Outsourcing Types, Relative Wages, and the Demand for Skilled Workers: New Evidence from US Manufacturing

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Abstract

Existing studies on the impact of outsourcing activities on relative wages and the demand for skilled workers mainly focus on aggregate outsourcing activities, in which imported intermediate inputs are used as a proxy. These studies also typically focus on the manufacturing sector at a high aggregation level. We depart from the existing studies by focusing on various types of outsourcing and on the manufacturing sector at a lower aggregation level. We show that downstream materials and service outsourcing are skill-biased whereas upstream materials outsourcing is not. We also produce other supplementary results pertaining to the impact of technology, different capital inputs on relative wages, and the demand for skilled workers.

Keywords: downstream materials outsourcing, upstream materials outsourcing, service outsourcing, relative wages, skilled workers

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1. Introduction

The pivotal roles of international outsourcing and skill-biased technology in explaining the dramatic increase in relative wages of skilled workers in industrialized economies have been extensively documented and analyzed in the literature.[1] In this literature, the notion of outsourcing is typically confined mainly to the imported intermediate inputs. For analytical purposes, using imported intermediate inputs can be justified, given that imports of intermediate inputs should be expected to affect the relative demand for manufacturing workers and relative wages,[2] nevertheless, some important insights into the role of different types of outsourcing cannot be sufficiently emphasized.

In principle, firms differ in the extent of their specialization in activities along the vertical chain of production. Some firms may engage in many activities along the chain, extending from upstream (intermediate inputs) production to downstream (final goods) production, while some other firms may specialize either in upstream or downstream production. The upstream production of intermediate inputs may involve an intensity of skills different from that of the downstream production of final goods.

Firms that specialize in downstream production may outsource their upstream materials, while firms that specialize in upstream production outsource their downstream materials. Both types of firm may also outsource their services, for example, repair and maintenance services for machinery, communication services, financial services, and IT services, in order to focus on their core activities.[3] If upstream production is more skill-intensive, outsourcing downstream production can reduce their dependency on unskilled workers and hire more skilled workers to take advantage of the increasing productivity of the upstream activities driven by specialization. Given this difference in skill intensity along production chain, the negative impacts on the relative skilled labor demand would likewise be expected if they outsource upstream production. Obviously, types of outsourcing that are different

[1] See, for instance, Feenstra and Hanson (1996, 1999) for US, Feenstra and Hanson (1997) for Mexico, Anderton and Brenton (1999) for the UK, Geishecker (2002) for Germany, and Hsieh and Woo (2005) for Hong Kong.

[2] Note that it is generally accepted that changes in labor supply fail to account for this phenomenon.

[3] The above decomposition of outsourcing into three different types is consistent with the definition of outsourcing put forward by Grossman and Helpman (2002, 2005). They basically define outsourcing as the extent to which the production materials, parts, or service activities are contracted out to outside partners.

may have different impacts on both the demand for skilled-workers and on relative wages. Therefore, focusing on the various types of outsourcing activities should enable us to get richer results. To the best of our knowledge, these refined notions of outsourcing have largely been unexplored in the literature.

A study by Amiti and Wei (2006) is perhaps the closest to our paper. Their paper analyzes the impacts of both materials and service outsourcing on overall labor productivity. They argue that, by engaging in materials and service outsourcing, firms can delegate parts of the production process that are inefficient to other, more efficient firms. They can then focus on those activities in which they have comparative advantage and increase output. Consequently, the average productivity of the remaining workers should increase. It should be noted, however, that Amiti and Wei (2006) only look at aggregate workers; they do not really examine the impact of outsourcing activities on the demand for skilled workers relative to that for unskilled workers. Furthermore, in contrast with this study, they do not really decompose materials outsourcing any further. Our approach, which separates materials outsourcing into upstream and downstream materials outsourcing, allows us to capture the notion of the vertical specialization of firms along different stages of the production process and to examine the impacts of this vertical specialization on the labor market.

Our empirical estimations are based on the disaggregated six-digit NAICS US data on manufacturing industries (sectors 31-33). To investigate the more detailed impacts of outsourcing, we combine two datasets. The first is the *2002 Annual Survey of Manufacturers*, which contains six-digit NAICS data on US manufacturing, such as estimates for employment, plant hours, payrolls, value added by manufacturers, capital expenditures, and cost of materials for most manufacturing industries. The second dataset is the *2002 Economic Census*, which contains detailed data on production structures and costs, and also on downstream and upstream materials and service outsourcing. In addition to these two data sources, we use the *US International Trade Statistics*, provided by the US Census Bureau, for the data on imports.

Our empirical strategy is to estimate the relative demand for skilled workers derived from a modified version of the translog cost function pioneered by Brown and Christensen (1981). Our results show that upstream materials outsourcing is not skill-biased, whereas downstream materials and service outsourcing is skill-biased. Our results thus partly contrast with conventional findings, which assert that outsourcing is always skill-biased.

The intuitions behind our results can be explained as follows. Downstream materials- and service-outsourcing activities enable skill-intensive firms to reallocate their resources to the upstream production activities, which are skill-intensive. The productivity of skilled workers engaged in the upstream production activities will then be enhanced. Accordingly, these kinds of outsourcing activities should have a positive impact on the relative wages of skilled workers. Upstream materials-outsourcing activities, on the other hand, have an opposite impact. They enable firms to specialize in those downstream production activities which are not skill-intensive, thereby having a negative impact on the relative wages of skilled workers.

We also report two further interesting results. First, we find that, when disaggregating capital into machinery and buildings, the former is a substitute for, and the latter a complement of, skilled workers. This is partly in contrast with the existing empirical evidence, which shows capital stocks and skilled workers as complements.[4] Second, we also show that technological progress is skill-biased.

This paper is organized as follows. Section 2 briefly reviews the existing empirical results on the impact of outsourcing activities on the relative demand for skilled workers. Section 3 discusses our empirical model and its derivation, together with our empirical strategy. Section 4 gives detailed descriptions of our data and data measurement. Section 5 presents our empirical results, and Section 6 offers some conclusions.

2. Overview of the Related Literature

Throughout the 1980s and 1990s, the US economy witnessed a widening gap between skilled and unskilled wages. Various theoretical propositions have been put forward to explain this phenomenon. Trade economists, for instance, have argued that the gap can be attributed to international trade in intermediate goods, or "outsourcing" as it is often referred to in the literature. Feenstra and Hanson (1996) were the first to empirically verify this outsourcing-based theoretical proposition. They show that around 15-33 percent of the relative increase in wages of skilled workers can indeed be explained by international outsourcing. Later, Feenstra and Hanson (1999), using

[4] See Geishecker (2002), Anderton and Brenton (1999), and Feenstra and Hanson (1997).

imported intermediate inputs, revealed that skill-biased technological change can also significantly explain the observation. Subsequent to the publication of these two seminal papers, many authors have replicated these results using data from other industrialized countries, such as the UK, Germany, and Hong Kong, and have found supporting evidence.[5]

More recently, some papers have shed further light on the issues of wage inequality. Blum (2004), for instance, shows that a structural shift in the sectoral composition of the economy could also explain the rising wages of, and demand for, skilled workers. His argument is motivated by an observation that in the US, there have been some falls in the level of employment and capital accumulation in the manufacturing sector and, at the same time, some increases in the level of employment and capital accumulation in the non-manufacturing sector, for example, in services and in the retail and wholesale trade sectors. He further asserts that if capital is complementary to skilled workers in the non-manufacturing sector, the above sectoral shift would have caused an increase in the wage inequality between skilled and unskilled workers in the economy. He empirically tested his assertion using US data and shows that the sectoral reallocation from manufacturing to services, retail, and wholesale trade sectors can indeed account for the increasing wage gap.

In contrast to Blum’s (2004) model, in which capital is immobile across countries, Sachs and Schatz (1998) develop a model in which capital is allowed to flow outside the country. They show that such a capital outflow can raise the relative wages of skilled workers in the non-traded goods sectors. Despite the above essential difference, both models do indeed highlight the important role of capital inputs and structural change in explaining the wage inequality between skilled and unskilled workers. Our paper will also investigate the role of capital inputs empirically. In particular, we will decompose capital inputs into two categories. The first category is machinery and equipment, and the second is buildings and other structures. We show that different capital inputs will have different implications for relative wages and for demand for skilled workers.

The study of Amiti and Wei (2006) is, in content, perhaps the closest paper to ours. They evaluate the impacts of international outsourcing, or offshoring in their terminology, on the productivity of the US manufacturing sector. The starting point of

[5] See Feenstra and Hanson (1997) for Mexico, Anderton and Brenton (1999) and Hijzen et al. (2005) for the UK, Geishecker (2002) for Germany, and Hsieh and Woo (2005) for Hong Kong.

their paper is the twin stylized observations of increasing trends in productivity and international outsourcing in the US in recent decades. In their framework, production technology is determined by both materials and service offshoring. They argue that if firms are able to internationally fragment the inefficient parts of their production process by outsourcing, they can then specialize in other parts of the production process where they have a comparative advantage. Accordingly, the average productivity of labor in the economy should increase. In addition to the specialization effect, the average productivity will also increase due to a host of other effects such as restructuring effects, learning externalities, and variety effects brought about by offshoring.[6] Their empirical results substantiate their argument. They are able to show that outsourcing does make a positive impact on overall labor productivity. Unfortunately, few conclusions can be drawn about the impact of outsourcing on wage inequality.

Interestingly, in an earlier work, Amiti and Wei (2005), using a similar framework, found that offshoring has either a small negative effect on employment when a disaggregated manufacturing sector is used, or no effect at all when a more aggregated manufacturing sector is used. Thus, the effect of offshoring on employment seems to be inconclusive.

Our paper departs from Amiti and Wei (2005 and 2006) by focusing specifically on the impacts of outsourcing on the relative wages of skilled to unskilled workers and on the demand for skilled workers, instead of on the impacts of outsourcing on overall productivity and employment. The notion of outsourcing in our context follows that of Abraham and Taylor (1996) in the sense that outsourcing and in-house production are substitutes; therefore, they should affect the demand for labor regardless of location. As such, rather than merely focusing on the trade-related aspects of outsourcing, we take into consideration both domestic and international outsourcing. Our paper also differs from their papers in many other respects. First, we categorize workers as skilled or unskilled, while they view workers as one whole group. Second, we further decompose outsourcing activities into upstream and downstream materials outsourcing and service outsourcing, while they look at aggregate materials and service outsourcing. Third, we estimate a cost share of skilled workers using a cross-industry analysis, while they estimate a production function

[6] A more detailed description of these effects can be found in Amiti and Wei (2006).

using a panel data analysis. Finally, our paper focuses on a more disaggregated level of the manufacturing sector than theirs does.

The main contributions of our paper are as follows. To the best of our knowledge, our paper is the first empirical paper that looks at various types of outsourcing activities; that is, upstream and downstream materials outsourcing, and service outsourcing.[7] Next, our paper produces a new empirical finding that shows that outsourcing is not always skill-biased. Downstream materials outsourcing and service outsourcing are skill-biased, but upstream materials outsourcing is not.

3. The Empirical Model

Our empirical strategy is to estimate a relative demand for skilled workers. The most essential structural variables in our analysis are those that capture various types of outsourcing activities.

The production function for an industry *i* is given by the following expression:

$$Y_i = F_i\left(L_{Hi}, L_{Li}, K_i; out_i^s, out_i^m, T_i\right). \tag{1}$$

The output for industry *i*, Y_i, depends on three primary factors, namely high-skilled workers, L_{Hi}, low-skilled workers, L_{Li}, and capital, K_i. The service outsourcing, out_i^s, materials outsourcing, out_i^m, and the level of production technology, T_i are assumed to enter the production function via neutral and non-neutral technological shifts. Note that Amiti and Wei (2006) use a production function similar to that in (1), but their variables are confined to a neutral technological shift fashion. Furthermore, we disaggregate the labor input according to the skill attribute in order to capture the impacts of outsourcing on the relative demand for skilled workers.

Subsequently, we derive a short-run cost function, assuming that capital stock K_i is quasi fixed, in order to take into account the extent to which it may be different from its long-run equilibrium. Accordingly, the short-run (variable) cost function, where the levels of capital and output are fixed, can be derived from the following optimization problem:

$$c_i\left(w_{Hi}, w_{Li}; K_i, Y_i, out_i^s, out_i^m, T_i\right) = \underset{L_{Hi}, L_{Li}}{Min}\ w_{Hi}L_{Hi} + w_{Li}L_{Li} \quad \text{subject to (1).} \tag{2}$$

[7] It should also be noted that the present paper also departs from Görg and Hanley (2003) in the sense that they split sample industries into upstream and downstream industries, but we look at the impacts of outsourcing upstream and downstream activities by manufacturing industries.

The next step is to choose a functional form fitting the short-run unit cost function (2). Following Brown and Christensen (1981), the unit cost function (2) can be approximated by a general translog function with variable and quasi fixed input-factors. For notational simplicity, we temporarily drop the industry subscript *i*. Without loss of generality, we also assume symmetry. Expression (2) can be further written into

$$\ln c = \alpha_o + w'\alpha + z'\beta + \frac{1}{2}\mathrm{H}'\Omega\mathrm{H}\,, \tag{3}$$

where $w' = \left(\ln w_H \quad \ln w_L\right), \alpha' = \left(\alpha_H \quad \alpha_L\right)$, $z' = \left(\ln K \quad \ln Y \quad \ln out^m \quad \ln out^s \quad \ln T\right)$, $\beta' = \left(\beta_K \quad \beta_Y \quad \beta_M \quad \beta_S \quad \beta_T\right)$, $\mathrm{H}' = \left(w' \quad z'\right)$, and Ω is a 7×7 matrix of coefficients. We relegate the expansion of (3) and the restrictions on parameters ensuring the linear homogeneity of (3) to Appendix (A1).

The crucial property of the translog function can be derived by differentiating (3) with respect to $\ln w_k$, $k = H, L$. Let $WS_k = \left(\partial \ln c / \partial \ln w_k\right) = L_k w_k / c$, $k = H, L$ denote the cost share of skilled and unskilled workers in variable costs. Since skilled and unskilled workers are the only variable factors of production, the share of both factors must add up to unity and only one of them is linearly independent. As such, we focus on the estimation of the skilled workers' cost-share equation. By differentiating (3) with respect to $\ln w_{Hi}$, and invoking the symmetry assumption and linear homogeneity restriction, we obtain

$$WS_{Hi} = \alpha_H + \gamma \ln \frac{w_{Hi}}{w_{Li}} + \phi_{HK} \ln K_i + \phi_{HY} \ln Y_i + \phi_{HS} \ln out_i^s + \phi_{HM} \ln out_i^m + \phi_{HT} \ln T_i\,. \tag{4}$$

It is conventionally known that the cost share is essentially an expression of the relative demand for skilled workers, which in turn reflects not only the relative employment but also the relative factor prices. However, we are going to modify the above specification for the following reasons.

First, it is questionable whether the relative-wage term in (4) should be incorporated in the estimation. This is because the dependent variable is a composite measure of not only the relative demand for skilled workers, but also relative wages. Hence, the relative-wage term should be excluded from the estimation of (4) since relative wages are unlikely to be exogenous and there is a problem of a definitional relationship between the share of skilled workers' wage bills and the wage terms. Furthermore, as noted by Berman, Bound, and Griliches (1994), the cross-industry variation in wages provides little information, because the wage differential across industries is mainly explained by the difference in the skill content of workers, so we do not expect high-wage industries to economize on the high-skilled workers. As such, an estimation of (4), with the relative-wage term included, would yield biased coefficients. Accordingly, we drop the relative-wage term from the estimation of (4).

Second, the empirical model analogous to (4) has been prevalently employed to explore the impacts of materials outsourcing on the relative demands for skilled workers in various economies by many studies, such as Hanson and Harrison (1999), Anderton and Brenton (1999), Dell'mour et al. (2000), Geishecker (2002), and Hsieh and Woo (2005). None of them, to the best of our knowledge, has actually investigated the possibility that various types of sourced materials that are utilized in different stages of production have different effects on the relative demand for skilled workers. Outsourcing or contracting out some activities along the vertical chain of the production process enables firms to specialize in other activities along the vertical chain where they have a comparative advantage. For instance, General Motors may outsource activities that deal with the product design and the production of high-tech components (upstream activities), and may specialize in car production (downstream activity), whereas Apple may outsource the production of its iPod players (Apple's downstream activity), and specialize in R&D and product design (upstream activity). Consequently, it seems unrealistic to assume that upstream outsourcing should have the same impact on the relative demand for skilled workers as downstream outsourcing.

Therefore, we believe that it is worthwhile to further investigate the role of various types of outsourcing such as upstream and downstream materials outsourcing and also service outsourcing. Accordingly, out_i^m in (4) will be further broken down into upstream materials outsourcing (out_i^{mu}) and downstream materials outsourcing (out_i^{md}).

Lastly, the vector of three-digit NAICS manufacturing industry dummies (D_i) is also introduced to control for industry-fixed effects. By adding a stochastic error term u_i with $E(u_i)=0$ and $Var(u_i)=\sigma^2$, the estimated econometric model can be specified as follows:

$$WS_{Hi} = \alpha_H + \phi_{HK} \ln K_i + \phi_{HY} \ln Y_i + \phi_{HS} \ln out_i^s + \phi_{HM_u} \ln out_i^{mu} + \phi_{HM_d} \ln out_i^{md}$$

$$+\phi_{HT}\ln T_i + \phi_{HD} D_i + u_i \, . \qquad (5)$$

In addition to the wage-share equation, we also estimate the following employment-share equation to control for inter-industry differences in the relative wages of skilled workers:

$$ES_{Hi} = \alpha_H + \gamma \ln \frac{w_{Hi}}{w_{Li}} + \phi_{HK} \ln K_i + \phi_{HY} \ln Y_i + \phi_{HS} \ln out_i^{s} + \phi_{HM_u} \ln out_i^{mu} + \phi_{HMd} \ln out_i^{md}$$
$$+\phi_{HT} \ln T_i + \phi_{HD} D_i + u_i , \qquad (6)$$

where ES_{Hi} is the share of skilled-worker employment in the total employment and w_{Hi} / w_{Li} is the relative wages of skilled to unskilled workers. Admittedly, as is also noted in Anderton and Brenton (1999), the ad hoc specification of (6) is less satisfactory from a theoretical point of view. Nevertheless, it should give us some interesting insights into the impact of various types of outsourcing on the employment of skilled workers. It should also enable us to compare our results with those obtained in previous studies that also estimate such an employment equation, such as, for example, Machin et al. (1996).

Two econometric problems may arise when estimating specifications (5) and (6), and they need to be corrected. Firstly, due to the variation in the size of the industries in our sample, the stochastic-error term u_i is likely to be heteroskedastic, thereby producing a biased estimator of σ^2 in the standard ordinary least squares (OLS) method. To tackle this problem, we employ White's (1980) heteroskedastic-robust standard-error procedure in the estimation of (5) and (6).

Secondly, there may be an endogeneity-bias problem in the estimation of (5) and (6). That is, the industry-specific level of technology (T_i), which is measured by high-technology capital stocks such as computers and data processing equipment, may be correlated with an unobserved variable in the error term. In order to verify whether there is indeed such a problem, we run an Instrumental Variable (IV) regression and apply a Hausman Test to the results. We use the rate of capacity utilization and value added per establishment as our instruments, and express them as a logarithm. Both are proxies for the industry-specific production performance. Intuitively, an industry that possesses high production performance, as measured by its capacity utilization and value added per establishment, should be more likely to rely heavily on high-technology capital stocks in order to maintain a higher production efficiency and lower production costs.

4. Data

4.1 Data Sources

Our data are retrieved from the following data sources provided by the US Bureau of Census: the *2002 Annual Survey of Manufactures (ASM)*, the *2002 Economic Census*, and the *US International Trade Statistics*. The *2002 ASM* provides six-digit NAICS statistics for the manufacturing industry. The manufacturing sector (sectors 31-33) in this survey is defined as comprising establishments that engage in the mechanical, physical, or chemical transformation of materials, substances, or components into new products. From this survey, we obtain data on the wages and employment of skilled and unskilled workers across the manufacturing sector. Although this survey also provides data on materials used in the production, unfortunately it does not provide sufficiently detailed statistics on materials and service outsourcing, or on proxies for technology capital. As noted by Feenstra and Hanson (1999), we do not normally think of, say, the purchase of steel by a US automobile producer as outsourcing. But it is more common to consider the purchase of automobile parts by such a company as outsourcing. Moreover, unlike the existing empirical studies on the impacts of outsourcing on the relative demand for labor, there is no reason to confine the extent of outsourcing merely to sourcing of materials.[8] We therefore supplement the above data with the *2002 Economic Census*.

From the *2002 Economic Census*, we obtain detailed information on the cost and production structure of manufacturing firms and also on their use of technological capital (e.g. computers, data processing equipment, etc.), their purchase of intermediate materials (e.g. components, containers, packaging, etc.), and services (e.g. communication services; accounting, auditing, and bookkeeping services; computer services, etc.). We focus specifically on the six-digit NAICS manufacturing-sector data (sectors 31-33).

[Insert Table 1 Here]

Our combined data from the *2002 ASM* and the *2002 Economic Census* yields 474 six-digit NAICS manufacturing industries.

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[8] For example, in Feenstra and Hanson (1999) and Amiti and Wei (2006), the (imported) materials are used as proxies of "broad measures" of materials outsourcing. One can argue that these measures may be imprecise as the use of raw materials should not by definition be considered as the result of outsourcing decisions of firms.

4.2 Dependent Variables

Using both data sets, we can express the wage share of skilled workers in industry i (WS_{Hi}) in equation (5) as the ratio of the total wage bills of non-production workers to the total annual payrolls. The employment share of skilled workers in industry i (ES_{Hi}) in equation (6) is measured by the ratio of the total number of non-production workers to the total number of workers.

4.3 Outsourcing

Upstream materials outsourcing (out_i^{mu}) is measured by the share of the total production costs taken up by the costs of intermediate parts and materials employed in the upstream production stage. The downstream materials outsourcing (out_i^{md}) is measured by the share of the costs of contracting-out activities, such as reprocessing, repackaging, and blending, in the total production costs. The scatter plots of WS_{Hi} against $\ln out_i^{mu}$ and $\ln out_i^{md}$ are represented in Figure 1A and Figure 2A, respectively. As expected, the former shows a negative relationship between $\ln out_i^{mu}$ and WS_{Hi}, while the latter shows a positive correlation between $\ln out_i^{md}$ and WS_{Hi}. Thus, different types of materials outsourcing, that is, upstream- or downstream-materials outsourcing, should have different impacts on the relative demand for skilled workers.

[Insert Figures 1A and 2A Here]

Service outsourcing (out_i^s) is measured by the share of services purchased in the total production costs of industry i. Examples of services that are outsourced are repair and maintenance services of machinery and equipment; communication services; accounting, auditing, and bookkeeping services; and computer and hardware services. Figure 3A depicts a positive relationship between $\ln out_i^s$ and WS_{Hi}.

[Insert Figure 3A Here]

4.3 Control and Instrumental Variables

Capital Inputs

Similar to Geishecker (2002), we use the value of buildings and other structures

(K_i^{BLD}), and also machinery and equipment (K_i^{MCH}) in industry *I*, as proxies for the total amount of capital inputs employed in industry *i* (K_i). The expected sign of the coefficient of $\ln K_i$ could be either negative or positive, depending on whether or not capital inputs and high-skilled workers are substitutes.

Figure 4A depicts a positive relationship between the ratio of the total value of buildings and other structures to the total value of the assets and the wage share of skilled workers. Figure 5A depicts a negative relationship between the ratio of the total value of machinery and equipment to the total value of the assets and the wage share of skilled workers. The relationship portrayed in Figure 5A is the exact opposite of the one portrayed in Figure 4A. It appears that machinery and equipment, and skilled workers are substitutes. Where firms are machinery- and equipment-intensive, their workers tend to have a lower wage share. By contrast, buildings and other structures, and skilled workers are complements. The skilled workers of firms that are more buildings and other structures-intensive tend to have a higher wage share. We should thus expect that these two types of capital input will affect the demand for skilled workers differently.

[Insert Figures 4A and 5A Here]

Industrial Production

We also control for industry size using the logarithm of the total amount of sales ($\ln Y_i$) as a proxy. A larger size industry would be expected to have a larger demand for skilled workers. This implies that the coefficient of $\ln Y_i$ should be positive.

Industry-Specific Technology

The level of technology of an industry *i* (T_i) is measured by the ratio of high-technology capital to the total value of assets of industry *i*. As in Amiti and Wei (2006), we proxy high-technology capital using the value of computers and data-processing equipment used in industry *i*. WS_{Hi} and $\ln T_i$, as shown in Figure 6A, are positively related. This implies that high-technology capital and skilled workers are complements, and thus we should expect that the regression coefficient for high-technology capital has a positive sign.

[Insert Figure 6A Here]

Import Shares

In the analysis, we also control for the impact of imports on workers' wages and employment. We know from the standard Heckscher-Ohlin theory that when domestic production is supplanted by imports, a substitution of this kind should negatively affect wages and employment. We thus incorporate the industrial import-share (IM_i) variable in our regressions. This variable is proxied by the ratio of the imports of industry *i*'s product (six-digit NAICS) to its total domestic consumption. The data are retrieved from the *US International Trade Statistics*, US Bureau of Census.

Instrument Variables

As mentioned previously, we run IV regressions with a heteroskedasticity-robust variance estimator using capacity utilization and value added per establishment as our instruments for the level of technology (T_i). We use the ratio of electricity and fuel consumption used in production to the total capital expenditure as a proxy for capacity utilization, and we use the ratio of the total industry value added to the total number of establishments as a measure of the value added per establishment.

Statistics summarizing all the variables elaborated above and the matrix of correlations among these variables are presented in Appendices (A2) and (A3).

5. Empirical Results

Tables 2 to 5 present our regression results. Column (1) in all tables shows the results we obtained using a regression specification that uses aggregated capital inputs and materials outsourcing. Column (2) gives the results we obtained when the control variable imports are excluded from the regression. Column (3) presents our results when capital inputs were further disaggregated into buildings and other structures ($\ln K_i^{BLD}$) and machinery and equipment ($\ln K_i^{MCH}$). Finally, Column (4) presents the results we obtained when materials outsourcing was further decomposed into upstream materials outsourcing, $\ln out_i^{mu}$, and downstream materials outsourcing, $\ln out_i^{md}$.[9]

[9] Since values of materials outsourcing are missing for some industries, the number of observations in the actual estimation is slightly reduced to 465 and 452 observations.

5. 1. The Wage-Share of Skilled Workers

According to the standard Heckscher–Ohlin paradigm, imports and domestic production are substitutes, and hence imports should affect relative wages and the demand for skilled workers. Therefore, to take into consideration this import effect, we also run a regression with import share ($\ln IM_i$) as an explanatory variable. The result of this regression is presented in Column (1). Consistent with Leamer (1998), we find that the import share is not significant, which suggests that international trade has no influence on the wage gap between skilled and unskilled workers.

[Insert Table 2 Here]

As revealed in Table 2, the coefficients of all structural variables for all specifications are statistically significant at the 5 percent significance level.[10] The aggregate proxy for capital inputs (see Columns (1) and (2)) is statistically significant and has negative sign, implying that capitals and skilled workers are substitutes. Our results are thus consistent with Geishecker's (2003) result that shows a negative relationship between capitals and the relative demand for skilled workers.

To see this more clearly, the capital stock is separated out into two components, buildings and other structures ($\ln K_i^{BLD}$) and machinery and equipment ($\ln K_i^{MCH}$) in Columns (3) and (4). We found that $\ln K_i^{BLD}$ has a positive effect, whereas $\ln K_i^{MCH}$ has a negative effect. Our results suggest that buildings and other structures are complementary to skilled workers, while machinery and equipment are not.

In line with Amiti and Wei (2006), the coefficients of $\ln Y_i$ are positive and statistically significant at the 1 percent level of significance in all regression specifications. This suggests that larger industries are more likely to be characterized by a higher wage share of skilled workers. Employing skilled workers is relatively more expensive than employing unskilled workers, and larger firms would be more able to afford it as they can tap the benefit of the economies of scale.

The estimated coefficients of materials outsourcing ($\ln out_i^m$) in Columns (1), (2), and (3) are all negative and statistically significant at a 5 percent level of significance. This result is in contrast to those of Feenstra and Hanson (1996, 1999), Anderton and Brenton (1999), and Geishecker (2002), who all find a positive relationship. In these

[10] These results are also consistent with *F*-tests. As reported in Table 2, the results, based on *F* statistics, assert that all coefficients are *jointly* statistically significant at the 95 percent level of confidence.

papers, materials outsourcing is proxied by imported intermediate materials. The negative relationship between materials outsourcing and the wage share of skilled workers as depicted in Columns (1), (2), and (3) may be consistent with the results of studies done by Siegel and Griliches (1991) and Egger and Egger (2006). These show that materials outsourcing leads to a short-run deterioration in the overall productivity of labor and therefore in the efficiency of production. If indeed there is a negative short-run effect of materials outsourcing, then we should expect a negative relationship between materials outsourcing and relative wages of skilled workers.

We further break down materials outsourcing into upstream ($\ln out_i^{mu}$) and downstream materials ($\ln out_i^{md}$) outsourcing. From the results presented in Column (4), we can see that upstream materials outsourcing negatively affects the wage share of skilled workers, while downstream materials outsourcing positively affects the wage share of skilled workers. As elaborated previously, materials used in upstream production stages include intermediate parts and materials, and activities involved in downstream production stages include reprocessing and repackaging activities. The former is often more skill-intensive than the latter. Consequently, in contrast with performing these skill-intensive activities in-house, outsourcing them from the market is unlikely to yield a rise in the wages paid to skilled workers in downstream industries, and thus a negative relationship of this kind may indeed prevail. On the other hand, contracting out downstream materials allows firms to specialize in the production of upstream materials, therefore resulting in higher productivity and thus higher wage shares for skilled workers. Accordingly, a positive relationship between downstream materials outsourcing and the wages of skilled workers relative to those of unskilled workers does prevail.

We also show that service outsourcing has a positive impact on relative wages. Service outsourcing in our context includes purchases of communication, accounting, auditing, bookkeeping, and computer services. This result is consistent with Amiti and Wei (2006).

The coefficients of the level of technology ($\ln T_i$) are positive and statistically significant at a 1 percent level of significance. This suggests that technology is skill-biased. This result confirms the findings of previous studies such as those of Anderton and Brenton (1999), Geishecker (2002), and Amiti and Wei (2006): technology and skilled workers are complementary. So as we show here, higher technology results in a larger wage share for skilled workers.

In our regressions, we also include dummies for industries. As expected, chemical, machinery, computer, and electronic products are relatively skill-intensive, while textile mills, clothing, leather and allied products, and wood product manufacturing are not.[11]

[Insert Table 3 Here]

Finally, as noted by Feenstra and Hanson (1997), the estimation of the wage-share equations might be subject to not only a potential heteroskedasticity problem, but also an endogeneity problem, thereby resulting in inefficient and biased estimators. More specifically, it is possible that $\ln T_i$ is correlated with an unobserved variable in the error term (u_i). To verify this, we run IV regressions and apply the Hausman test for the endogeneity problem to the results. Our null hypothesis posits that $\ln T_i$ is not correlated with u_i. The result of the Hausman test shows that the null hypothesis cannot be rejected, suggesting that there is no endogeneity problem. As pointed out by Hausman (1978), when $\ln T_i$ is indeed uncorrelated with the unobserved variable in u_i, the OLS and IV estimators would essentially produce the same qualitative results.[12] Indeed, when we compare the results from the OLS regressions presented in Table 2 and the results from IV regressions presented in Table 3, we observe that the explanatory variables that are significant in the OLS regressions are also significant in IV regressions, and they all have the same predicted signs.

5.2. The Employment Share of Skilled Workers

In this sub-section, we discuss the results of our OLS and IV estimations of the employment-share equation (6). They are reported in Tables 4 and 5, respectively. The result of the Hausman test for the endogeneity problem is reported in Table 5. It shows that the null hypothesis of no correlation between $\ln T_i$ and u_i cannot be rejected for all specifications, thus suggesting that there is no endogeneity problem.[13]

[Insert Tables 4 and 5 Here]

We also include the relative-wage variable, $\ln(w_H / w_L)$, in the estimations and

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[11] The results are not shown in Table 2. They are available upon request.

[12] That is, the estimators from OLS and IV estimation should differ only by the sampling errors.

[13] The coefficients of instruments in the first stage regression are statistically significant at a 1 percent level of significance for all specifications with the adjusted R-squared ranging from 0.5766 to 0.6172.

find that the coefficients of $\ln(w_H / w_L)$ have a negative sign and are statistically significant at a 1 percent level of significance. This implies that an increase in $\ln(w_H / w_L)$ triggers a replacement of skilled workers by unskilled workers.

We show that the independent variable, $\ln IM_i$, is not significant (see Column (1)). This suggests that the conventional H-O framework cannot really explain the change in the employment share of skilled workers. We also show that capital inputs have a negative impact on the employment share of skilled workers (see Column (2)). When we break down capital inputs into buildings and other structures, and machinery and equipment, we find that the former are skill-biased, while the latter are not (see Columns (3) and (4)). Next, we also show that industry size has a positive impact on employment share.

As with our previous results, we find that aggregate materials outsourcing has a negative impact on the relative demand for skilled workers. When we separate materials outsourcing into upstream and downstream materials outsourcing, we find that the latter has a positive impact on the relative demand for skilled workers, whereas the former has a negative impact. We also show that service outsourcing has a positive impact on the relative demand for skilled workers.

The coefficients of $\ln T_i$ are positive. This suggests that technology is skill-biased. This is consistent with our earlier results from the estimation of the wage-share equation. Lastly, we find that chemical, fabricated metal, machinery, computers, and electronic products are skill intensive, while textile, clothing, leather, and wood products are not.

6. Concluding Remarks

In this paper, we estimate the impacts of outsourcing on relative wages and the demand for skilled workers using six-digit NAICS US manufacturing-sector data. We break down outsourcing into three categories, namely upstream and downstream materials outsourcing, and service outsourcing. Our results show that downstream materials and service outsourcing have a positive impact on the wages of skilled workers relative to those of unskilled workers and the relative demand for skilled workers, while upstream materials outsourcing has the opposite impact.

The positive impact of downstream materials and service outsourcing on relative wages and the demand for skilled workers can be explained by the idea that these types of outsourcing allow firms to specialize in the upstream production activities, which usually employ a greater number of skilled workers. Therefore, an increased attention to upstream production activities will naturally induce firms to hire more skilled workers. In contrast, downstream production activities and services tend to be less skill-intensive than upstream production activities; hence, firms that focus more on the former do not really require numerous skilled workers. Accordingly, their demand for skilled workers will fall.

Our empirical results also shed further light on the different roles played by different types of capital inputs. We discover that the nature of the relationship between capital inputs and skilled workers depends on the types of capital input employed in the production process. We find that machinery and equipment are substitutes for skilled workers, while buildings and other structures are complementary to skilled workers. With regard to the role of technology, we find a positive relationship between technology and the demand for skilled workers. It can thus be concluded that technology is skill-biased.

It may be more interesting in future research to rigorously investigate the roles of domestic and international outsourcing as explanatory factors for wage inequalities. Furthermore, a natural extension to our empirical analysis would be to conduct a dynamic panel-data analysis rather than a cross-sectional analysis like that carried out for this paper. Such an analysis should enable us to obtain richer results. Unfortunately, more recent detailed six-digit NAICS manufacturing-sector data are not available at the time of writing. We therefore leave this to our future research.

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Appendix

(A1) Given assumption of symmetry, the translog cost function (3) can be expressed as:

$$\ln c = \alpha_0 + \alpha_H \ln w_H + \alpha_L \ln w_L + \gamma_{LH} \ln w_L \ln w_H + \frac{1}{2}\gamma_{HH}(\ln w_H)^2 + \frac{1}{2}\gamma_{LL}(\ln w_L)^2$$
$$+ \beta_K \ln K + \phi_{HK} \ln w_H \ln K + \phi_{LK} \ln w_L \ln K + \frac{1}{2}\delta_{KK}(\ln K)^2 + \beta_Y \ln Y + \phi_{HY} \ln w_H \ln Y$$
$$+ \phi_{LK} \ln w_L \ln Y + \delta_{KY} \ln K \ln Y + \frac{1}{2}\delta_{YY}(\ln Y)^2 + \beta_S \ln out^s + \phi_{HS} \ln w_H \ln out^s$$
$$+ \phi_{LS} \ln w_L \ln out^s + \frac{1}{2}\delta_{SS}(\ln out^s)^2 + \delta_{SK} \ln out^S \ln K + \delta_{SY} \ln out^s \ln Y + \beta_M \ln out^m$$
$$+ \phi_{HM} \ln w_H \ln out^m + \phi_{LM} \ln w_L \ln out^m + \frac{1}{2}\delta_{MM}(\ln out^m)^2 + \delta_{MK} \ln out^m \ln K$$
$$+ \delta_{MY} \ln out^m \ln Y + \delta_{MS} \ln out^m \ln out^s + \beta_T \ln T + \phi_{HT} \ln w_H \ln T + \phi_{LT} \ln w_L \ln T$$
$$+ \frac{1}{2}\delta_{TT}(\ln T)^2 + \delta_{TK} \ln T \ln K + \delta_{TY} \ln T \ln Y + \delta_{TS} \ln T \ln out^s + \delta_{TM} \ln T \ln out^m.$$

In addition, since the linear homogeneity property of the translog function must be satisfied, the following parameter restrictions are inevitably required:

$$\alpha_H + \alpha_L = 1 \text{ and } \gamma_{HL} + \gamma_{HH} = \gamma_{LH} + \gamma_{LL} = \phi_{Hj} + \phi_{Lj} = 0,$$

where $j = K, Y, M, S$, and T.

(A2) Summary Statistics

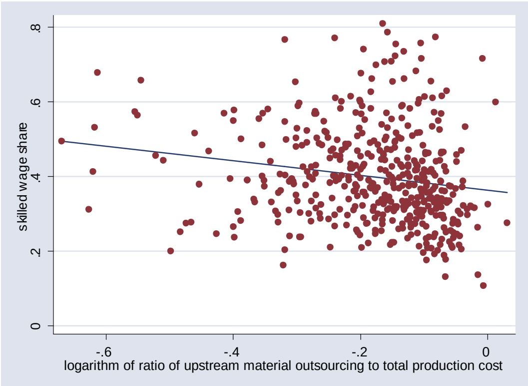
Variable	Obs	Mean	Std. Dev.	Min	Max
WS_{Hi}	473	0.398688	0.128719	0.107686	0.809284
ES_{Hi}	473	.2920663	.1181443	.0871373	.7155634
$\ln K_i$	473	11.57682	1.402426	6.760415	15.81277
$\ln K_i^{BLD}$	468	9.626691	1.539867	4.844187	15.01045
$\ln K_i^{MCH}$	473	0.398688	0.128719	0.107686	0.809284
$\ln Y_i$	473	15.19392	1.195375	11.69909	19.08729
$\ln out_i^m$	473	-0.15894	0.213304	-3.21235	-0.034746
$\ln out_i^{mu}$	471	-0.18833	0.137927	-1.00866	-0.030587
$\ln out_i^{md}$	459	-4.11236	1.273217	-10.4188	-0.47696
$\ln out_i^s$	469	-5.08162	0.90867	-8.68661	-2.20799
$\ln T_i$	468	1.856451	0.391024	0.584914	3.035576
$\ln IM_i$	473	-2.01712	1.328415	-13.5	-0.0104

(A3) Correlation Matrix of Independent Variables

	$\ln K_i^{BLD}$	$\ln K_i^{MCH}$	$\ln Y_i$	$\ln out_i^{mu}$	$\ln out_i^{md}$	$\ln out_i^{s}$	$\ln T_i$	$\ln IM_i$
$\ln K_i^{BLD}$	1							
$\ln K_i^{MCH}$	0.6512	1						
$\ln Y_i$	0.4203	0.6426	1					
$\ln out_i^{mu}$	0.0965	0.1141	0.255	1				
$\ln out_i^{md}$	-0.0688	-0.0561	-0.1412	-0.4494	1			
$\ln out_i^{s}$	-0.0794	-0.0871	-0.1838	-0.2705	0.5024	1		
$\ln T_i$	0.077	0.1202	0.1629	0.0549	0.0792	0.2957	1	
$\ln IM_i$	-0.0699	-0.1279	-0.3968	-0.2546	0.2164	0.0963	0.0292	1

Table 1 Three-digit NAICS manufacturing industry code (Sectors 31-33).

2002 NAICS Code	**Report Title**
311	Food Manufacturing
312	Beverage and Tobacco Product Manufacturing
313	Textile Mills
314	Textile Product Mills
315	Apparel Manufacturing
316	Leather and Allied Product Manufacturing
321	Wood Product Manufacturing
322	Paper Manufacturing
323	Printing and Related Support Activities
324	Petroleum and Coal Products Manufacturing
325	Chemical Manufacturing
326	Plastics and Rubber Products Manufacturing
327	Nonmetallic Mineral Product Manufacturing
331	Primary Metal Manufacturing
332	Fabricated Metal Product Manufacturing
333	Machinery Manufacturing
334	Computer and Electronic Product Manufacturing
335	Electrical Equipment, Appliance, and Component Manufacturing
336	Transportation Equipment Manufacturing
337	Furniture and Related Product Manufacturing
339	Miscellaneous Manufacturing



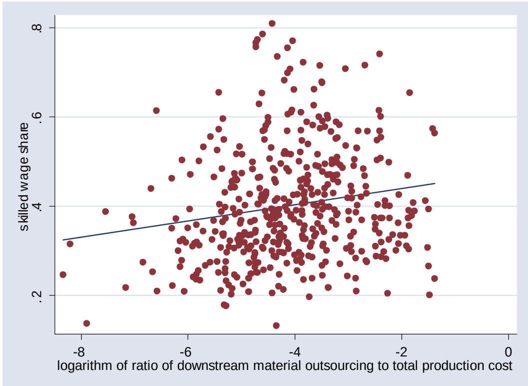
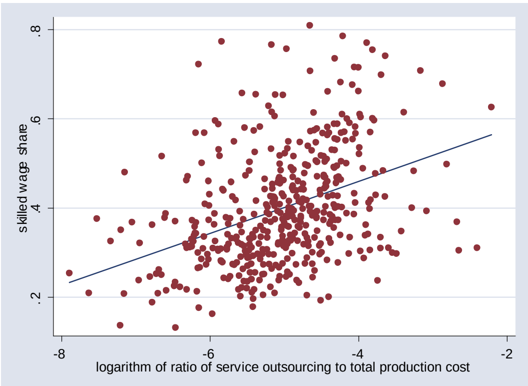


Figure 1A

Figure 2A



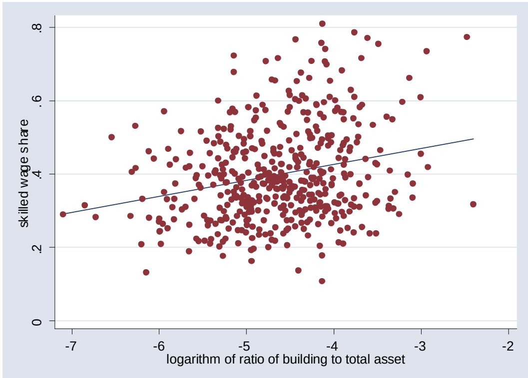


Figure 3A

Figure 4A

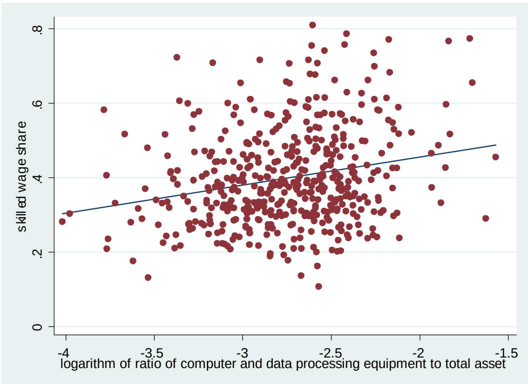


Figure 5A

Figure 6A

Table 2 OLS estimation with heteroskedasticity-robust variance estimators for non-production wage share

Variable	(1)	(2)	(3)	(4)
$\ln K_i$	-.070485(.0126)***	-.0691555(.0121)***	----	----
$\ln K_i^{BLD}$	----	----	.0279638(.0081)***	.0222022(.0078)***
$\ln K_i^{MCH}$	----	----	-.0954548(.0117)***	-.0984122(.0117)***
$\ln Y_i$	.0741474(.0143)***	.0722082(.0133)***	.0680672(.0137)***	.0763347(.0133)***
$\ln out_i^m$	-.1026495(.0480)**	-.1033926(.0483)**	-.1264937(.0491)***	----
$\ln out_i^{mu}$	----	----	----	-.1162443(.0495)**
$\ln out_i^{md}$	----	----	----	.0111673(.0046)**
$\ln out_i^s$	.0446323(.0070)***	.0446084(.0069)***	.0430307(.0067)***	.0352395(.0075)***
$\ln T_i$	.0621345(.0162)**	.0611889(.0156)***	.0619721(.0154)***	.0713033(.0151)***
$\ln IM_i$	.002676(.0039)	----	----	----
Constant	.1740138(.1231)	.1817248(.1172)	.2442866(.1234)*	.2034584(.1214)*
R-squared	0.5490	0.5485	0.5778	0.5948
F statistic	24.36***	25.30***	27.93***	26.84***
No. of Obs.	465	465	465	452

Note: 1) robust standard errors in parentheses, 2) * statistically significant at 10 percent, 3) ** statistically significant at 5 percent, 4) *** statistically significant at 1 percent.

Table 3 Instrumental variable estimates with heteroskedasticity-robust variance estimators for non-production wage share.

Variable	(1)	(2)	(3)	(4)
$\ln K_i$	-.0966811(.0162)***	-.09423(.0152)***	----	----
$\ln K_i^{BLD}$	----	----	.0243746(.0083)***	.0180049(.0082)**
$\ln K_i^{MCH}$	----	----	-.1101216(.0138)***	-.1126119(.0131)***
$\ln Y_i$	.0974795(.0177)***	.093969(.0162)***	.0843162(.0164)***	.0926931(.0157)***
$\ln out_i^m$	-.1420326(.0529)***	-.14318(.0533)***	-.1536721(.0533)***	----
$\ln out_i^{mu}$	----	----	----	-.132627(.0496)***
$\ln out_i^{md}$	----	----	----	.0122447 (.0047)**
$\ln out_i^s$	.0379679(.0083)***	.037954(.0082)***	.0387463(.0076)***	.0305174(.0085)***
$\ln T_i$	.1349419(.0302)***	.1329736(.0293)***	.1107754(.0274)***	1187505(.0257)***
$\ln IM_i$	.0047177(.0043)	----	----	----
Constant	-.0490066(.1655)	-0.03451(.1566)	.0810549(.1616)	..045763(.157)
R-squared	0.5189	0.5190	0.5641	0.5823
F statistic	22.48***	23.19***	26.01***	25.39***
Hausman test statistic(p-value)	2.32(1.00)	16.12(0.9111)	0.97(1.00)	3.01(1.00)
No. of Obs.	465	465	465	452

Note: 1) robust standard errors in parentheses, 2) * statistically significant at 10 percent, 3) ** statistically significant at 5 percent, 4) *** statistically significant at 1 percent, 5) Hausman specification test is distributed as chi-squared distribution with degrees of freedom equal to the number of instruments under the null hypothesis that $\ln T_i$ is uncorrelated with the error term.

Table 4 OLS estimation with heteroskedasticity-robust variance estimators for non-production employment share.

Variable	(1)	(2)	(3)	(4)
$\ln(w_H/w_L)$	-.156266(.0289)***	-.1549583(.0287)***	-.1730969(.0291)***	-.1871572(.0312)***
$\ln K_i$	-.0559354(.0123)***	-.05504275(.0116)***	----	----
$\ln K_i^{BLD}$	----	----	.02547996(.0076)***	.02084408(.0074)***
$\ln K_i^{MCH}$	----	----	-.08107041(.0113)***	-.0858007(.0114)***
$\ln Y_i$	.061330(.0135)***	.06013335(.0125)***	.05792525(.0128)***	.06658104(.0125)***
$\ln out_i^m$	-.0849718(.04347)*	-.08544506(.0436)*	-.1051191(.0447)**	----
$\ln out_i^{mu}$	----	----	----	-.1018513(.0491)**
$\ln out_i^{md}$	----	----	----	.009487451(.0043)**
$\ln out_i^s$	.03914103(.0066)***	.03909266(.0066)***	.0381617(.0064)***	.03228012(.0073)***
$\ln T_i$	.05020533(.0157)***	.04954298(.0151)***	.05199395(.0149)***	.06196547(.0148)***
$\ln IM_i$	.001504368(.0037)	----	----	----
Constant	.1708056(.1139)	.1745268(.1092)	.2409251(.1160)**	.2106188(.1174)*
R-squared	0.5523	0.5521	0.5790	0.5969
F statistic	23.02***	23.90***	24.80***	23.50***
No. of Obs.	465	465	465	452

Note: 1) robust standard errors in parentheses, 2) * statistically significant at 10 percent, 3) ** statistically significant at 5 percent, 4) *** statistically significant at 1 percent.

Table 5 Instrumental variable estimates with heteroskedasticity-robust variance estimators for non-production employment share.

Variable	(1)	(2)	(3)	(4)
$\ln(w_H/w_L)$	-.1859667(.0319)***	-.1826022(.0310)***	-.1913028(.0303)***	-.2042324(.0324)***
$\ln K_i$	-.0798355(.0160)***	-.07749905(.0148)***	----	----
$\ln K_i^{BLD}$	----	----	.02306583(.0077)***	.01784023(.0076)**
$\ln K_i^{MCH}$	----	----	-.0941091(.0134)***	-.09835439(.0128)***
$\ln Y_i$	.08223176(.0172)***	.07922251(.0154)***	.07134585(.0153)***	.08008163(.0147)***
$\ln out_i^m$	-.1142604(.0478)**	-.1150295(.0481)**	-.1246902(.0485)**	----
$\ln out_i^{mu}$	----	----	----	-.1131556(.0494)**
$\ln out_i^{md}$	----	----	----	.01044543(.0044)**
$\ln out_i^s$	.03474913(.0076)***	.03468615(.0076)***	.03547988(.0072)***	.02917135(.0081)***
$\ln T_i$	.1100077(.0296)***	.1078033(.0283)***	.08974336(.0262)***	.09902341(.0249)***
$\ln IM_i$	.003509386(.0041)	----	----	----
Constant	.009901217(.1504)	.02032706(.1424)	.1295635(.1473)	.1028038(.1460)
R-squared	0.5295	0.5301	0.5700	0.5884
F statistic	21.79***	22.54***	24.02***	22.66***
Hausman spec. test statistic(p-value)	0.09(1.00)	2.88(1.00)	1.39(1.00)	0.6(1.00)
No. of Obs.	465	465	465	452

Note: 1) robust standard errors in parentheses, 2) * statistically significant at 10 percent, 3) ** statistically significant at 5 percent, 4) *** statistically significant at 1 percent, 5) Hausman specification test is distributed as chi-squared distribution with degrees of freedom equal to the number of instruments under the null hypothesis that $\ln T_i$ is uncorrelated with the error term.