i>	0.0141 [0.84]	0.0093 [0.87]	0.0118 [1.12]	0.0119 [1.14]
<i>Industry</i> : <i>R&D/Y</i>	-0.0013 [0.08]	-0.0072 [0.78]	-0.0101 [1.18]	-0.0109 [1.27]
<i>OSS</i>	0.0028 [0.37]	-0.0082 [1.91]*	-0.0100 [2.47]**	
<i>OSS</i> × <i>ISCED</i> : <i>high</i>				0.0257 [3.15]***
<i>OSS</i> × <i>ISCED</i> : <i>med</i>				-0.0115 [2.78]***
<i>OSS</i> × <i>ISCED</i> : <i>low</i>				-0.0144 [2.65]***
<i>OSM</i>			-0.0034 [0.81]	
<i>OSM</i> × <i>ISCED</i> : <i>high</i>				0.0043 [1.46]
<i>OSM</i> × <i>ISCED</i> : <i>med</i>				-0.0036 [0.89]
<i>OSM</i> × <i>ISCED</i> : <i>low</i>				-0.0096 [1.84]*
Constant	1.4427 [6.32]***			
Observations	5775	5775	5775	5775
R ²	0.49	0.83	0.83	0.83

Note: t-statistics in brackets, *** significant at 1%, ** at 5%, * at 10%.
 Default categories: *Age* :> 50, *ISCED*:low, *FirmSize* :> 1000.
 Occupation, region, industry dummies and industry time trends included.
 Cluster bootstrapped t-test with 500 repetitions.

Table 6: Exogeneity tests of offshoring, reduced sample due to lags

Instrumented	OSS^{narrow}	OSS^{narrow} OSM^{narrow}	OSS^{broad}	OSS^{broad} OSM^{broad}
Instruments	$OSS_{Germany,t}^{narrow}$ $OSS_{Germany,t}^{broad}$	$OSS_{Germany,t}^{narrow,broad}$ $OSM_{Germany,t,t-1}^{narrow}$	$OSS_{Germany,t}^{broad}$ $OSS_{Germany,t-1}^{broad}$	$OSS_{Germany,t-1}^{broad,narrow}$ $OSM_{Germany,t,t-1}^{broad}$
	F= 45.03 p=0.00	F=30.57/F=32.72 p=0.00/p=0.00	F= 28.56 p=0.00	F= 31.60/F=53.47 p=0.00/p=0.00
		First Stage F-test		
Kleibergen-Paap rk LM statistic	$\chi^2(2) = 132.88$ p=0.00	$\chi^2(3) = 121.02$ p=0.00	$\chi^2(2) = 64.20$ p=0.00	$\chi^2(3) = 80.49$ p=0.00
		Underidentification test		
Kleibergen-Paap rk Wald F statistic	F=70.31	F=33.69	F=28.56	F=22.43
	19.93	16.87	19.93	16.87
		Weak identification test		
		Stock-Yogo critical values for wrong rejection rate of 10%		
Hansen J statistic	$\chi^2(1) = 1.65$ p=0.20	$\chi^2(2) = 3.54$ p=0.17	$\chi^2(1) = 0.04$ p=0.84	$\chi^2(2) = 1.52$ p=0.47
		Overidentification test of all instruments		
C-Test	$\chi^2(1) = 0.17$ p=0.68	$\chi^2(2) = 0.09$ p=0.95	$\chi^2(1) = 0.05$ p=0.83	$\chi^2(2) = 1.85$ p=0.40
		Exogeneity of regressors		
Observations	5775	5775	5775	5775

Table 7: Cumulated wage effects of increased offshoring, at 1992 median wages

	High-Skilled	Medium-Skilled	Low-Skilled
Median hourly wage (1992)	18.37	8.19	4.92
Narrow Definition of Offshoring			
Coefficients, Table 4, Column IV			
OSS	0.519	-	-0.3014
OSM	-	-	-0.0162
Percentage Point Change, 1992-2004			
OSS=0.12			
OSM=2.23			
Cumulated yearly wage change in GBP (1732 work hours)			
OSS	1999.74	-	-310.86
OSM	-	-	-308.36
Broad Definition of Offshoring			
Coefficients, Table 5, Column IV			
OSS	0.026	-0.0115	-0.0144
OSM	-	-	-0.0096
Percentage Point Change, 1992-2004			
OSS=1.57			
OSM=4.81			
Cumulated yearly wage change in GBP (1732 work hours)			
OSS	1278.70	-256.02	-191.83
OSM	-	-	-393.73

Note: assumed 1732 annual work hours in 1992 according to OECD (2008, Factbook)

Table 8: Education-Specific Offshoring - Regression Results

	Narrow				Broad			
	I	II	III	IV	V	VI	VII	VIII
$OSS \times ISCED : high$	-1.8381 [1.05]	-0.5163 [0.35]			-0.0132 [0.37]		-0.0011 [0.05]	
$OSS \times ISCED : med$	-1.7730 [1.07]	-2.3101 [1.81]*			-0.0319 [0.78]		-0.0530 [1.59]	
$OSS \times ISCED : low$	-2.0036 [1.39]	-2.8231 [2.46]**			-0.0561 [1.04]		-0.0844 [2.23]**	
$OSM \times ISCED : high$	-0.0331 [0.49]		0.0011 [0.02]		-0.4067 [1.60]	-0.5388 [3.32]***		
$OSM \times ISCED : med$	-0.1883 [2.73]***		-0.1455 [1.98]*		-0.2599 [1.92]*	-0.3696 [5.34]***		
$OSM \times ISCED : low$	-0.2387 [3.04]***		-0.2184 [2.91]***		-0.1609 [2.03]**	-0.2506 [6.10]***		
$(OSS + OSM) \times ISCED : high$				-0.0059 [0.09]				0.0260 [1.81]*
$(OSS + OSM) \times ISCED : med$				-0.1468 [2.03]**				-0.0201 [1.03]
$(OSS + OSM) \times ISCED : low$				-0.2160 [2.95]***				-0.0345 [1.95]*
Observations	5775	5775	5775	5775	5775	5775	5775	5775
R-squared	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83

Note: t-statistics in brackets, *** significant at 1%, ** at 5%, * at 10%.

Complete set of control variables included.

t-tests on the basis of clustered standard errors by education and year.

Table 9: Cumulated wage effects of increased offshoring, at 1992 median wages: education-specific offshoring

	High-Skilled	Medium-Skilled	Low-Skilled
Median hourly wage (1992)	18.37	8.19	4.92
Narrow Definition of Offshoring			
Coefficient, Table 8, Column IV			
OSS+OSM	-	-0.1468	-0.2160
Percentage Point Change, 1992-2004 OSS+OSM=2.35			
Cumulated yearly wage change in GBP (1732 work hours)			
OSS+OSM	-	-4893.08	-4323.73
Broad Definition of Offshoring			
Coefficient, Table 8, Column VIII			
OSS+OSM	0.0260	-	-0.0345
Percentage Point Change, 1992-2004 OSS+OSM=6.38			
Cumulated yearly wage change in GBP (1732 work hours)			
OSS+OSM	5282.85	-	-1872.82

Note: assumed 1732 annual work hours in 1992 according to OECD (2008, Factbook)