Service Offshoring and White-Collar Employment*

Rosario Crinò[†]
University of Milan and CESPRI

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Abstract

This paper empirically studies the effects of service offshoring on U.S. white-collar employment, using data for more than one hundred occupations. A model of firms' behavior based on homothetic weak separability allows for tractable derivation of labor demand elasticities to service offshoring for each occupation. Estimation of the model is performed with quasi-maximum likelihood, to account for high degrees of censoring in the employment variable. Results show that service offshoring raises high skilled employment and lowers medium and low skilled employment. Within each skill group, however, service offshoring penalizes tradeable occupations and benefits complex non tradeable occupations.

JEL codes: F16, J23, C34.

Keywords: Service Offshoring; White-Collar Employment; Tradeable Occupations; Homothetic Weak Separability; Censored Demand System Estimation.

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[†]Address: CESPRI - Bocconi University, via Sarfatti 25, 20136 Milan (Italy). Email: rosario.crino@unibocconi.it. Phone: (+39) 02 58363380. URL: http://www.cespri.unibocconi.it/

1. Introduction

In this paper, I empirically study the effects of service offshoring on U.S. white-collar employment. I use a highly detailed database containing employment and wage figures for more than one hundred occupations to address the following research questions: 1) What are the effects of service offshoring on occupations with different skill levels? 2) What are the effects on occupations with different tradeable features?

Service offshoring has become a phenomenon in recent years. Thanks to improvements in information and communication technologies, trade in services has soared and firms have discovered new opportunities to globalize their operations (Freund and Weinhold, 2002; Lipsey, 2006). During the 1980s and the first half of the 1990s, offshoring almost exclusively entailed foreign relocation of intermediate stages of production and gave rise to trade in intermediate inputs and components[1]. Nowadays, offshoring also entails relocation of service activities - like accounting, bookkeeping, customer service operations, computer programming - and gives rise to the exchange of bits of information across affiliated and unaffiliated firms located in different countries. The increase in service offshoring has been so rapid and widespread that some authors have started referring to it as "The Third Industrial Revolution" (Blinder, 2006).

The rise in service offshoring has attracted much attention in the media and has become an important topic of discussion in political talks (Amiti and Wei, 2005a). One of the most debated issues has been the effects on the white-collars (Bhagwati *et al.*, 2004; Mankiw and Swagel, 2006). Being employed in service activities, these workers are likely to be highly exposed to service offshoring. At the same time, they show two notable features. First, they usually perform "good jobs", that is jobs paying high wages and requiring high skill levels. Second, they have generally been shielded from offshoring in the past (Feenstra and Hanson, 1996, 1999, 2003; Crinò, 2007). For these reasons, understanding how white-collar employment responds to service offshoring has become a major goal for international trade economists.

Service offshoring entails relocation of narrow activities, each of which is performed by a specific occupation. Accordingly, the employment effects of service offshoring may differ substantially across detailed occupations. There are at least two possible determinants of heterogeneity. The first is represented by differences in skill levels. According to standard factor proportion arguments, the interplay between relative skill intensities and endowments shapes the effects of service offshoring (Bhagwati *et al.*, 2004; Deardorff, 2005; Markusen, 2005; Trefler, 2005a,b). The second is represented by differences in tradeable features. Occupations whose activities can be easily traded entail lower offshoring costs, holding fixed the skill level (Grossman and Rossi-Hansberg, 2006)[2].

[1] See Campa and Goldberg (1997), Feenstra (1998), Hummels, Rapoport and Yi (1998), Hummels, Ishii and Yi (2001) for studies assessing the quantitative importance of trade in intermediate inputs and components (*material offshoring*).

[2] See Autor *et al.* (2003) and Levi and Murname (2004) for a similar argument applied to the effects of computers and new technologies.

The main contribution of this paper is to investigate the role of these two dimensions of heterogeneity *jointly* from an empirical perspective. To this purpose, I exploit a rich database on employment and wages at the occupation-industry level for the U.S.. The data come from the Occupational Employment Statistics (OES) of the Bureau of Labor Statistics. The information available therein allows me to disaggregate employment into 112 occupations, of which 58 are white-collar. Employment and wage figures are available for 144 industries over the period 1997-2002. This constitutes an extremely suitable panel for studying the effects of service offshoring on white-collar employment, because it offers high occupational and industrial detail and covers the period of sharpest increase in service offshoring. I combine the OES data with a proxy for service offshoring at the industry-level. This proxy is defined as the share of imported services on total non energy input purchases (Amiti and Wei 2005a,b, 2006). To construct the proxy, I use affiliated and unaffiliated import data on 14 categories of private services, which are available from the Bureau of Economic Analysis.

The high level of occupational detail poses two methodological issues. First, firms' technology has to be modelled in such a way that guarantees tractable derivation of demand functions for all occupations, without imposing excessively restrictive assumptions on the relationship among them. Second, estimation of these demand functions has to account for the fact that the dependent (employment) variable is often severely censored, because many occupations are not employed in many industries.

I deal with the first issue by means of a model of firms' behavior that uses mild restrictions on the relationship among occupations. Following Fuss (1977), the model assumes that firms' technology satisfies *homothetic weak separability* in groups of homogeneous occupations. This assumption makes derivation of labor demand functions tractable even for high numbers of occupations, because it implies that firms' optimization process can be solved in two separate stages: in the first stage, firms choose the optimal mix of occupations in each group; in the second stage, they adjust the overall level of employment in each group. I propose an extension of the original model, in which service offshoring is allowed to affect the two stages of the optimization process and, through this channel, the labor demand function for each occupation.

The assumption of homothetic weak separability has been widely used in consumption theory to derive demand elasticities for highly disaggregated goods. It has instead been rarely applied in the literature on offshoring and labor demand. Due to data availability, previous studies have been forced to take a parsimonious approach, in which flexible cost functions are used to derive demand equations for small numbers of labor inputs[3]. The model presented in this paper integrates homothetic weak separability in that framework and generalizes it to a potentially high number of labor types.

In estimating the demand functions derived from the model, I deal with the censoring issue by modifying the quasi-maximum likelihood estimator originally developed by Meyerhoefer *et*

[3] See, among others, Berman *et al.* (1994), Feenstra and Hanson (1996, 1999, 2003), Morrison and Siegel (2001), Hijzen *et al.* (2005), Ekholm and Hakkala (2005).

al. (2005). This estimator is designed to provide consistent estimates of the parameters in the presence of censoring and panel data. The modification I propose makes the estimator appealing for applications to panel data of moderate cross-sectional dimension, which are typical of studies using industry-level data.

Exploiting the estimated labor demand elasticities to service offshoring, I address the two main research questions of the paper. I start by quantifying the effects of service offshoring on broad aggregates of occupations with different skill levels. This first dimension is meant to reveal potential skill-biased effects of service offshoring. Indeed, results show that service offshoring *is* skill-biased, because it raises overall employment in high skilled occupations and lowers overall employment in medium and especially low skilled occupations.

This finding, however, hides significant heterogeneity in the response of specific occupations within each skill group. As anticipated, one possible explanation for this heterogeneity is the presence of differences in tradeable features across occupations with similar skill levels. Occupations are more likely to be "tradeable" if they perform routine tasks, require low degrees of face-to-face contact and provide services whose output can be conveniently transmitted from remote destinations. Using this definition, I show that tradeable features do indeed matter significantly. Independent of their skill level, tradable occupations are negatively affected by service offshoring. Interestingly, complex and highly specialized non tradeable occupations tend to benefit from it.

These results have three main implications. First, they seem at odds with the widespread concern that service offshoring will lower incentives to invest in education and eventually slow down the process of human capital accumulation in developed countries[4]. Although the white-collars represent the most skilled fraction of the workforce, the negative employment effects of service offshoring are concentrated on occupations with the lowest levels of education, whereas high skilled occupations benefit from service offshoring. Second, the very heterogeneous responses between tradeable and non tradeable occupations suggest that service offshoring may progressively shift the educational demand towards programs that prepare workers to perform the latter set of jobs. Together with a stimulus to acquire higher education, service offshoring is therefore likely to induce a change in the *composition* of educational demand; in this sense, my findings are in line with the argument in Blinder (2006). Finally, results also suggest that standard trade theories should combine the usual classification of labor into broad skill groups with a parallel classification that emphasizes the tradeable / non tradeable nature of specific occupations.

The empirical literature on service offshoring is still very limited, although growing rapidly. Amiti and Wei (2005a,b) have found only small negative effects on total employment in the U.K. and the U.S.. This paper suggests that one reason for this is the high heterogeneity in the response of specific occupations: since service offshoring benefits some occupations and

[4] See Trefler (2005a,b), Blinder (2006) and Mankiw and Swagel (2006) for a deep discussion of this concern.

penalizes others, its aggregate effects may end up being small. Other studies have used the same database and similar definitions of tradeable features as the ones in this paper to estimate the number of workers employed in tradeable occupations in several developed countries. In the U.S. case, these workers account for 20-25% of the labor force[5]. This represents an upper bound to the number of jobs that service offshoring can potentially destroy. This paper looks more closely at the causal effects of service offshoring, by estimating the *actual* response of each tradeable occupation. Moreover, it also studies the effects on the non tradeable occupations, which have generally been neglected in previous studies[6].

The remainder of the paper is structured as follows: section 2 presents the data and some preliminary evidence; section 3 describes the theoretical model; section 4 explains the estimation strategy; section 5 presents and discusses the results and section 6 concludes.

2. Data and preliminary evidence

In this section, I describe the data and provide preliminary evidence on the relationship between service offshoring and white-collar employment[7]. Due to data availability, my panel covers the period 1997-2002 and consists of 144 industries, of which 135 are in the manufacturing sector and 9 in the service sector. Table 1 reports the list of service industries, while the list of manufacturing industries is reported in the Appendix (Table A4).

2.1. Service offshoring

I follow Amiti and Wei (2005a,b; 2006) and proxy service offshoring with the share of imported services in total non energy input purchases ($SOSS$). The underlying idea is that offshoring entails foreign relocation of service activities, whose output has to be imported back to the U.S., where it will enter the production process together with other intermediate inputs. The more intense the use of offshoring, the higher the share of total inputs accounted for by imported services.

Industry-level data on service imports are not available for the U.S.. Therefore, I have to estimate them for the 144 industries in my sample. I accomplish this task by attributing to each industry a share in the *economy-wide* level of service imports. The Bureau of Economic Analysis (BEA) provides time-series data on affiliated and unaffiliated imports for 14 categories

[5] Bardhan and Kroll (2003), Garner (2004), Jensen and Kletzer (2005), Kroll (2005), Van Welsum and Vickery (2005), Blinder (2006, 2007), Kletzer (2007).

[6] The existing literature has also studied the productivity effects of service offshoring and the associated consequences for aggregate welfare in developed countries. Empirical studies generally show that service offshoring boosts the productivity of domestic inputs (Mann, 2003; Amiti and Wei, 2006;Olsen, 2006). Theoretical models usually conclude that service offshoring is likely to raise aggregate welfare in developed countries (Bhagwati *et al.*, 2004; Deardorff, 2005; Markusen, 2005; Antras *et al.*, 2006a,b; Grossman and Rossi-Hansberg, 2006). A notable exception is represented by Samuelson (2004).

[7] Further details on these variables and on the other regressors used in the econometric analysis can be found in the Appendix.

of private services, which are listed in Table 2[8]. I use the 1997 BEA Import Matrix to estimate the share of each industry in the 1997 economy-wide level of imports of each of these services. For a generic industry j ($j = 1, ..., J = 144$) and service category h ($h = 1, ..., H = 14$), denote this share by ϑ_{jh}^{97}. I maintain the assumption that ϑ_{jh}^{97} stayed constant between 1997 and 2002. Under this assumption, I apply ϑ_{jh}^{97} to the time-series of imports of service h (M_{ht}); this gives me a time-varying estimate of the level of imports of that service in industry j. I then sum these estimates across all services and normalize the resulting quantity by the value of non energy inputs purchased by industry j (NE_j). Formally:

$$SOSS_{jt} = NE_{jt}^{-1} \sum_{h=1}^{14} \vartheta_{jh}^{97} M_{ht}$$

Between 1997 and 2002, service offshoring has sharply increased in the U.S.. On average, $SOSS$ was equal to 2.5% in 1997; by the end of 2002, this figure increased to 5.4%, for an overall rise of 116% (Figure 1). Interestingly, service offshoring has been always higher - and has risen faster - in the manufacturing sector: in 1997, $SOSS$ was equal to 2.6% in manufacturing and to 2.3% in the service sector; by the end of 2002, these figures rose, respectively, to 5.6% and 3.1%.

2.2. White-collar employment

The Occupational Employment Statistics (OES) of the Bureau of Labor Statistics (BLS) contain detailed information on employment and wages at the occupation-industry level for the period 1997-2005. An industry-year panel can however be constructed only for the shorter time horizon between 1997 and 2002, because data from 2003 on are available on a six-month basis and thus not fully comparable with those for earlier years.

Only for 9 service industries can the OES data be matched with information on other relevant variables like output, capital stock, consumption of intermediate inputs and service offshoring. Within the service sector, however, these industries may face the most significant effects of service offshoring: workers in the remaining private service industries, in fact, generally provide non-tradeable services (think of sectors like transportation, education, art and entertainment), whereas the public sector is likely to be shielded from offshoring for political reasons (Blinder, 2006).

[8] These data represent payments by U.S. residents to foreign residents. The bulk of the exchange in these services occurs between U.S. firms and other firms located abroad (Bhagwati *et al.*, 2004). Hence, payments to foreign residents provide a good proxy for *imports*. I am intentionally neglecting a second important form of service offshoring: the hiring of foreign workers who *physically* move to the U.S. to provide their services. This type of offshoring is common to those services that require the physical presence of the supplier in the foreign country (e.g. construction, transportation, etc.). Unfortunately, lack of data on the inflows of foreign workers hired by U.S. firms prevents me from investigating this issue. I will therefore take the common approach in the literature (Amiti and Wei, 2005a,b; 2006) and analyze only those cases in which service offshoring occurs between firms located in different countries and gives rises to *trade* in services.

I disaggregate employment into 112 *minor* occupations, that can be attributed to 13 *major* groups of workers performing homogeneous tasks. Out of these 13 groups, 8 are white-collar, for a total of 58 minor occupations. As Table 3 shows, the sample accounts for a large fraction of total U.S. white-collar employment: with the only exception of "Life, physical and social science occupations", the sample covers 55-86% of the 2002 level of national employment in each group[9].

The OES data do not contain any measures of skill at the level of the minor occupations. To construct a proxy, I therefore use individual-level data from the 5% 2004 Public Use Microdata Sample (PUMS) and estimate the average level of schooling required to perform each occupation. PUMS classifies individuals into 16 different schooling categories, ranging from 0 (no schooling) to 16 (Ph.D.). My proxy is obtained by averaging out the individual-level figures over all workers aged 15 to 65 and sharing the same occupation. I then define high skilled white-collar occupations as those whose average worker has at least a bachelor's degree, medium skilled white-collar occupations as those whose average worker has an associate degree in college and low skilled white-collar occupations as those whose average worker has lower levels of educations.

Following previous studies, I identify as "tradeable" those occupations that show the following features jointly: 1) involvement in routine tasks that are repeated almost mechanically; 2) provision of impersonal services that do not require face-to-face contact; 3) production of services that can be easily transmitted from remote destinations with low degradation of quality (Bardhan and Kroll, 2005; Blinder, 2006, 2007). To this purpose, I use the description of the main activity performed by each of the 58 white-collar occupations[10]. The resulting classification may be arbitrary, but is only meant to identify the set of occupations performing activities that can be most easily traded; the actual effects of service offshoring on these occupations will be revealed by the econometric analysis.

Table 4 reports the list of white-collar occupations, with the corresponding average level of schooling and the change in employment between 1997 and 2002; tradeable occupations are marked with an asterisk[11]. As emphasized in previous studies, there is no clear relationship between the tradeable nature of an occupation and its skill level (Grossman and Rossi-Hansberg, 2006): tradeable occupations appear in fact in every skill group.

Almost 1.5 million white-collar jobs have been lost in the U.S. during the period of analysis. This figure is consistent with those reported in Forrester Research (2003), Kirkegaard (2004) and Blinder (2006)[12]. The overall decline in white-collar employment has been extremely

[9] Among the blue-collar groups, the highest share of national employment accounted for by the sample is found for production workers (82.3%). The lowest share (14.4%) is found for "Building and grounds cleaning and maintenance occupations": these workers are highly concentrated in industries excluded from the sample, like hotels and restaurant. For the remaining groups, the sample accounts for 33-47% of national employment.

[10] Available from BLS at http://www.bls.gov/soc/socguide.htm.

[11] The list of blue-collar occupations is available from the author upon request.

[12] Although apparently high in absolute terms, similar numbers do not seem as impressive if compared with

widespread across occupations. Nevertheless, two interesting pieces of evidence emerge. First high skilled white-collar employment has *increased*, while medium and low skilled employment has declined[13]. Note, however, that the increase in high skilled employment has been driven only by five occupations: 1) lawyers; 2) advertising, marketing, promotions, public relations and sales managers; 3) management analysts; 4) aerospace engineers; 5) civil engineers. Second, with a limited number of exceptions, the tradeable occupations have experienced employment declines.

2.3. Preliminary evidence

The period under study has witnessed several economic and political changes, that could have affected the U.S. labor market independent of service offshoring. Among these factors, Baily and Lawrence (2004) cite the increase in oil prices, the appreciation of the dollar and the overall uncertainty that followed the terrorist attacks of September 11th and the war in Iraq. The effects of service offshoring have to be studied in isolation from these events.

A preliminary analysis in this direction can be conducted by estimating a log-linear (conditional) demand function for each of the 58 white-collar occupations, conditioning the effects of service offshoring on a large set of covariates. This function takes the form:

$$\ln e_{jt}^{n} = b_0 + b_1 \cdot \ln w_{jt}^{n} + b_2 \cdot SOSS_{jt} + b_3 \cdot \ln y_{jt} + \mathbf{d}'\mathbf{\Omega}_{jt} + \varrho_{jt} \quad \forall n \tag{2.1}$$

where n indexes occupations, j industries and t time, e is the number of employees, w is the wage, y is output, $\mathbf{\Omega}$ is a vector of control variables and ϱ is an idiosyncratic disturbance. The vector $\mathbf{\Omega}$ includes: time dummies, that capture the effects of year-specific macroeconomic and political factors which are constant across industries; a proxy for technological progress, that accounts for the effects of the introduction of new technologies; the level of output, that controls for scale effects; a proxy for material offshoring, that controls for the fact that some white-collar jobs may be relocated abroad as a result of offshoring intermediate inputs[14]. Finally, all variables enter in deviation from industry-specific means, to control for industry-specific effects.

The estimated (conditional) labor demand elasticities to service offshoring are reported in Table A1, together with heteroskedasticity-robust standard errors[15]. I start commenting upon the elasticities along the first dimension of analysis, that is by looking at the effects of service offshoring across skill categories. Interestingly, the vast majority (11 out of 15) of occupations in the high skilled group are characterized by positive elasticities to service offshoring; 5 of these

the average turnover occurring in the U.S. labor market: Baily and Farrell (2004) and Mankiw and Swagel (2006) report that the average number of monthly job changes in the U.S. exceeds 2 million.

[13] Several other studies have provided direct or indirect evidence of similar trends by skill category (Mann, 2003; Kirkegaard, 2004; Jensen and Kletzer, 2005; Feenstra, 2007).

[14] As an example, think of occupations like transportation and storage managers. These jobs may be moved abroad when firms decide to relocate the production of intermediate inputs. Without controlling for this possibility, these effects may be captured by $SOSS$, and thus confounded with those of service offshoring.

[15] The remaining set of estimated parameters from equation (2.1) are available from the author upon request.

elasticities are also significant at conventional levels, whereas only 1 of the negative elasticities is significantly different from zero ("Accountants and auditors"). At the same time, there is some (less startling) evidence of a concentration of negative elasticities in the medium and low skilled groups: out of 43 occupations, 26 are characterized by negative elasticities; out of these, 13 are significantly different from zero.

Within each skill group, there is high heterogeneity in the response of specific occupations. Some of this heterogeneity seems to depend on differences in tradeable features across occupations. In Table 5, I report a selection of elasticities including all the tradeable occupations and a sub-sample of non tradeable occupations; the latter includes highly complex, specialized and technical jobs, like lawyers, life and physical scientists, chief executives, financial managers, aerospace engineers, management and budget analysts. The elasticities are always negative for the tradeable occupations and always positive for the selected non tradeable occupations. In the vast majority of cases, the elasticities are also significantly different from zero. This suggests that tradeable occupations face negative employment effects from service offshoring, independent of their skill level. At the same time, service offshoring seems to stimulate employment in very complex and highly specialized non tradeable occupations.

The approach based on equation (2.1) has several advantages. First, it is computationally simple. Second, estimates of (conditional) labor demand elasticities to service offshoring coincide with a single parameter, b_2. The approach, however, has also several limitations. First, due to the high fraction of zero observations that plague the employment data, the log transformation causes significant losses of observations and estimated parameters may be inconsistent. Second, the severe loss of observations limits the number of parameters that can be identified. In particular, the number of observations is sometimes too small to estimate all the cross-wage elasticities. Hence, I have insofar excluded any substitutability / complementarity among occupations by setting these elasticities equal to zero. With a high level of detail in the employment variable, such an assumption is far too restrictive. For these reasons, the estimates presented in this section should only be taken as suggestive. In the next section, I will develop a model of firms' behavior that overcomes both limitations of the log-linear approach.

3. A model of firms' behavior

The model presented in this section is similar to the one developed by Fuss (1977). I generalize the representation of the technology given therein, in order to allow service offshoring to affect firms' optimization process and, through this channel, the demand function for each occupation.

The model is based on two assumptions. First, the technology satisfies Homothetic Weak Separability (HWS) in the 13 major occupational groups reported in Table 3[16]. Second, service

[16]Each group contains occupations that perform homogeneous tasks: managerial activities, business and financial operations, etc.. The grouping of minor occupations into major groups is reported in the Appendix (Table A5).

offshoring enters the technology as a shift-factor, that is as a variable which is out of firms' control during the optimization process, but nevertheless affects the latter by determining the position of the technological frontier. This assumption is nowadays standard in studies of the effects of trade and technology on labor demand and wage inequality[17].

HWS implies that changes in the level of employment of a minor occupation do not affect the marginal rate of technical substitution between any pair of occupations that belong to a different major group[18]. Under HWS, therefore, the relationship between occupations in the same group is unrestricted. The relationship between occupations in different groups is instead restricted in the following way: if the occupations in a group become relatively more expensive, firms will substitute away from them by rising *proportionally* the demand for all minor occupations in a different group[19].

Exploiting HWS, the demand functions for the minor occupations can be retrieved by breaking down firms' optimization process in two stages: in the first stage, firms choose the optimal occupational mix in each major group; in the second stage, they choose the optimal level of employment in each major group. I will exploit this results, known as Two-Stage Optimization (TSO), to keep derivation of labor demand elasticities tractable[20].

3.1. The model

3.1.1. Primal representation of the technology under HWS

I assume that each industry j can be described by a representative firm with a twice differentiable and strictly quasi-concave production function. Output (Y) depends on labor, L, and a vector of non labor inputs $\boldsymbol{\delta}$ with generic entry δ^{r}[21]. The labor input consists of minor occupations - indexed by the subscript $n = 1, ..., N$ - that can be grouped into major occupational groups - indexed by the superscript $i = 1, ..., I$. I will refer to the n-th minor occupation in the i-th major group as L_n^i. The production function, then, has the form

$$Y_j = f\left(L_1^1, ..., L_n^i, ..., L_N^I, \boldsymbol{\delta}'\right) \tag{3.1}$$

[17] See, among others, Berman *et al.* (1994) and Feenstra and Hanson (1996, 1999).

[18] For instance, the marginal rate of technical substitution between two managerial occupations is not affected by changes in the number of any type of production workers.

[19] This assumption could in principle be tested [see, among others, Woodland (1978), Moschini (1992), Diewert and Wales (1995) and Koebel (2006) for tests of HWS]. Unfortunately, formal tests are unfeasible in my case due to the high level of occupational detail, which restricts dramatically the number of degrees of freedom and limits the power of those tests. Nevertheless, previous studies have convincingly argued that HWS is likely to hold when working with narrowly defined occupations (Weiss, 1977).

[20] TSO has mainly been exploited in consumption theory to derive optimal demand functions for highly disaggregated goods [see Edgerton (1997) for an example]. In production theory, it has been applied to study optimal demand for different types of energy by Fuss (1977), Denny *et al.* (1982), Woodland (1993), Chakir *et al.* (2004).

[21] Non labor inputs include, capital, energy and non energy materials.

I assume that (3.1) exhibits positive marginal products of all inputs, satisfies the Hicksian stability conditions and is homothetically weakly separable in the major occupational groups. Under HWS, (3.1) can be re-expressed as $Y_j = f\left(\varphi^1, ..., \varphi^i, ..., \varphi^I, \boldsymbol{\delta}'\right)$, where the $\varphi^i = \varphi(L_1^i, ..., L_N^i)$ are homothetic aggregator functions (quantity indexes) for the minor occupations in each group[22].

3.1.2. From the primal to the dual: the short-run cost function

Following Berndt and Christensen (1973), dual to the production function in (3.1) there exists a cost function $C(w_1^1, ..., w_n^i, ..., w_N^I, \mathbf{p}', Y)$, which is twice differentiable in the wages of the minor occupations (w) and in the prices of the non labor inputs ($\mathbf{p}$) and satisfies HWS in the major occupational groups. That is,

$$C(w_1^1, ..., w_n^i, ..., w_N^I, \mathbf{p}', Y) = C(\vartheta^1, ..., \vartheta^i, ..., \vartheta^I, \mathbf{p}', Y)$$

where the $\vartheta^i = \vartheta(w_1^i, ..., w_N^i)$ are homothetic aggregators (wage indexes) for the wages of the minor occupations in each group.

Because HWS implies this alternative representation of the cost function, the optimal demand for each occupation can be derived in two stages: in stage (1), firms choose the optimal occupational mix within each major group, by minimizing the value of all the aggregators; in stage (2), firms choose the optimal level of employment in each group, by minimizing total costs. Hence, HWS implies that TSO is consistent.

I now generalize the above results to include service offshoring and to deal with lack of information on the price of capital. Following previous studies, I employ a short-run cost function, in which capital is treated as a quasi-fixed factor (Berman *et al.*, 1994). In this set-up, derivation of optimal demand functions will be conditioned upon the observable *level* of the capital stock, k. I further assume that, along with k, the short-run optimization process is conditioned upon a set of shift-factors, including service offshoring, material offshoring, a proxy for technological progress and time-dummies. Without loss of generality, I collect k and all the shift-factors into the vector $\mathbf{z}$, with generic entry z^u. The short-run cost function is then defined as $C_{SR}(w_1^1, ..., w_n^i, ..., w_N^I, \mathbf{p}', Y; \mathbf{z}')$ and the following result holds.

Lemma 1. *If $C_{SR}(w_1^1, ..., w_n^i, ..., w_N^I, \mathbf{p}', Y; \mathbf{z}')$ is homothetically weakly separable in the variable inputs, TSO conditioned upon $\mathbf{z}$ is consistent. In fact, $C_{SR}(w_1^1, ..., w_n^i, ..., w_N^I, \mathbf{p}', Y; \mathbf{z}')$ can be rewritten as*

$$C_{SR}(w_1^1, ..., w_n^i, ..., w_N^I, \mathbf{p}', Y; \mathbf{z}') = C_{SR}(\chi^1, ..., \chi^i, ..., \chi^I, \mathbf{p}\prime, Y; \mathbf{z}') \tag{3.2}$$

where

$$\chi^i = \chi(w_1^i, ..., w_N^i; \mathbf{z}') \quad \forall i \tag{3.3}$$

[22]For more details, see Gorman (1959), Green (1964) and Blackorby *et al.* (1978).

Proof. See Appendix. ■

In this framework, TSO can still be used to keep derivation of labor demand functions tractable. Moreover, because $\mathbf{z}$ appears as an argument in both (3.2) and (3.3), a change in one of its arguments will exert effects at both stages of the optimization process. First, firms will re-optimize the employment *mix* within each major group. Second, they will adjust the *level* of employment in all major groups.

The labor demand elasticity for each minor occupation will combine these two effects; it is worth recalling that a change in the level of employment in a major group translates to all its minor occupations proportionally. Take the generic n-th occupation in major group i and use $\xi^i_{n,SOSS}$ and $\rho_{i,SOSS}$ to denote the effect of a 1% change in service offshoring at the first stage and at the second stage of the optimization process, respectively. $\xi^i_{n,SOSS}$ measures the percentage change in the employment of n, holding fixed the level of employment in group i: that is, $\xi^i_{n,SOSS} \equiv \partial \log L^i_n / \partial SOSS|_{L^i=\overline{L^i}}$. Instead, $\rho_{i,SOSS}$ measures the percentage change in the level of employment in group i. This in turn is equal to the combination of two terms: the first depends on the presence of $SOSS$ as an independent argument of the cost function in (3.2), while the second works through the changes induced by $SOSS$ in all the wage aggregators. Formally:

$$\rho_{i,SOSS} = \frac{\partial \log L^i}{\partial SOSS} + \left[\sum_{i=1}^{I} \frac{\partial \log L^i}{\partial \log \chi^i} \cdot \frac{\partial \chi^i}{\partial SOSS} \right] \tag{3.4}$$

The generic argument of the summation in brackets is the product between the own (cross) price elasticity of demand for group i and the change induced by $SOSS$ in the corresponding aggregator. Combining $\xi^i_{n,SOSS}$ and $\rho_{i,SOSS}$ one gets the final expression for the labor demand elasticity of occupation n:

$$\varkappa_{n,SOSS} = \xi^i_{n,SOSS} + s^i_n \cdot \rho_{i,SOSS} \tag{3.5}$$

where s^i_n is the share of occupation n in the wage bill of group i.

3.1.3. Functional forms

I follow Fuss (1977) and Moschini (1992) and specify a Flexible and Separable Translog (FAST) model for equations (3.2) and (3.3). The FAST model offers a non-nested framework in which HWS can be combined with the flexible nature of the translog. In this way, imposing HWS does not cause loss of flexibility[23].

[23] HWS could also be imposed by applying appropriate parametric restrictions on the translog representation of $C_{SR}(w^1_1, ..., w^i_n, ..., w^I_N, \mathbf{p}', Y; \mathbf{z}')$. It is well known, however, that these restrictions would destroy the flexibility of the translog and force the wage aggregators to have a Cobb-Douglas representation, with a constant unitary elasticity of substitution among minor occupations (Berndt and Christensen, 1974; Blackorby *et al.*, 1977; Denny and Fuss, 1977).

Under FAST, the short-run cost function in (3.2) has the following form:

$$\begin{aligned}\ln C_{jt} \;=\;& \ln\alpha_0 + \sum_{i=1}^{I}\alpha_i \ln\chi_{jt}^i + \sum_{r=1}^{R}\alpha_r \ln p_{jt}^r + \alpha_Y \ln Y_{jt} + \sum_{u=1}^{U}\alpha_u z_{jt}^u \\ &+\frac{1}{2}\sum_{i=1}^{I}\sum_{q=1}^{Q}\alpha_{iq}\ln\chi_{jt}^i \ln\chi_{jt}^q + \frac{1}{2}\sum_{r=1}^{R}\sum_{s=1}^{S}\alpha_{rs}\ln p_{jt}^r \ln p_{jt}^s + \sum_{i=1}^{I}\sum_{r=1}^{R}\alpha_{ir}\ln\chi_{jt}^i \ln p_{jt}^r \\ &+\frac{1}{2}\alpha_{YY}(\ln Y_{jt})^2 + \frac{1}{2}\sum_{u=1}^{U}\sum_{v=1}^{V}\alpha_{uv} z_{jt}^u z_{jt}^v + \sum_{u=1}^{U}\alpha_{uY} z_{jt}^u \ln Y_{jt} + \\ &+\sum_{i=1}^{I}\alpha_{iY}\ln\chi_{jt}^i \ln Y_{jt} + \sum_{i=1}^{I}\sum_{u=1}^{U}\alpha_{iu}\ln\chi_{jt}^i z_{jt}^u + \\ &+\sum_{r=1}^{R}\alpha_{rY}\ln p_{jt}^r \ln Y_{jt} + \sum_{r=1}^{R}\sum_{u=1}^{U}\alpha_{ru}\ln p_{jt}^r z_{jt}^u \end{aligned} \tag{3.6}$$

The aggregators in (3.3) are instead represented by:

$$\ln\chi_{jt}^i = \sum_{n=1}^{N}\beta_n \ln w_{n,jt}^i + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{M}\beta_{nm}\ln w_{n,jt}^i \ln w_{m,jt}^i + \sum_{n=1}^{N}\sum_{u=1}^{U}\beta_{nu}\ln w_{n,jt}^i z_{jt}^u \quad \forall i \tag{3.7}$$

Following Fuss (1977), it can be shown that this representation yields exact Divisia indexes for the wages of the minor occupations in each major group. I will exploit this result in section 4.2.

Lemma 2. *Given* $\mathbf{z}$ *a vector of shift-factors and quasi-fixed inputs, equation (3.7) corresponds to the Divisia index of the wages of the minor occupations in group* i

Proof. See Appendix. ■

With equations (3.6) and (3.7) at hand, I now solve the two-stage optimization process. Stage (1) requires to minimize each aggregator in (3.7) with respect to the level of employment in the minor occupations. Exploiting Shepard's Lemma, this yields I systems of wage-share equations of the form:

$$s_{n,jt}^i = \beta_n + \sum_{m=1}^{M}\beta_{nm}\ln w_{m,jt}^i + \sum_{u=1}^{U}\beta_{nu} z_{jt}^u \qquad \forall\; n \text{ and } \forall i \tag{3.8}$$

where $s_{n,jt}^i$ is the share of occupation n in the total wage bill of group i[24]. Stage (2) can be performed similarly, by minimizing (3.6) with respect to the level of employment in each major group and to the level of non labor inputs. By Shepard's Lemma, this yields the following system of share equations:

[24] Linear homogeneity in prices and symmetry imply the following restrictions: $\sum_{n=1}^N \beta_n = 1$; $\sum_{n=1}^N \beta_{nm} = \sum_{m=1}^N \beta_{mn} = 0$; $\sum_{n=1}^N \beta_{nu} = 0$; $\beta_{nm} = \beta_{mn}$

$$S_{jt}^{i(r)} = \alpha_{i(r)} + \sum_{i=1}^{I} \alpha_{iq(ir)} \ln \chi_{jt}^{i} + \sum_{r=1}^{R} \alpha_{ir(rs)} \ln p_{jt}^{r} + \alpha_{iY(rY)} \ln Y_{jt} + \sum_{u=1}^{U} \alpha_{iu(ru)} z_{jt}^{u} \quad \forall i \text{ and } \forall r \tag{3.9}$$

where $S_{jt}^{i(r)}$ is the share of major group i (non labor input r) on total variable costs[25].

Estimation of the systems in (3.8) and (3.9) is computationally feasible, because each system contains a moderate number of equations[26]. The estimated parameters can be used to compute labor demand elasticities to service offshoring for each minor occupation. This requires to specialize equation (3.5) to the translog case. The first term of (3.5), $\xi_{n,SOSS}^{i}$, has the following expression[27]:

$$\xi_{n,SOSS}^{i} = \frac{\beta_{n,SOSS}}{s_{n,jt}^{i}} \tag{3.10}$$

The expression for $\rho_{i,SOSS}$ is:

$$\begin{aligned} \rho_{i,SOSS} = & \frac{a_{i,SOSS}}{S_{jt}^{i}} + \left(\frac{a_{ii}}{S_{jt}^{i}} + S_{jt}^{i} - 1 \right) \cdot \left(\sum_{n=1}^{N} \beta_{n,SOSS} \ln w_{n,jt}^{i} \right) + \\ & + \sum_{q \neq i} \left(\frac{a_{iq}}{S_{jt}^{i}} + S_{jt}^{q} \right) \cdot \left(\sum_{n=1}^{N} \beta_{n,SOSS} \ln w_{n,jt}^{q} \right) \end{aligned} \tag{3.11}$$

where $a_{i,SOSS}/S_{jt}^{i}$ corresponds to the first addendum in (3.4), $\left(\frac{a_{ii}}{S_{jt}^{i}} + S_{jt}^{i} - 1\right)$ and $\left(\frac{a_{iq}}{S_{jt}^{i}} + S_{jt}^{q}\right)$ are the translog formulas for, respectively, the own and cross-price elasticities of demand for group i, and $\left(\sum_{n=1}^{N} \beta_{n,SOSS} \ln w_{n,jt}^{i}\right)$ are the changes in the aggregators induced by $SOSS$.

Summing up, this section has presented a model of firms' behavior that yields formulas for the labor demand elasticity of each minor occupation, while allowing for a flexible structure of substitutability / complementarity among occupations. To this purpose, the model exploits HWS and TSO. By assuming a FAST representation, I have characterized the first-stage of the optimization process with I systems of wage-share equations; the second-stage is instead characterized by just one system. Each system contains a moderate number of equations, which makes estimation tractable.

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[25] Linear homogeneity in prices and symmetry require the following restrictions: $\sum_{i=1}^{I} \alpha_i + \sum_{r=1}^{R} \alpha_r = 1; \sum_{i=1}^{I} \alpha_{iq} = \sum_{q=1}^{Q} \alpha_{qi} = \sum_{r=1}^{R} \alpha_{rs} = \sum_{s=1}^{S} \alpha_{sr} = \sum_{i=1}^{I} \alpha_{ir} = \sum_{r=1}^{R} \alpha_{ri} = 0;$ $\sum_{i=1}^{I} \alpha_{iY} = \sum_{r=1}^{R} \alpha_{rY} = \sum_{i=1}^{I} \alpha_{iu} = \sum_{r=1}^{R} \alpha_{ru} = 0; \alpha_{iq} = \alpha_{qi}; a_{ir} = a_{ri} = \alpha_{rs} = \alpha_{sr}.$

[26] The largest system in (3.8) is composed of twelve equations (minor occupations). The system in (3.9) contains fifteen equations (thirtheen major groups and two non labor inputs).

[27] The detailed derivation can be found in Eckholm and Hakkala (2005).

4. Estimation strategy

The stochastic version of (3.8) and (3.9) is

$$s^i_{n,jt} = \beta_n + \sum_{m=1}^{M} \beta_{nm} \ln w^i_{m,jt} + \sum_{u=1}^{U} \beta_{nu} z^u_{jt} + \varepsilon^i_{n,jt} + c_j \tag{4.1}$$

$$S^{i(r)}_{jt} = \alpha_{i(r)} + \sum_{i=1}^{I} \alpha_{iq(ir)} \ln \chi^i_{jt} + \sum_{r=1}^{R} \alpha_{ir(rs)} \ln p^r_{jt} + \alpha_{iY(rY)} \ln Y_{jt} + \sum_{u=1}^{U} \alpha_{iu(ru)} z^u_{jt} + \epsilon^i_{jt} + c_j \tag{4.2}$$

The term c_j is an industry-specific component accounting for individual heterogeneity, while $\varepsilon^i_{n,jt}$ and ϵ^i_{jt} are idiosyncratic disturbances, that satisfy the following properties:

Property 1 $E(\epsilon^i_{jt}) = 0$ and $E(\varepsilon^i_{n,jt}) = 0$ $\forall j, t, i, n$.

Property 2 $E(\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}') = \Gamma = \Gamma_\varepsilon \otimes I_{JT}$ where $\Gamma_\varepsilon = [\sigma^{nm}_\varepsilon]$. I_{JT} is an identity matrix of order JT; n and m are two generic equations from (4.1)[28].

$E(\boldsymbol{\epsilon}\boldsymbol{\epsilon}') = \Sigma = \Sigma_\epsilon \otimes I_{JT}$ where $\Sigma_\epsilon = [\sigma^{iq}_\epsilon]$. I_{JT} is an identity matrix of order JT; i and q are two generic equations from (4.2).

Property 3 $\boldsymbol{\epsilon} \sim N(\mathbf{0},\Sigma)$ and $\boldsymbol{\varepsilon} \sim N(\mathbf{0},\Gamma)$.

Proprety 4 $\begin{pmatrix} \boldsymbol{\epsilon} \\ \boldsymbol{\varepsilon} \end{pmatrix} \sim N\left(\mathbf{0}, \begin{bmatrix} \Sigma & \Psi \\ \Psi & \Gamma \end{bmatrix}\right)$ where $\Psi = E(\boldsymbol{\epsilon}\boldsymbol{\varepsilon}') = \Psi_{\epsilon\varepsilon} \otimes I_{JT}$ and $\Psi_{\epsilon\varepsilon} = [\sigma^{in}_{\epsilon\varepsilon}]$

These properties imply that the idiosyncratic disturbances are jointly normally distributed with zero mean, and correlated both across the equations of each system and across the two stages of the model[29].

Estimation of (4.1) and (4.2) is complicated by the high-degree of censoring of the dependent variables. This would make SUR estimates inconsistent. Censoring arises either from corner solutions or from the use of designated technologies. Estimation under designated technologies is unfeasible with a large number of occupations[30]. I therefore assume that censoring arises from

[28] The dimension of Γ_ε is system specific, and equal to the number of equations in each system.

[29] Cross-stage error correlation may seem inconsistent with HWS: some authors have indeed argued that, due to HWS, errors should be uncorrelated across different optimization stages, thereby yielding a fully block-recursive system (Bieri and de Janvri, 1972). La France (1991) and Edgerton (1993) have however shown that cross-stage error correlation is not inconsistent with HWS; rather, in order to obtain block-recursivity, one would need to impose very restrictive assumptions on the variance-covariance matrix of the error terms.

[30] Designated technologies are technologies that do not employ some of the occupations. Since it is impossible to figure out the specific technology of each industry, estimation is carried out by maximizing a likelihood function that includes all possible combinations of occupations available to the firm. For instance, with 3 occupations the firm has $3^2 - 2$ available options (assuming that at least one occupation has to be used in production). Clearly, the dimension of integration rises dramatically with the number of occupations.

corner solutions. Under this assumption, three alternative estimation approaches are available. I rely on the panel data version of the Amemiya's (1974) Tobit model proposed by Meyerhoefer *et al.* (2005)[31]. In its original version, the Amemiya's estimator cannot be used with panel data: because the Tobit model is non linear, individual heterogeneity cannot be wiped out by first-differencing or mean-differencing, and thus the conditional distribution of the dependent variable depends on the unobserved heterogeneity component even after the transformation and parameter estimates are inconsistent. This issue is known as "incidental parameters problem" (Neyman and Scott, 1948). Meyerhoefer *et al.* (2005) have shown that the Amemiya's Tobit model can be easily extended to panel data, by specifying a (conditional) distribution for the term of individual heterogeneity and using Quasi-Maximum Likelihood Estimation (QMLE) to obtain consistent estimates of the parameters[32]. In the next section, I will present a different treatment of QMLE, that can be used when the cross-sectional dimension of the panel is moderately small, as usually is in studies using industry-level data[33].

4.1. Quasi-Maximum Likelihood Estimation

QMLE works in two steps. In the first step, a distribution for the term of individual heterogeneity (c_j) is specified and integrated out from the joint density function of each system; estimation is then carried out on the marginal distributions of the dependent variables, conditional on the vector of regressors. In practice, this task can be accomplished by substituting in each equation the expression for the distribution of c_j and then using standard Tobit estimation individually on each equation. Under an appropriate and correctly specified distribution for c_j, estimated parameters are consistent and asymptotically normal (Wooldridge, 2002). In the second step, cross-equation restrictions like symmetry and linear homogeneity are imposed on the parameters through Minimum Distance Estimation (MDE). One relevant piece of information for MDE is the metric used to compute the estimator. MDE generally uses the inverse of the variance-covariance matrix of the unrestricted parameters. However, given that the latter have been estimated from the marginal distributions, the variance-covariance matrix has to be corrected; to this purpose, standard results holding in a single equational context (Wooldridge, 2002) can be generalized to a multi-equation framework.

My treatment of QMLE differs from that in Meyerhoefer *et al.* (2005) at both steps. In the

[31] The other two approaches have been proposed by Wales and Woodland (1983) and Lee and Pitt (1986) and exploit primal and dual representations of the technology, based on Kuhn-Tucker conditions and virtual prices. These methods are computationally cumbersome with large demand systems.

[32] QMLE has been originally introduced in a single equation framework by White (1982) and subsequenlty extended by Jakubson (1988).

[33] There may be other solutions to the incidental parameters problem. In a parametric framework like that required by QMLE, Muendler and Becker (2006) and Yen and Lin (2006) have developed estimators based on extensions of the Heckman's (1979) two-stage model. In a non-parametric framework, Honorè (1992) has shown that individual heterogeneity can be wiped out by an appropriate "trimming" of the distribution of the dependent variable. The first approach requires that the term of individual heterogeneity be independent of the regressors; this assumption is unlikely to hold in my case. The second approach has not insofar been extended to the estimation of systems of equations.

first step, the main difference lays in the specification of the distribution of c_j. In the second step, the main difference is the correction of the variance-covariance matrix. These departures from the original version of the estimator make it more suitable for panel data of moderate cross-sectional dimension. After presenting this version of QMLE, I will briefly compare it with the original one.

The most important aspect of the first step of QMLE is the specification of the distribution of c_j. First, notice from (4.1) and (4.2) that c_j appears in the systems of equations at both stages of the model: the distribution of c_j must therefore be the same at each stage. Second, assumptions have to be made on the relationship between c_j and the explanatory variables: if c_j were incorrectly assumed to be independent of the regressors, parameter estimates would be inconsistent (Hsiao, 2003). I therefore assume that c_j has conditional distribution depending on the subset of regressors that appear at both stages of the model. Specifically, I assume that the conditional distribution of c_j can be represented by a linear projection of the latter on the group means of the quasi-fixed and shift-factors[34]:

$$c_j = \sum_{u=1}^{U} \lambda_u \overline{z}_j^u + \eta_j \tag{4.3}$$

where λ_u are parameters to be estimated and η_j is a projection error uncorrelated with all the explanatory variables and satisfying $\eta_j \sim N(0, \sigma_\eta)$ and $E(\eta_j \epsilon_{jt}^i) = E(\eta_j \varepsilon_{n,jt}^i) = 0 \; \forall j, i, n, t$. Notice one important implication of equation (4.3): any correlation between the error term and the shift- and quasi-fixed factors is accounted for by the group means. Hence, this approach wipes out any potential endogeneity of these regressors arising from correlation between them and the term of unobserved heterogeneity.

The specified distribution for c_j has to be integrated out from the joint density function of each system of equations. This simply requires substituting (4.3) into (4.1) and (4.2). Substitution yields reduced forms of the structural equations:

$$s_{n,jt}^i = \beta_n + \sum_{m=1}^{M} \beta_{nm} \ln w_{m,jt}^i + \sum_{u=1}^{U} \beta_{nu} z_{jt}^u + \sum_{u=1}^{U} \lambda_u \overline{z}_j^u + \tau_{n,jt}^i \tag{4.4}$$

$$S_{jt}^{i(r)} = \alpha_{i(r)} + \sum_{i=1}^{I} \alpha_{iq(ir)} \ln \chi_{jt}^i + \sum_{r=1}^{R} \alpha_{ir(rs)} \ln p_{jt}^r + \alpha_{iY(rY)} \ln Y_{jt} + \sum_{u=1}^{U} \alpha_{iu(ru)} z_{jt}^u + \sum_{u=1}^{U} \lambda_u \overline{z}_j^u + \varpi_{jt}^i \tag{4.5}$$

where $\varpi_{jt}^i = \epsilon_{jt}^i + \eta_j$ and $\tau_{n,jt}^i = \varepsilon_{n,jt}^i + \eta_j$, with $\varpi_{jt}^i \sim N(0, \sigma_\varpi^2)$ and $\tau_{n,jt}^i \sim N(0, \sigma_\tau^2)$. Since each equation in the systems (4.4) and (4.5) contains the same regressors and individual heterogeneity has been integrated out, equation-by-equation pooled Tobit estimation yields consistent and $\sqrt{J}$-asymptotically normal estimates of the reduced-form parameters α, β, λ,

[34] This formulation has originally been proposed by Mundlak (1978).

σ_τ and σ_ϖ (Wooldridge, 2002).

In the second step of QMLE, I use MDE to impose symmetry and homogeneity restrictions on the reduced-form parameters. I focus the exposition of MDE on the systems in (4.4); MDE on (4.5) will proceed along the same lines. Collect the reduced-form parameters from (4.4) into the vector $\mathbf{\Pi}$ of dimension $\Upsilon \times 1$, with $\Upsilon = N \cdot (N+2U+2)$. N is the number of equations in the system and U is the number of shift- and quasi-fixed factors; the constant term and the error variance σ_τ justify the 2 additional parameters. The total number of restrictions to be imposed is $N(N-1)/2 + (N+U+1) + (N-1)U$: $N(N-1)/2$ are the symmetry restrictions; $N+U+1$ are the homogeneity restrictions; $(N-1)U$ are the restrictions needed to make the conditional distribution of c_j constant across equations. Define with ξ the mapping between $\mathbf{\Pi}$ and the structural (restricted) parameters $\boldsymbol{\beta}^*$, such that $\mathbf{\Pi} = \xi(\boldsymbol{\beta}^*)$; the Jacobian of the transformation $\xi(\cdot)$ has full column rank equal to $\Upsilon - N(N-1)/2 - (N+U+1) - (N-1)U$. Given the linear nature of the restrictions, I specialize $\xi(\boldsymbol{\beta}^*)$ to a linear function; hence, $\mathbf{\Pi} = H\boldsymbol{\beta}^*$, where H is a matrix of linear restrictions with dimension $\Upsilon \times (\Upsilon - N(N-1)/2 - (N+U+1) - (N-1)U)$. MDE is carried out by finding the vector $\widehat{\boldsymbol{\beta}}^*$ that minimizes the following quadratic form:

$$\widehat{\boldsymbol{\beta}}^* = \arg\min_{\boldsymbol{\beta}^*} [\widehat{\mathbf{\Pi}} - \mathbf{H}\boldsymbol{\beta}^*]' \widehat{\mathbf{\Xi}}^{-1} [\widehat{\mathbf{\Pi}} - \mathbf{H}\boldsymbol{\beta}^*] \tag{4.6}$$

where a "hat" indicates an estimated variable and $\mathbf{\Xi}$ is the variance-covariance matrix of $\widehat{\mathbf{\Pi}}$[35].

$\widehat{\mathbf{\Xi}}$ has to be corrected to account for the fact that $\widehat{\mathbf{\Pi}}$ has been obtained using the marginal distributions of the dependent variables; this does not allow to account for two types of correlation in the scores of the joint likelihood function. First, the scores are correlated across the equations of each system, but this correlation is missed because of equation-specific estimation. Second, the scores are serially correlated, but this correlation is missed because of the use of a pooled Tobit estimator.

I correct the variance-covariance matrix by generalizing results in Wooldridge (2002, p. 406) to a multi-equation context. Define with $\mathbf{\Pi}_n$ the sub-vector of $\mathbf{\Pi}$ containing only the reduced-form parameters from the n-th equation in (4.4); moreover, define with $l_{jt}(\mathbf{\Pi}_n)$ and $g_{jt}(\mathbf{\Pi}_n)$ the observation-specific Tobit log-likelihood and its score, respectively. Wooldridge (2002, p. 406) shows that the corrected variance-covariance matrix of $\mathbf{\Pi}_n$ has expression $J^{-1}(\mathbf{A}_n^{-1}\mathbf{B}_n\mathbf{A}_n^{-1})$, where $\mathbf{A}_n \equiv -E[\nabla^2_{\Pi_n} l_j(\mathbf{\Pi}_n)]$, $\mathbf{B}_n \equiv E[g_j(\mathbf{\Pi}_n)g_j(\mathbf{\Pi}_n)']$ and $g_j(\mathbf{\Pi}_n) = \sum_{t=1}^{T} g_{jt}(\mathbf{\Pi}_n)$. Matrix $\mathbf{B}_n$ takes account of serial correlation in the score. Consistent estimators of $\mathbf{A}_n$ and $\mathbf{B}_n$ are, respectively, $\widehat{\mathbf{A}}_n = J^{-1}\sum_{j=1}^{J}\sum_{t=1}^{T} g_{jt}(\widehat{\mathbf{\Pi}}_n)g_{jt}(\widehat{\mathbf{\Pi}}_n)'$ and $\widehat{\mathbf{B}}_n = J^{-1}\sum_{j=1}^{J} g_j(\widehat{\mathbf{\Pi}}_n)g_j(\widehat{\mathbf{\Pi}}_n)'$.

I generalize $\widehat{\mathbf{B}}_n$ to a multi-equation framework by means of the matrix $\widehat{\mathbf{B}} = J^{-1}\sum_{j=1}^{J} \mathbf{G}_j\mathbf{G}_j'$,

[35] Estimation has been carried out by using the `tobit` routine in Stata (version 9.2) for retrieving the $\widehat{\mathbf{\Pi}}$. A modification of the SAS code written by Meyerhoefer *et al.* (2005) has been used to implement the MDE and obtain the $\widehat{\boldsymbol{\beta}}^*$.

where $\mathbf{G}_j' = [\ g_j(\widehat{\mathbf{\Pi}}_1)' \ \ ... \ \ g_j(\widehat{\mathbf{\Pi}}_n)' \ \ ... \ \ g_j(\widehat{\mathbf{\Pi}}_N)'\ ]$. $\widehat{\mathbf{B}}$ takes account of both serial correlation in the score of each equation and correlation among scores of different equations. The multi-equation generalization of $\widehat{\mathbf{A}}_n$ is instead $\widehat{\mathbf{A}} = diag \begin{bmatrix} \widehat{\mathbf{A}}_1 & ... & \widehat{\mathbf{A}}_n & ... & \widehat{\mathbf{A}}_N \end{bmatrix}$. With these matrices at hand, I finally construct $\widehat{\mathbf{\Xi}}$ as:

$$\widehat{\mathbf{\Xi}} = \widehat{\mathbf{A}}^{-1}\widehat{\mathbf{B}}\widehat{\mathbf{A}}^{-1}$$

Meyerhoefer *et al.* (2005) specify a different distribution for c_j, by assuming that it depends on all the lags and leads of all the regressors [as in Chamberlain (1980, 1982)]. This implies that the estimation of $\widehat{\mathbf{\Pi}}$ has to be performed *cross-section by cross-section* and on each equation separately. This may be unfeasible in panels of moderate cross-sectional dimension. The formulation in (4.3) allows instead to exploit pooled Tobit estimation, thereby increasing the number of degrees of freedom at the first step of QMLE. This however requires a different correction for the variance-covariance matrix at the second step[36].

I use the estimated structural parameters $\widehat{\boldsymbol{\beta}}^*$ to compute the elasticities of labor demand to service offshoring for each of the 58 white-collar occupations. Equations (3.10) and (3.11) give the deterministic expressions for the two components of these elasticities. The stochastic expressions can be retrieved from (3.10) and (3.11) by replacing observed shares with their expectations, and translog parameters with the marginal effects of the associated variables. The expectation of $s^i_{n,jt}$ is equal to

$$E(s^i_{n,jt}) = \Phi\left(\frac{\widehat{\boldsymbol{\beta}}^{*\prime}_{n1}\mathbf{x}_{jt} + \widehat{\boldsymbol{\beta}}^{*\prime}_{n2}\overline{\mathbf{z}}_j}{\widehat{\sigma}^*_{\tau_n}}\right)(\widehat{\boldsymbol{\beta}}^{*\prime}_{n1}\mathbf{x}_{jt} + \widehat{\boldsymbol{\beta}}^{*\prime}_{n2}\overline{\mathbf{z}}_j) + \widehat{\sigma}^*_{\tau_n}\phi\left(\frac{\widehat{\boldsymbol{\beta}}^{*\prime}_{n1}\mathbf{x}_{jt} + \widehat{\boldsymbol{\beta}}^{*\prime}_{n2}\overline{\mathbf{z}}_j}{\widehat{\sigma}^*_{\tau_n}}\right)$$

where $\widehat{\boldsymbol{\beta}}^{*\prime}_n = \begin{bmatrix} \widehat{\boldsymbol{\beta}}^{*\prime}_{n1} & \widehat{\boldsymbol{\beta}}^{*\prime}_{n2} & \widehat{\sigma}^*_{\tau_n} \end{bmatrix}$ is the vector of estimated structural parameters from equation n, $\mathbf{x}$ collects all the observable regressors (wages and shift- and quasi-fixed factors) and $\overline{\mathbf{z}}$ contains group means of the shift- and quasi-fixed factors only. The marginal effect of the generic k-th element of $\mathbf{x}$ (x^k) can be computed by differentiating $E(s^i_{n,jt})$ with respect to x^k; this yields

$$\frac{\partial E(s^i_{n,jt})}{\partial x^k} = \Phi\left(\frac{\widehat{\boldsymbol{\beta}}^{*\prime}_{n1}\mathbf{x}_{jt} + \widehat{\boldsymbol{\beta}}^{*\prime}_{n2}\overline{\mathbf{z}}_j}{\widehat{\sigma}^*_{\tau_n}}\right)\beta^*_{n1,k}$$

The stochastic expressions of the labor demand elasticities vary across industries and over time; in what follows, I will report averages over the entire sample.

[36]See Meyerhoefer (2002) for the detailed derivation of the corrected variance-covariance matrix under the Chamberlain's specification for the distribution of c_j.

4.2. Instrumenting the wage indexes at the second stage

In estimating the second stage of the model [(4.5)], the log wage of major group i could be computed as a Divisia index of the observed log wages of the corresponding minor occupations. The Divisia index would be equal to $\ln \chi_{jt}^i = \sum_n 0.5(s_{n,j0}^i + s_{n,jt}^i) \ln w_{n,jt}^i$, where the subscript 0 indicates a base year of normalization - 2000 in my case -, in which all wages are set up to 1[37].

Unfortunately, this formulation would imply endogeneity of the $\ln \chi_{jt}^i$, because the $s_{n,jt}^i$ would appear as explained variables at the first stage and as explanatory variables at the second stage of the model (Fuss, 1977; Edgerton *et al*, 1996). By Lemma 2, however, the formulation of the aggregators in (3.7) yields exact Divisia indexes without making use of the $s_{n,jt}^i$. The fitted values of the aggregators can therefore be used in place of the true values to solve the endogeneity issue. I will take this approach in the estimation of (4.5).

5. Results

The estimated labor demand elasticities to service offshoring ($\varkappa_{n,SOSS}$) are reported in Table A2[38]. Not surprisingly, the size of the $\varkappa_{n,SOSS}$ differs (sometimes substantially) from that of the estimates obtained with the log-linear model. This happens because the log-linear model does not account for the substitutability / complementarity among occupations and may produce inconsistent estimates due to the high degree of censoring in the employment variable. With very few exceptions, however, the signs of the elasticities are the same across the two estimation methods.

Before commenting on the results, I check the regularity conditions of the cost function in (3.6) and discuss the statistical properties of the elasticities.

5.1. Regularity conditions and statistical properties of the elasticities

Verifying regularity conditions on the cost function is important when working with aggregators of detailed inputs: the restrictions may in fact fail to hold on the aggregates (Koebel, 2002). Since I have restricted the parameters of (3.6) to satisfy linear homogeneity in prices and symmetry, the only theoretical restrictions to be tested are monotonicity and concavity. Monotonicity holds if the predicted values of $S_{jt}^{i(r)}$ are non negative for each industry in each time period; while I do not report these results to save space, exploration of the fitted shares shows that monotonicity is indeed satisfied. Concavity holds if and only if the Hessian matrix of the cost function (i.e. the matrix of price elasticities) is negative semi-definite; a necessary condition for negative semi-definiteness is that all principal minors of the Hessian be negative. Following previous studies, I base my test on the mean price elasticities, obtained by averag-

[37] See the Appendix for details.

[38] The labor demand elasticities to the remaining shift factors are available from the author upon request.

ing out the observation-specific elasticities over the entire sample[39]. Results reported in the Appendix show that all principle minors of the Hessian are negative.

The $\varkappa_{n,SOSS}$ are complex non linear combinations of the parameters from the two stages of the model. Hence, analytical standard errors cannot be computed. In order to discuss the statistical properties of the elasticities, I therefore report estimates of their main components [as defined in equations (3.10) and (3.11)], for which analytical standard errors can be retrieved through the delta method. Column 1 and 2 of Table A3 report the estimated $\xi^i_{n,SOSS}$ with the corresponding standard errors. Two thirds of the estimates are significant at conventional levels[40]. $\xi^i_{n,SOSS}$ measures the percentage employment change in the n-th occupation induced by a 1% increase in service offshoring, for fixed levels of employment in the corresponding major group. The effects of service offshoring on the level of employment in each major group are instead measured by $\rho_{i,SOSS}$. In turn, this term is equal to the sum of two components, as shown in (3.11). Column 3 and 4 of Table A3 report estimates of the first component, $a_{i,SOSS}/S^i_{jt}$, with the associated standard errors. With the only exception of "Sales and related occupations", all estimates are significant. Column 5 combines the first and the second component to yield the final estimates of $\rho_{i,SOSS}$. The contribution of the second component is negligible: for no group do the $\rho_{i,SOSS}$ show a change in sign relative to the first component; also, the first component almost entirely drives the size of the $\rho_{i,SOSS}$.

5.2. The effects of service offshoring

Effects by skill group A simple look at Table A2 reveals that an overwhelming fraction of high skilled occupations (11 out of 15) are characterized by positive elasticities to service offshoring. All of the high skilled occupations whose employment has increased between 1997 and 2002 show positive elasticities: service offshoring has therefore contributed to raising employment in these occupations. At the same time, elasticities are positive also for many of the occupations whose employment has declined (life and physical scientists, engineering managers, computer hardware engineers, sales and mechanical engineers): service offshoring has therefore prevented additional job losses in these occupations. Evidence is less startling for the medium and low skilled occupations, even though there is a higher concentration of negative elasticities in these groups: the number of negative elasticities equals 24, out of a total number of 43 occupations.

In Table 6, I report estimated coefficients and marginal effects from probit and logit regressions of a dummy equal to 1 if an elasticity is positive, on indicator variables for the three skill groups. The omitted group is the low skilled, so that results have to be interpreted as differ-

[39] In the translog case, concavity is a local property, and should therefore be checked at each observation; in general, however, concavity is unlikely to hold over the entire sample. Therefore, existing studies have usually checked concavity on average [see, among others, Hijzen *et al.* (2005)].

[40] I cannot compute $\xi^i_{n,SOSS}$ for the lawyers, because this occupation is the only one that appears in the major group "Legal Occupations".

ences in the probability of finding a positive elasticity when moving from the low-skill category to the other two. Standard errors are obtained with a bootstrap resampling method and based on 2000 replications. The Table shows that the probability of finding a positive elasticity is higher (38%) in the high-skill group, whereas it is statistically equal between medium and low skilled occupations.

I will now use the estimated elasticities to quantify the net employment effects of service offshoring on the three skill groups. To this purpose, I will simulate a counterfactual world in which service offshoring stayed constant at the 1997 levels. I will compute the number of jobs that would have existed in each skill group in 2002 and subtract them from the employment levels actually observed in that year. A positive number will therefore indicate that service offshoring has increased employment, *ceteris paribus*. Table 7 reports the results. Service offshoring has produced positive net effects on the high skilled and negative net effects on the other two groups. High-skilled white-collar employment was 2% higher than it would have been if service offshoring remained at the 1997 levels; medium and low skilled employment were instead lower by 0.1% and 0.4%, respectively. I also report the corresponding numbers of jobs created / destroyed by service offshoring in each skill group. These numbers are only suggestive. The simulation exercise is based on the assumption that the labor demand elasticities remained constant along the growth path of service offshoring; in the translog case, however, the elasticities measure local effects, so that such an assumption may be excessively restrictive.

These results are consistent with anecdotal evidence reported, among others, by Bhagwati *et al.* (2004): the authors suggest that, by offshoring low skill-intensive service activities, U.S. firms have been able to afford new projects that would otherwise have been financially unfeasible; this has raised employment and wages for highly qualified white-collar workers[41].

The effects of service offshoring on each skill group are however quite small in magnitude. There are two reasons for this. On the one hand, the size of the elasticities generally is small. On the other hand, there is high heterogeneity in the response of specific occupations, so that negative (positive) effects on some of them are compensated by positive (negative) effects on others. Where does this heterogeneity come from? In the next section I discuss one of the possible sources: the difference in tradeable features across occupations.

[41] Quoting the authors:

> "The Information Management Consultants (IMC) of Reston, Virginia, several years ago considered producing software that would allow biotech companies to exploit better the new human genome research. The project seemed financially nonviable if undertaken entirely in the United States. But having its Indian subsidiary do the bulk of the coding work made the project viable. The outcome was a thriving line of business in bio-informatics for IMC and employment at six-figure salaries in the United States. For each engineer in India, the firm now employs six engineers in the United States (Bhagwati *et al.*, 2004, p. 99).

Effects on tradeable and non tradeable occupations Table 8 reports the elasticities for the same selection of occupations used in section 2.3. The Table confirms the main evidence emerged therein: service offshoring negatively affects the tradeable occupations and expands employment in non tradeable jobs performing very complex, specialized and technical activities. Elasticities are in fact negative for all the tradable occupations and positive for all the selected non tradeable occupations.

These results show that tradeable features matter substantially in determining the effects of service offshoring: occupations whose services can be traded face negative effects from service offshoring. At the same time, service offshoring benefits a substantial number of complex non tradeable jobs. Such a pattern takes place even among occupations with similar skill levels. These findings bring about interesting implications for the education system (see the discussion below).

Overall, this section suggests that: 1) Service offshoring is "skilled biased", because it raises high skilled white-collar employment and lowers the number of medium and especially low skilled white-collar jobs; 2) Within broadly defined skill groups, however, tradeable occupations tend to be penalized by service offshoring, whereas complex and specialized non tradeable occupations tend to benefit from it. I will now discuss the main implications of these results.

5.3. Discussion

There is a widespread concern that, by hurting the most skilled fraction of the workforce, service offshoring will lower the incentives to invest in education and slow down the process of human capital accumulation in developed countries[42]. Indeed, *on average*, the white-collars are employed in jobs that require high levels of education and pay high wages. Needless to say, however, that "*on average*" hides a lot of heterogeneity. Some of the white-collars are very highly educated, others less. According to the results of the previous section, service offshoring lowers employment only in the least-skilled occupations, while actually boosting employment in the most skilled. This evidence seems at odds with the above concern.

The previous findings also show that the employment responses to service offshoring may markedly differ across occupations with similar skill levels. In particular, tradeable occupations tend to be negatively affected by service offshoring; complex and highly specialized non tradeable jobs, instead, generally benefit from it. Consistent with Blinder (2006), this suggests that service offshoring is likely to affect not only the level, but also the composition of educational demand. Along with a generic stimulus to acquire tertiary education, service offshoring may bring about a shift in educational demand towards the programs and the degrees that allow workers to qualify for complex non tradeable jobs.

An important message of the above results, therefore, is that traditional classifications of labor into skill groups should be combined with information on the tradeable features of the

[42] See Trefler (2005a,b), Blinder(2006) and Mankiw and Swagel (2006) for a detailed discussion of this concern.

occupations, in order to capture the complex effects of service offshoring. This is true for both empirical and theoretical studies. Insofar, theoretical contributions have generally kept the two dimensions separate. A first set of models have adopted traditional definitions of skills, but given low weight to differences in tradeable features across occupations (Bhagwati *et al.*, 2004; Deardorff, 2005; Markusen, 2005). A second set of models have instead stressed the role of tradeable features of different occupations (tasks), but given low weight to differences in skill levels (Grossman and Rossi-Hansberg, 2006). The first stream of literature produces the clear-cut result that developed countries will increasingly specialize in high skill-intensive activities, as service offshoring rises[43]. The second set of models predict instead that highly complex non tradeable activities will be retained domestically and will complement with more routine jobs performed abroad. Both predictions find empirical support in the results of this paper. It may therefore be promising to combine the two views into a unified framework. Very recent theoretical models have indeed moved in that direction (Markusen and Strand, 2007).

6. Conclusion and lines for further research

Service offshoring has sharply increased in recent years and it will probably continue to rise in the near future, thanks to improvements in information and communication technologies. The white-collars are likely to bear the bulk of the employment effects. These workers have generally been shielded from offshoring in the past and are usually employed in "good jobs". Understanding the effects of service offshoring on white-collar employment has therefore become a relevant goal for international trade economists.

In this paper, I have used a highly detailed database on occupational employment and wages for the U.S. to address the following research questions: 1) What are the effects of service offshoring on occupations with different skill levels? 2) What are the effects on occupations with different tradeable features?

I have used a model of firms' behavior that allows for a relatively flexible structure of substitutability / complementarity across occupations, while keeping derivation of labor demand elasticities fairly tractable. I have estimated the demand functions derived from this model with a variant of quasi-maximum likelihood that accounts for high degrees of censoring and can be used in panel data of moderate cross-sectional dimension.

The main findings are the following. Service offshoring produces net skill-biased effects on white-collar employment, because it raises the total number of workers in high skilled occupations and lowers the total number of workers in medium and especially low skilled occupations. Within each skill group, tradeable occupations are penalized by service offshoring, whereas complex non tradeable occupations generally benefit from it.

Several other issues remain to be investigated. First, it would be interesting to analyze the

[43] See also Trefler (2005a,b) for a discussion on this point.

effects of service offshoring on other developed countries. Many Western European firms have started offshoring service activities to Eastern Europe. European countries differ significantly from the U.S. as far as the structure of the labor market is concerned, so that the effects of service offshoring on white-collar employment may be different on the two sides of the Atlantic. Second, the short-run approach of this paper has prevented me from studying some indirect effects that service offshoring may produce in the long-run, by increasing the level of the capital stock and the scale of firms' operations. Since capital usually complements with more skilled labor (Griliches, 1969) and scale may be skill-biased (Epifani and Gancia, 2006), these indirect effects may strengthen the short-run impact of service offshoring. Finally, service offshoring may exert effects at the *worker-level*, which cannot be studied from industry-level data. Workers displaced by service offshoring may incur economic losses in terms of wages and occupation–industry specific knowledge; such losses may be aggravated by unfavorable re-employment outcomes (Jacobson *et al.*, 1993; Kletzer, 1998). The increasing availability of matched employer-employee databases can be exploited to study these issues, by looking at effects of service offshoring on worker displacement and on the occupational and industrial dynamics of worker flows.

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Appendix

Data

This section provides additional details on data sources and variable definitions.

Occupational data The OES is an annual survey that covers approximately 400,000 establishments each year over a total of 1.2 million establishments[44]. Each year's survey is based on a probability sample, stratified by area, industry, and establishment size, designed to represent the total number of establishments.

Employment and wage estimates for each year are obtained using survey results for that year and for the previous two years, so that the estimates are always based on 3 years of sample data. Industry-level employment figures are computed from each survey as a weighted average of establishment employment. Construction of industry-level wage figures is more complicated. For each occupation, the survey asks establishments to report the number of employees that earn wages falling into one of 12 contiguous intervals; for each interval, a mean wage rate is then computed. These mean wage rates are used, together with the corresponding employment figures for each interval, to compute occupational wages as weighted averages of the mean wage rates. Finally, in order to retrieve wage estimates for each year, data from the current survey are combined with that from the previous two years. The latter are adjusted to take account of inflation, by applying a weighting factor based on the BLS Employment Cost Index.

The OES survey is based on the Standard Occupational Classification (SOC) system, which distinguishes occupations in 23 major groups (2-digit), each containing minor occupations at the 6-digit level. The total number of minor occupations surveyed is 770. This figure is much higher than the number of occupations used in this paper. The reason is that the occupational classification method employed by the BLS changed in 1999, with the adoption of the SOC system. Due to the change, comparable wage estimates for the periods 1997-1998 and 1999-2002 are available only for 374 6-digit SOC occupations. Out of this number, I restricted attention only to those occupations with positive employment in at least one industry and in at least one year of the sample period; this yielded a total number of 275 6-digit occupations.

Out of the 23 major groups, 10 consist of occupations that cannot be considered as productive inputs in an even broadly defined production process: "Arts, design, entertainment, sports and media occupations", "Community and social service occupations", "Healthcare support occupations", "Military specific occupations", "Education, training and library occupations", "Protective service occupations", "Farming, fishing and forestry occupations", "Personal care and service occupations", "Healthcare practitioners and technical occupations", "Food preparation and serving related occupations"; these groups, moreover, are characterized by excessive presence of missing values. I therefore excluded these occupations from the analysis. The remaining 13 groups contain 229 6-digit SOC occupations. These had to be merged with their counterparts for the period 1997-1998. Since a correspondence table is not available yet from the BLS, I merged occupations based on the definition of the main activity they perform (available from BLS)[45]. Finally, to make the dimension of the prob-

[44] Each establishment is surveyed once every three years, so that three years are necessary for the full number of establishments to be surveyed.

[45] The correspondence scheme is available from the author upon request.

lem tractable, I aggregated the 6-digit occupations into the corresponding 5-digit occupations. This yielded the final number of 112 occupations.

The OES report data on wages and employment both for the minor occupations and for the major groups. The latter, however, are estimated considering also minor occupations for which employment and wage figures are not reported to avoid disclosure. Hence, I estimated my own data for employment and wages of the major groups, by taking into account only the minor occupations used in the analysis: total employment for each major group, then, has been obtained as the sum of the number of employees in the constituent minor occupations; average wages have been obtained as employment-weighted averages of the wages of the minor occupations belonging to each major group.

Wage and employment estimates for these occupations are available for 140 3-digit SIC manufacturing industries and 9 service industries. Due to excessive number of missing values, 5 manufacturing industries were excluded from the analysis, yielding the 135 industries reported in Table A4[46]. Starting from 2002, the NAICS classification replaced the SIC. Hence, OES started reporting data at 4- and 5-digit NAICS levels. In order to make 2002 data comparable with earlier period estimates, I converted the 4-digit NAICS data into 3-digit SIC industries based on the correspondence table provided by the U.S. Census Bureau; wage estimates were computed as employment weighted averages of the wages earned by each occupation in the NAICS sectors corresponding to each SIC industry.

Finally, for those occupations and industries with zero employment, the OES do not provide a wage estimate. Hence, I assumed that firms hire workers in each occupation based on the economy-wide average wage for that occupation; that is, when firms make decisions as to the number of workers to hire, the expected cost to them for each occupation corresponds to the wage paid for that occupation in the economy as a whole. Therefore, I replaced missing wage estimates for the occupations and industries with zero employment with the economy-wide average wages for the same occupations provided in the national OES files.

The upper part of Table A5 reports descriptive statistics on the wage bill share of each of the 58 white-collar occupations and of each of the 13 major groups. The Table also reports the share of each occupation in the economy-wide level of employment in 2002 and the percentage number of zero employment observations, averaged out over the period 1997-2002. The degree of censoring varies widely across occupations, ranging from values virtually close to zero to values exceeding the 95% of observations[47].

Material offshoring Following Feenstra and Hanson (1996, 1999), I proxied material offshoring with the share of imported intermediate inputs in total non-energy inputs purchases. Formally:

$$MOSS_{jt} = \frac{1}{NE_{jt}} \sum_{h} \left(\phi_{jh}^{97} Y_{jt} \cdot \frac{M_{ht}}{Y_{ht} + M_{ht} - X_{ht}} \right)$$

where ϕ_{jh}^{97} is the input-output coefficient giving the value of input h used in 1997 by industry j to produce one dollar of its total output (Y_j), while Y_h, M_h and X_h indicate, respectively, production, imports and exports of input h. Input-output coefficients have been retrieved from the 1997 BEA input-output matrix; data on imports and exports came from NBER (Feenstra *et al.*, 2002); data on

[46] The excluded industries are: "Logging" (241); "Newspaper publishing, or publishing and printing" (271); "Periodicals publishing, or publishing and printing" (272); "Miscellaneous printing" (274); "Greetings cards" (277).

[47] Descriptive statistics for the blue-collar occupations are available from the author upon request.

industry output came from the U.S. Census Bureau ("Annual Survey of Manufactures") and BEA ("Gross-Domestic-Product-by-Industry Data"), as explained below. Notice that this proxy has been constructed differently from that of service offshoring. The reason is that constructing the proxy for service offshoring in the same way as $MOSS$ would require information on service production with the same level of aggregation as the information on service imports and exports. Unfortunately, the two classifications differ (see Table 1 and 2 in the text).

Technological progress The proxy for technological progress is the share of high-tech capital on total capital stock. This proxy has been constructed as follows. First, I used data on private, non residential, fixed assets provided by BEA at the 2-digit SIC level to calculate the share of high-tech capital on total capital stock for each 2-digit industry in the manufacturing sector and for each of the service industries; high-tech capital includes computer and peripheral equipment, software, communications, photocopy and related equipment, office and accounting equipment. Then, for the service industries, I retrieved data on the total capital stock from BEA ("Gross-Domestic-Product-by-Industry Data"); for the manufacturing industries, I calculated the total capital stock by extending the series in the NBER Productivity Database (Bartelsman and Gray, 1996) through a perpetual inventory method using data on investments in equipment and structures from the Annual Survey of Manufactures and depreciation rates equal to 7.7 for equipment and 3.5 for structures (Amiti and Wei, 2006). Finally, I applied the shares of high-tech capital computed before to the total capital stock so obtained for each industry.

Other variables Data on real output have been obtained by deflating the total value of shipments reported in the Annual Survey of Manufactures with the price deflator for shipments available from BEA ("Industry Economic Accounts – Supplemental Estimates"). Data on expenditures in materials and electricity by 6-digit NAICS came from the Annual Survey of Manufactures; the latter provides also information on the quantity of purchased electricity. I converted these figures at the 3-digit SIC level by means of the conversion table provided by the U.S. Census Bureau. Data on the same variables for the service industries came from BEA ("Gross-Domestic-Product-by-Industry Data").

I computed the price deflator for electricity by normalizing at one the average unit values in 2000[48]. Computation of the non energy material deflator was more complicated. First I retrieved nominal non energy materials as difference between material costs and electricity expenditures. Then, I deflated material costs with the 2-digit SIC deflator provided by BEA ("Industry Economic Accounts – Supplemental Estimates") and obtained real non energy material costs as difference between real material costs and real expenditures on electricity. Finally, by dividing nominal non energy material costs by real non energy material costs I obtained an industry-level proxy for the price deflator of non energy materials.

Descriptive statistics on these variables are reported in the bottom part of Table A5.

[48] Average unit values for electricity have been obtained by dividing the cost of purchased electricity by the quantity of purchased electricity.

Proofs

Lemma 1 Assume that $C_{SR}(w_1^1, ..., w_n^i, ..., w_N^I, \mathbf{p}', Y; \mathbf{z}')$ is weakly separable in the variable inputs and that firms choose the optimal amount of minor occupations in two stages. Due to the separability assumption, at the first stage, for any given level of employment in each major group, firms choose the optimal demand for each minor occupation by looking only at the wages of the minor occupations in the group and at the given level of the shift-factors and of the quasi-fixed inputs. Total expenditure in major group i will thus be given by $\chi^i = \chi(w_1^i, ..., w_N^i, L^i; \mathbf{z}') = \min_{L_1^i,...,L_N^i} [\sum_n w_n^i L_n^i \text{ s.t. } L^i = L(L_1^i, ..., L_N^i)$ and $\mathbf{z}']$. Further assuming homotheticity of the χ^i implies that $\chi^i = h(L^i \cdot \chi(w_1^i, ..., w_N^i; \mathbf{z}'))$, where h is a positive monotonic transformation and $\chi(w_1^i, ..., w_N^i; \mathbf{z}')$ is linearly homogeneous in the vector of wages.

Once the first stage of the optimization process has been solved, firms choose the optimal number of employees in each major group and the optimal amount of non-labor inputs to minimize total costs. Hence, it will hold that $C_{SR}(\chi^1, ..., \chi^i, ..., \chi^I, \mathbf{p}', Y; \mathbf{z}') = \min_{L^1,...,L^I,\boldsymbol{\delta}'} [\sum_i \chi^i + \mathbf{p}'\boldsymbol{\delta} \text{ s.t. } y = f(L^1, ..., L^I, \boldsymbol{\delta}')$ and $\mathbf{z}'] = \min_{L^1,...,L^I,\boldsymbol{\delta}'} [\sum_i h(L^i \cdot \chi(w_1^i, ..., w_N^i; \mathbf{z}')) + \mathbf{p}'\boldsymbol{\delta} \text{ s.t. } y = f(L^1, ..., L^I, \boldsymbol{\delta}')$ and $\mathbf{z}'] = C_{SR}(w_1^1, ..., w_n^i, ..., w_N^I, \mathbf{p}', Y; \mathbf{z}')$. Hence, under HWS in the variable inputs, TSO conditioned upon $\mathbf{z}$ implies that $C_{SR}(w_1^1, ...w_n^i, ..., w_N^I, \mathbf{p}', Y; \mathbf{z}')$ has an equivalent representation in $C_{SR}(\chi^1, ..., \chi^i, ..., \chi^I, \mathbf{p}', Y; \mathbf{z}')$ with $\chi^i = \chi(w_1^i, ..., w_N^i; \mathbf{z}')$. As a result, TSO conditioned upon $\mathbf{z}$ is consistent.

Lemma 2 The Divisia index for the wages of the minor occupations in major group i is $\Delta \ln \chi_{jt}^i = \sum_n s_{n,jt}^i \Delta \ln w_{n,jt}^i$, which has a discrete approximation in

$$\ln \chi_{jt}^i - \ln \chi_{j0}^i = \sum_n 0.5(s_{n,j0}^i + s_{n,jt}^i)(\ln w_{n,jt}^i + \ln w_{n,j0}^i) \tag{A1}$$

where the subscript 0 indicates the base year of normalization (2000), in which all wages are set up to 1. From equation (3.8), this normalization implies $s_{n,j0}^i = \beta_n + \sum_{u=1}^{U} \beta_{nu} z_{jt}^u$, while from equation (3.7) it implies $\ln \chi_{j0}^i = 0$. Substituting back into equation (A1) yields:

$$\ln \chi_{jt}^i = \sum_n 0.5 \left(\beta_n + \sum_{u=1}^{U} \beta_{nu} z_{jt}^u + s_{n,jt}^i \right) \ln w_{n,jt}^i \tag{A2}$$

Substituting equation (3.8) into equation (A2) yields:

$$\ln \chi_{jt}^i = \sum_n 0.5 \left(\beta_n + \sum_{u=1}^{U} \beta_{nu} z_{jt}^u + \beta_n + \sum_{m=1}^{M} \beta_{nm} \ln w_{m,jt}^i + \sum_{u=1}^{U} \beta_{nu} z_{jt}^u \right) \ln w_{n,jt}^i$$

Finally, rearranging terms gives:

$$\ln \chi_{jt}^i = \sum_{n=1}^{N} \beta_n \ln w_{n,jt}^i + \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{M} \beta_{nm} \ln w_{n,jt}^i \ln w_{m,jt}^i + \sum_{n=1}^{N} \sum_{u=1}^{U} \beta_{nu} \ln w_{n,jt}^i z_{jt}^u$$

Hence, in the presence of shift-factors and quasi-fixed inputs, equation (3.7) is the correct specification for the Divisia index of the wages of the minor occupations in each major group.

Estimated price elasticities matrix

This section reports the estimated price elasticities matrix for the short-run translog cost function in equation (3.6). Negative principal minors for this matrix (in bold) represent a necessary condition for the cost function to be concave in input prices. Elasticities are computed for each industry in each time period and then averaged out over the entire sample.

	P11	P13	P15	P17	P19	P23	P37	P41	P43	P47	P49	P51	P53	Pen	Pnonen
P11	**-0.745**	-0.031	0.044	0.261	-0.271	0.142	-0.018	0.477	0.167	-0.561	-0.023	0.396	-0.127	-0.067	0.508
P13	-0.139	**-0.241**	-1.142	0.111	-0.018	0.104	0.185	0.069	1.502	-0.894	1.160	0.291	-0.171	-0.246	-0.416
P15	0.267	-1.458	**-6.423**	0.656	0.304	1.737	-0.937	0.085	-0.242	0.703	-2.512	1.862	-0.814	4.742	2.183
P17	0.484	0.046	0.209	**-0.848**	-0.187	0.319	0.055	-0.030	-0.128	-0.453	0.116	0.856	0.282	1.309	-1.878
P19	-1.216	-0.016	0.238	-0.454	**-0.310**	-0.589	0.056	-0.001	0.297	0.407	0.096	0.768	0.086	2.264	-1.474
P23	0.191	0.033	0.347	0.212	-0.144	**-0.226**	-0.002	-0.590	-0.209	0.646	-0.065	-0.661	0.051	-0.821	0.940
P37	-0.336	0.789	-3.116	0.566	0.235	-0.057	**-0.215**	0.233	0.045	-0.759	1.552	0.142	0.341	0.798	-0.066
P41	0.817	0.029	0.025	-0.021	0.001	-0.888	0.021	**-1.024**	0.117	-1.676	0.024	-0.669	0.030	1.770	1.598
P43	0.241	0.477	-0.062	-0.098	0.092	-0.284	0.003	0.093	**-0.105**	-0.976	0.173	0.580	-0.500	-1.557	1.864
P47	-0.725	-0.258	0.159	-0.317	0.117	0.722	-0.052	-1.300	-0.891	**-0.523**	0.176	-0.147	0.482	0.036	2.673
P49	-0.102	1.094	-1.856	0.264	0.087	-0.271	0.344	0.051	0.511	0.565	**-0.143**	-0.190	0.608	-0.299	-0.510
P51	0.157	0.026	0.126	0.183	0.066	-0.255	0.003	-0.164	0.160	-0.050	-0.017	**-0.805**	0.001	0.156	0.565
P53	-0.201	-0.061	-0.232	0.252	0.031	0.053	0.029	0.026	-0.570	0.601	0.236	0.018	**-0.693**	0.339	0.325
Pen	-0.085	-0.070	1.057	0.909	0.642	-0.949	0.053	1.340	-1.402	0.031	-0.089	0.508	0.264	**-1.755**	-0.301
Pnonen	0.025	-0.003	0.016	-0.046	-0.016	0.014	0.000	0.037	0.059	0.089	-0.004	0.069	0.007	-0.010	**-0.082**

Note: P11 = wage of group "Management occupations"; P13 = wage of group "Business and financial operations occupations"; P15 = wage of group "Computer and mathematical occupations"; P17 = wage of group "Architecture and engineering occupations"; P19 = wage of group "Life, physical, and social science occupations"; P23 = wage of group "Legal occupations"; P37 = wage of group "Building and grounds cleaning and maintenance occupations"; P41 = wage of group "Sales and related occupations"; P43 = wage of group "Office and administrative support occupations"; P47 = wage of group "Construction and extraction occupations"; P49 = wage of group "Installation, maintenance, and repair occupations"; P51 = wage of group "Production occupations"; P53 = wage of group "Transportation and material moving occupations"; Pen = price index for electricity; Pnonen = price index for non energy materials.

Table 1 - Service Industries Included in the Sample

Wholesale trade
Retail trade
Finance and insurance
Real estate, rental and leasing
Legal services
Computer systems design and related services
Management of companies and enterprises
Professional, scientific, and technical services
Motion picture and sound recording industries

Table 2 - Categories of Private Services Used to Compute the Proxy for Service Offshoring

Financial services	Management, consulting and public relation services
Insurance services	Industrial engineering
Computer and information services	Installation, maintenance and repair of equipment
Research, development and testing services	Legal services
Business, professional and technical services	Operational leasing
Advertising	Accounting, auditing and bookkeeping
Telecommunication	Other business, professional and technical services

Note: Affiliated and unaffiliated data on payments to foreign residents for these services are available from BEA ("U.S. International Services: Table 1 - Trade in Private Services, 1992-2004")

Table 3 - Share of National Employment Accounted for by the Sample

Major Occupational Group	**%, 2002**
White-Collars	
Management occupations	55.8
Business and financial operations occupations	54.6
Computer and mathematical occupations	59.3
Architecture and engineering occupations	76.8
Life, physical, and social science occupations	14.9
Legal occupations	75.8
Sales and related occupations	85.8
Office and administrative support occupations	54.8
Blue-Collars	
Building and grounds cleaning and maintenance occupations	14.4
Construction and extraction occupations	42.7
Installation, maintenance, and repair occupations	33.8
Production occupations	82.3
Transportation and material moving occupations	46.9

Note: Author's calculations based on BLS (Occupational Employment Statistics)

Table 4 - Employment Change and Skill Level by Minor Occupation

Occupation	**School**	**Change 97-02**		**Occupation**	**School**	**Change 97-02**	
		%	#			%	#
High Skilled	-	*1.73*	*41,852*	*Medium Skilled*	-	*-23.96*	*-1,067,024*
Lawyers	15	16.0	52,633	Chief executives	12	-36.5	-778,571
Life scientists	14	-18.8	-8,340	Medical and health services managers	12	227.4	10,803
Physical scientists	14	-13.9	-11,834	Financial managers	12	-13.2	-56,426
Engineering managers	13	-36.1	-85,622	Human resources managers	12	-15.2	-18,724
Advert., MKTG, Prom., PR and Sal. Manag.	13	42.7	133,241	Purchasing managers	12	-48.0	-71,445
Petroleum engineers	13	-29.0	-577	Administrative services managers	12	-25.8	-43,723
Computer hardware engineers	13	-78.6	-179,054	Marine engineers and naval architects	12	8.5	202
Management analysts	13	331.3	180,403	Computer systems analysts*	12	-22.1	-75,292
Aerospace engineers	13	61.3	21,110	Computer programmers*	12	-25.6	-104,111
Market and survey researchers*	13	-53.0	-16,173	Mining and geological engineers	12	76.6	911
Sales engineers	13	-10.9	-7,779	Industrial engineers	12	26.0	30,175
Mechanical engineers	13	-7.2	-13,106	Materials engineers	12	42.3	5,840
Civil engineers	13	19.7	18,311	Database administrators*	12	3.8	2,113
Accountants and auditors*	13	-3.7	-21,943	Agricultural engineers	12	-58.3	-1,650
Life, physical, and social science technicians	13	-15.1	-19,418	Budget analysts	12	-13.8	-3,016

Table 4 - Employment Change and Skill Level by Minor Occupation (concl.)

Occupation	**School**	**Change 97-02**		**Occupation**	**School**	**Change 97-02**	
		%	#			%	#
Medium Skilled (cont.)	-	-	-	Statistical assistants*	11	-35.1	-5,297
Compliance officers	12	194.1	21,059	Demonstrators and product promoters	11	-12.2	-8,808
Advertising sales agents	12	30.9	11,748	Financial clerks*	10	6.0	82,507
Human resourc., train. and lab. rel. spec.	12	23.0	32,911	Parts salespersons	10	-19.5	-54,734
Computer support specialists*	12	-10.0	-29,828	Information and record clerks*	10	-48.2	-162,233
Low Skilled	-	*-2.16*	*-389,828*	Other off. and admin. supp. workers*	10	-13.9	-253,106
Construction managers	11	-22.1	-5,185	Order, recept. and inform. clerks	10	-22.4	-162,705
Industrial production managers	11	-22.1	-45,066	Switchb. operat., incl. answ. service*	10	-23.4	-22,205
Transp., storage, and distrib. managers	11	52.5	15,357	Matererial record., sched., dispatch., and distrib. work.	10	26.9	473,753
Sales representatives	11	15.3	200,892	Retail salespersons	10	-2.4	-92,927
Cost estimators*	11	6.3	3,710	Exec. secretaries and admin. assist.	9	30.6	286,391
Buyers and purchasing agents	11	9.6	24,519	Weighers, measur., check., and samplers, recordkeep.	9	22.1	7,951
Property, real estate, and commun. assoc. manag.	11	-6.3	-8,649	Telemarketers*	9	-52.5	-162,966
First-line superv. of off. and admin. supp. work.	11	-17.2	-145,094	Cashiers, except gaming	9	-3.8	-110,445
Engineering technicians, except drafters	11	-40.8	-208,769	-	-	-	-
Drafters	11	-18.1	-36,720	*Total White-Collars*	-	*-6.0*	*-1,415,000*

Note: Author' calculations based on BLS (Occupational Employment Statistics). Occupations with a star are defined as "tradeable", because they show the following three features: 1) involvement in routine tasks that are repeated almost mechanically; 2) provision of impersonal services that do not require face-to-face contact; 3) production of services that can be easily transmitted from remote destinations with low degradation of quality. School is the level of education required, on average, to perform each occupation. Legend: 9= High-school graduate; 10= Some college, not degree; 11= Vocational or technical degree; 12= Associate degree in college; 13= Bachelor's degree; 14= Master's degree; 15= Professional school degree; 16= Doctorate degree (Source: 5% 2004 PUMS)

Table 5 - Labor Demand Elasticities to Service Offshoring for Selected Occupations: Log-Linear Model

Tradeable Occupations	**Elasticity**	**Std. Err.**	**Non Tradeable Occupations**	**Elasticity**	**Std. Err.**
Market and survey researchers	-0.0009	0.0062	Lawyers	0.0231	0.0104**
Accountants and auditors	-0.0039	0.0022*	Life scientists	0.0679	0.0785
Computer systems analysts	-0.0143	0.0025***	Physical scientists	0.0092	0.0089
Computer programmers	-0.0252	0.0046***	Engineering managers	0.0126	0.0064*
Database administrators	-0.0143	0.0031***	Advertising, MKTG, Prom., Pub. Rel. and Sales Manag.	0.0076	0.0032**
Computer support specialists	-0.0150	0.0031***	Computer hardware engineers	0.0248	0.0111**
Cost estimators	-0.0163	0.0039***	Management analysts	0.0150	0.0071**
Statistical assistants	-0.0265	0.0075***	Aerospace engineers	0.0095	0.0064
Financial clerks	-0.0113	0.0054**	Sales engineers	0.0057	0.0141
Information and record clerks	-0.0133	0.0062**	Mechanical engineers	0.0043	0.0111
Other office and administrative support workers	-0.0121	0.0055**	Civil engineers	0.0034	0.0056
Switchboard operators, including answering service	-0.0063	0.0034*	Chief executives	0.0070	0.0032**
Telemarketers	-0.0153	0.0106	Financial managers	0.0059	0.0023***
			Purchasing managers	0.0017	0.0029
			Administrative services managers	0.0101	0.0023***
			Budget analysts	0.0164	0.0045***

Note: Standard errors are heteroskedasticity-robust. *significant at 10%; **significant at 5%; ***significant at 1%.

Table 6 - Service Offshoring and Skill Intensity - Probit and Logit Results

Coefficients	**Probit**	**Logit**
High skilled	1.0537	1.7047
	[0.4584]**	[0.8882]*
Medium skilled	0.6299	1.0116
	[0.4141]	[0.7895]
Constant	-0.4307	-0.6931
	[0.2755]	[0.6285]
Marginal Effects		
High skilled	0.3853	0.3824
	[0.1430]***	[0.1712]**
Medium skilled	0.2443	0.2439
	[0.1530]	[0.1823]
Log-likelihood	-36.9070	
Pseudo-R^2	0.0812	
Observations	58	

Note: The dependent variable is a dummy equal to 1 if the labor demand elasticity to service offshoring ($\varkappa_{n,SOSS}$) is positive; the explanatory variables are dummies for the three skill groups (omitted category: low skilled). Bootstrapped standard errors obtained with 2000 replications are reported in brackets. * significant at 10%; ** significant at 5*; *** significant at 1%.

Table 7 - Counterfactual Experiment

Skill Group	**Implied Effect of Service Offshoring in 2002**	
	%	#
High skilled	2.0	49,009
Medium skilled	-0.1	-2,863
Low skilled	-0.4	-62,176
Total white-collars	*-0.1*	*-16,030*

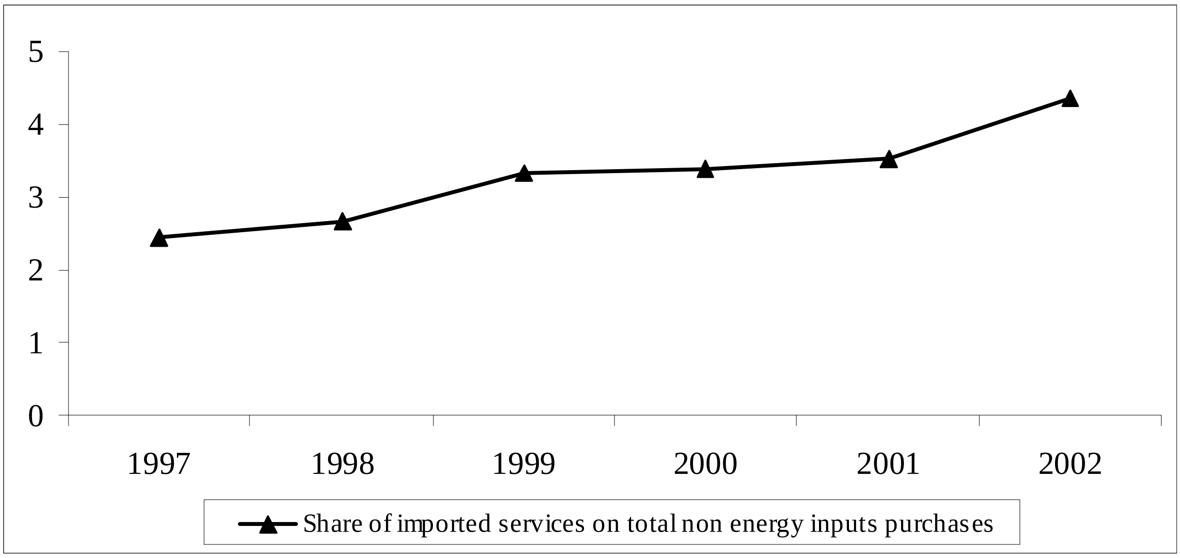
Note: The experiment uses the estimated labor demand elasticities to service offshoring reported in Table A2 to simulate a counterfactual world in which service offshoring is assumed to stay constant at the 1997 levels. A positive number indicates that employment was higher in 2002 than it would have been if service offshoring actually remained at the 1997 levels. In that case, service offshoring raised employment *ceteris paribus*.

Table 8 - Labor Demand Elasticities to Service Offshoring for Selected Occupations: Quasi-Maximum Likelihood Estimation

Tradeable Occupations	$\varkappa_{n,SOSS}$	**Non Tradeable Occupations**	$\varkappa_{n,SOSS}$
Market and survey researchers	-0.0016	Lawyers	0.0722
Accountants and auditors	-0.0200	Life scientists	0.0201
Computer systems analysts	-0.0052	Physical scientists	0.0064
Computer programmers	-0.0252	Engineering managers	0.0195
Database administrators	-0.0066	Advertising, MKTG, Prom., Pub. Rel. and Sales Manag.	0.0023
Computer support specialists	-0.0043	Computer hardware engineers	0.0589
Cost estimators	-0.0117	Management analysts	0.0741
Statistical assistants	-0.0181	Aerospace engineers	0.0113
Financial clerks	-0.0182	Sales engineers	0.0206
Information and record clerks	-0.1501	Mechanical engineers	0.0100
Other office and administrative support workers	-0.0911	Civil engineers	0.0150
Switchboard operators, including answering service	-0.1544	Chief executives	0.0028
Telemarketers	-0.0009	Financial managers	0.0016
		Purchasing managers	0.0102
		Administrative services managers	0.0072
		Budget analysts	0.0002

Note: Reported figures are averages over the entire sample. $\varkappa_{n,SOSS}$ measures the percentage employment change in occupation n after a 1% percentage change in service offshoring. This elasticity is computed as $\varkappa_{n,SOSS} = \xi^i_{n,SOSS} + s^i_n \cdot \rho_{i,SOSS}$, where $\xi^i_{n,SOSS}$ measures the percentage employment change in occupation n at given levels of employment in major group i; $\rho_{i,SOSS}$ measures the percentage employment change in major group i; s^i_n is the share of occupation n in the wage bill of major group i. Estimates of $\xi^i_{n,SOSS}$ and $\rho_{i,SOSS}$ are reported in Table A3, whereas average values of s^i_n are reported in Table A5.

Figure 1 - Service Offshoring (%)§



§ Unweighted averages. Service imports based on affiliated and unaffiliated data

Source: Author's calculations based on: BEA ("U.S. International Services: Table 1 – Trade in Private Services, 1992-2004"); BEA ("1997 Import Matrix"); BEA ("GDP-by-industry data"); U.S. Census Bureau ("Annual Survey of Manufactures").

Appendix Tables

Table A1 – Labor Demand Elasticities to Service Offshoring from Log-Linear Model

Occupation	Elasticity	Std. Err.
High Skilled		
Lawyers	0.0231	0.0104**
Life scientists	0.0679	0.0785
Physical scientists	0.0092	0.0089
Engineering managers	0.0126	0.0064*
Advertising, marketing, promotions, public relations and sales managers	0.0076	0.0032**
Petroleum engineers	-0.0080	0.0756
Computer hardware engineers	0.0248	0.0111**
Management analysts	0.0150	0.0071**
Aerospace engineers	0.0095	0.0064
Market and survey researchers	-0.0009	0.0062
Sales engineers	0.0057	0.0141
Mechanical engineers	0.0043	0.0111
Civil engineers	0.0034	0.0056
Accountants and auditors	-0.0039	0.0022*
Life, physical, and social science technicians	-0.0241	0.0081
Medium Skilled		
Chief executives	0.0070	0.0032**
Medical and health services managers	-0.0796	0.1175
Financial managers	0.0059	0.0023***
Human resources managers	0.0016	0.0018
Purchasing managers	0.0017	0.0029
Administrative services managers	0.0101	0.0023***
Marine engineers and naval architects	-0.0817	0.2481
Computer systems analysts	-0.0143	0.0025***
Computer programmers	-0.0252	0.0046***
Mining and geological engineers	-0.2672	0.3383
Industrial engineers	-0.0071	0.0108
Materials engineers	-0.0012	0.0098
Database administrators	-0.0143	0.0031***
Agricultural engineers	-0.0030	0.0017*
Budget analysts	0.0164	0.0045***
Compliance officers	-0.0079	0.0067
Advertising sales agents	0.0338	0.0110***
Human resources, training and labor relations specialists	0.0088	0.0032***
Computer support specialists	-0.0150	0.0031***
Low Skilled		
Construction managers	0.0006	0.0035
Industrial production managers	0.0023	0.0064
Transportation, storage, and distribution managers	0.0014	0.0063
Sales representatives	0.0162	0.0051***
Cost estimators	-0.0163	0.0039***
Buyers and purchasing agents	-0.0042	0.0072
Property, real estate, and community association managers	-0.0869	0.0632
First-line supervisors/managers of office and administrative support workers	0.0058	0.0028**
Engineering technicians, except drafters	0.0029	0.0120
Drafters	0.0098	0.0109
Statistical assistants	-0.0265	0.0075***
Demonstrators and product promoters	-0.0125	0.0049***
Financial clerks	-0.0113	0.0054**
Parts salespersons	-0.0028	0.0033
Information and record clerks	-0.0133	0.0062**
Other office and administrative support workers	-0.0121	0.0055**
Order, receptionist and information clerks	0.0059	0.0043
Switchboard operators, including answering service	-0.0063	0.0034*
Material recording, scheduling, dispatching, and distributing workers	-0.0114	0.0056**
Retail salespersons	-0.0210	0.0110*
Executive secretaries and administrative assistants	0.0114	0.0027***
Weighers, measurers, checkers, and samplers, recordkeeping	-0.0102	0.0062
Telemarketers	-0.0153	0.0106
Cashiers, except gaming	-0.0031	0.0063

Note: Standard errors are heteroskedasticity-robust. *significant at 10%; **significant at 5%; ***significant at 1%. Occupations in bold are defined as “tradeable” (see note to Table 4).

Table A2 – Labor Demand Elasticities to Service Offshoring Estimated with Quasi-Maximum Likelihood

Occupation	$\varkappa_{n,SOSS}$
High Skilled	
Lawyers	0.0722
Life scientists	0.0201
Physical scientists	0.0064
Engineering managers	0.0195
Advertising, marketing, promotions, public relations and sales managers	0.0023
Petroleum engineers	-0.0922
Computer hardware engineers	0.0589
Management analysts	0.0741
Aerospace engineers	0.0113
Market and survey researchers	-0.0016
Sales engineers	0.0206
Mechanical engineers	0.0100
Civil engineers	0.0150
Accountants and auditors	-0.0200
Life, physical, and social science technicians	-0.0155
Medium Skilled	
Chief executives	0.0028
Medical and health services managers	-0.0649
Financial managers	0.0016
Human resources managers	0.0048
Purchasing managers	0.0102
Administrative services managers	0.0072
Marine engineers and naval architects	0.2242
Computer systems analysts	-0.0052
Computer programmers	-0.0252
Mining and geological engineers	0.0168
Industrial engineers	-0.0215
Materials engineers	-0.0118
Database administrators	-0.0066
Agricultural engineers	0.7575
Budget analysts	0.0002
Compliance officers	0.0556
Advertising sales agents	0.0696
Human resources, training and labor relations specialists	-0.0060
Computer support specialists	-0.0043
Low Skilled	
Construction managers	0.0049
Industrial production managers	-0.0009
Transportation, storage, and distribution managers	-0.0068
Sales representatives	0.0030
Cost estimators	-0.0137
Buyers and purchasing agents	-0.0117
Property, real estate, and community association managers	-0.0003
First-line supervisors/managers of office and administrative support workers	0.1323
Engineering technicians, except drafters	0.0054
Drafters	0.0133
Statistical assistants	-0.0181
Demonstrators and product promoters	-0.2371
Financial clerks	-0.0182
Parts salespersons	-0.0196
Information and record clerks	-0.1501
Other office and administrative support workers	-0.0911
Order, receptionist and information clerks	0.0498
Switchboard operators, including answering service	-0.1544
Material recording, scheduling, dispatching, and distributing workers	-0.0002
Retail salespersons	-0.0249
Executive secretaries and administrative assistants	0.1310
Weighers, measurers, checkers, and samplers, recordkeeping	0.6125
Telemarketers	-0.0009
Cashiers, except gaming	-0.0173

Note: Reported figures are averages over the entire sample. $\varkappa_{n,SOSS}$ measures the percentage employment change in occupation n after a 1% percentage change in service offshoring. This elasticity is computed as $\varkappa_{n,SOSS} = \xi_{n,SOSS} + s^i_n \cdot \rho_{i,SOSS}$, where $\xi_{n,SOSS}$ measures the percentage employment change in occupation n at given levels of employment in major group i; ρ_{iSOSS} measures the percentage employment change in major group i; s^i_n is the share of occupation n in the wage bill of major group i. Estimates of $\xi_{n,SOSS}$ and $\rho_{i,SOSS}$ are reported in Table A3, whereas average values of s^i_n are reported in Table A5. Occupations in bold are defined as "tradeable" (see note to Table 4).

Table A3 – Main Components of the Labor Demand Elasticities to Service Offshoring Estimated with Quasi-Maximum Likelihood

Occupation	$\xi_{n,soss}$ §		$\alpha_{I,soss}/S_i$ §§		$\rho_{I,soss}$ §§§
	Estimate	Std. Err.	Estimate	Std. Err.	
Management Occupations			***0.0051***	***0.0016****	***0.0059***
Chief executives	0.0000	0.0008			
Advert., MKTG, prom., P.R. and sales man.	0.0017	0.0024			
Administrative services managers	0.0070	0.0003**			
Financial managers	0.0012	0.0012			
Human resources managers	0.0046	0.0021**			
Industrial production managers	-0.0019	0.0027			
Purchasing managers	0.0101	0.0003***			
Transp,, storage, and distrib. man.	-0.0069	0.0098			
Construction managers	0.0049	0.0207			
Engineering managers	0.0191	0.0035***			
Medical and health services managers	-0.0649	0.0208***			
Prop., real est., and comm.. assoc. man.	-0.0003	0.0006			
Business and Financial Operations Occupations			***-0.0200***	***0.0125****	***-0.0268***
Buyers and purchasing agents	-0.0033	0.0017*			
Compliance officers	0.0559	0.0187***			
Cost estimators	-0.0112	0.0036***			
Human res., train. and lab. rel. spec.	-0.0027	0.0025			
Management analysts	0.0749	0.0127***			
Accountants and auditors	-0.0088	0.0021***			
Budget analysts	0.0006	0.0002***			
Computer and Mathematical Occupations			***-0.0500***	***0.0296****	***-0.0410***
Computer programmers	-0.0099	0.0014***			
Computer support specialists	0.0057	0.0022***			
Computer systems analysts	0.0077	0.0017***			
Database administrators	-0.0038	0.0019**			
Architecture and Engineering Occupations			***0.0047***	***0.0027****	***0.0060***
Aerospace engineers	0.0112	0.0105			
Agricultural engineers	0.7575	0.8933			
Civil engineers	0.0149	0.0075**			
Computer hardware engineers	0.0587	0.0152***			
Industrial engineers	-0.0236	0.0051***			
Marine engineers and naval architects	0.2242	0.8334			
Materials engineers	-0.0120	0.0139			
Mechanical engineers	0.0086	0.0057			
Mining and geological engineers	0.0168	0.0258			
Petroleum engineers	-0.0922	0.2212			
Drafters	0.0128	0.0059**			
Engineering technicians, except drafters	0.0040	0.0012***			
Life, Physical, and Social Science Occupations			***-0.0040***	***0.0026****	***-0.0058***
Life scientists	0.0205	0.0261			
Physical scientists	0.0080	0.0114			
Market and survey researchers	-0.0004	0.0021			
Life, physical, and social science technicians	-0.0128	0.0066*			
Legal Occupations			***0.0734***	***0.0124*****	***0.0722***
Lawyers	-	-			
Sales and Related Occupations			***0.0013***	***0.0026***	***0.0018***
Cashiers, except gaming	-0.0173	0.0104*			
Parts salespersons	-0.0196	0.0531			
Retail salespersons	-0.0250	0.0089***			
Advertising sales agents	0.0696	0.0129***			
Sales representatives	0.0016	0.0015			
Demonstrators and product promoters	-0.2371	0.0798***			
Sales engineers	0.0205	0.0062***			
Telemarketers	-0.0009	0.0004**			
Office and Administrative Support Occupations			***0.0030***	***0.0016****	***0.0040***
First-line supervisors/managers	0.1319	0.0018***			
Switchboard operators, including answering service	-0.1544	0.0395***			
Financial clerks	-0.0189	0.0021***			
Information and record clerks	-0.1501	0.0243***			
Order, receptionist and information clerks	0.0495	0.0024***			
Material rec., sched., dispatc., and distrib. workers	-0.0015	0.0014			
Weighers, measurers, checkers, and samplers, recordkeeping	0.6124	0.0058***			
Executive secretaries and administrative assistants	0.1304	0.0011***			
Other office and administrative support workers	-0.0917	0.0009***			
Statistical assistants	-0.0181	0.0001***			

Note: Asymptotic standard errors are computed through the delta method. *significant at 10%; **significant at 5%; ***significant at 1%. Reported figures are averages over the entire sample.

§ See note to Table A2

§§ Measures the percentage employment change in a major group after a 1% change in service offshoring, without accounting for the effects passing through the wage aggregators [see equation (3.11) in the text].

§§§ See note to Table A2

Table A4 – Manufacturing Industries Included in the Sample

3-digit SIC Code	SIC Definition	3-digit SIC Code	SIC Definition
201	Meat Products	245	Wood Buildings and Mobile Homes
202	Dairy Products	249	Miscellaneous Wood Products
203	Canned, Frozen, and Preserved Fruits, Vegetables, and Food Specialties	251	Household Furniture
204	Grain Mill Products	252	Office Furniture
205	Bakery Products	253	Public Building and Related Furniture
206	Sugar and Confectionery Products	254	Partitions, Shelving, Lockers, and Office
207	Fats and Oils	259	Miscellaneous Furniture and Fixtures
208	Beverages	261	Pulp Mills
209	Miscellaneous Food Preparations and Kindred	262	Paper Mills
211	Cigarettes	263	Paperboard Mills
212	Cigars	265	Paperboard Containers and Boxes
213	Chewing and Smoking Tobacco and Snuff	267	Converted Paper and Paperboard Products, Except Containers and Boxes
214	Tobacco Stemming and Redrying	273	Books
221	Broadwoven Fabric Mills, Cotton	275	Commercial Printing
222	Broadwoven Fabric Mills, Manmade Fiber and Silk	276	Manifold Business Forms
223	Broadwoven Fabric Mills, Wool (including Dyeing and Finishing)	278	Blankbooks, Looseleaf Binders, and Bookbinding
224	Narrow Fabric and Other Smallwares Mills Cotton, Wool, Silk, and Manmade Fiber	279	Service Industries For The Printing Trade
225	Knitting Mills	281	Industrial Inorganic Chemicals
226	Dyeing and Finishing Textiles, Except Wool Fabrics	282	Plastics Materials and Synthetic Resins, Synthetic Rubber, Cellulosic and Other Manmade Fibers, Except Glass
227	Carpets and Rugs	283	Drugs
228	Yarn and Thread Mills	284	Soap, Detergents, and Cleaning Preparations; Perfumes, Cosmetics, and Other Toilet Preparations
229	Miscellaneous Textile Goods	285	Paints, Varnishes, Lacquers, Enamels, and Allied Products
231	Men's and Boys' Suits, Coats, and Overcoats	286	Industrial Organic Chemicals
232	Men's and Boys' Furnishings, Work Clothing, and Allied Garments	287	Agricultural Chemicals
233	Women's, Misses', and Juniors' Outerwear	289	Miscellaneous Chemical Products
234	Women's, Misses', Children's, and Infants' Undergarments	291	Petroleum Refining
235	Hats, Caps, and Millinery	295	Asphalt Paving and Roofing Materials
236	Girls', Children's, and Infants' Outerwear	299	Miscellaneous Products Of Petroleum and Coal
237	Fur Goods	301	Tires and Inner Tubes
238	Miscellaneous Apparel and Accessories	302	Rubber and Plastics Footwear
239	Miscellaneous Fabricated Textile Products	305	Gaskets, Packing, and Sealing Devices and Rubber
242	Sawmills and Planing Mills, General	306	Fabricated Rubber Products, Not Elsewhere
243	Millwork, Veneer, Plywood, and Structural Wood	308	Miscellaneous Plastics Products
244	Wood Containers	311	Leather Tanning and Finishing

Table A4 – Manufacturing Industries Included in the Sample (cont.)

3-digit SIC Code	**SIC Definition**	**3-digit SIC Code**	**SIC Definition**
313	Boot and Shoe Cut Stock and Findings	354	Metalworking Machinery and Equipment
314	Footwear, Except Rubber	355	Special Industry Machinery, Except Metalworking
315	Leather Gloves and Mittens	356	General Industrial Machinery and Equipment
316	Luggage	357	Computer and Office Equipment
317	Handbags and Other Personal Leather Goods	358	Refrigeration and Service Industry Machinery
319	Leather Goods, Not Elsewhere Classified	359	Miscellaneous Industrial and Commercial Machinery and Equipment
321	Flat Glass	361	Electric Transmission and Distribution Equipment
322	Glass and Glassware, Pressed Or Blown	362	Electrical Industrial Apparatus
323	Glass Products, Made Of Purchased Glass	363	Household Appliances
324	Cement, Hydraulic	364	Electric Lighting and Wiring Equipment
325	Structural Clay Products	365	Household Audio and Video Equipment, and Audio Recordings
326	Pottery and Related Products	366	Communications Equipment
327	Concrete, Gypsum, and Plaster Products	367	Electronic Components and Accessories
328	Cut Stone and Stone Products	369	Miscellaneous Electrical Machinery, Equipment, and Supplies
329	Abrasive, Asbestos, and Miscellaneous	371	Motor Vehicles and Motor Vehicle Equipment
331	Steel Works, Blast Furnaces, and Rolling And	372	Aircraft and Parts
332	Iron and Steel Foundries	373	Ship and Boat Building and Repairing
333	Primary Smelting and Refining Of Nonferrous Metals	374	Railroad Equipment
334	Secondary Smelting and Refining Of Nonferrous Metals	375	Motorcycles, Bicycles, and Parts
335	Rolling, Drawing, and Extruding Of Nonferrous Metals	376	Guided Missiles and Space Vehicles and Parts
336	Nonferrous Foundries (Castings)	379	Miscellaneous Transportation Equipment
339	Miscellaneous Primary Metal Products	381	Search, Detection, Navigation, Guidance, Aeronautical, and Nautical Systems, Instruments, and Equipment
341	Metal Cans and Shipping Containers	382	Laboratory Apparatus and Analytical, Optical, Measuring, and Controlling Instruments
342	Cutlery, Handtools, and General Hardware	384	Surgical, Medical, and Dental Instruments and Supplies
343	Heating Equipment, Except Electric and Warm Air; and Plumbing Fixtures	385	Ophthalmic Goods
344	Fabricated Structural Metal Products	386	Photographic Equipment and Supplies
345	Screw Machine Products, and Bolts, Nuts, Screws, Rivets, and Washers	387	Watches, Clocks, Clockwork Operated Devices, and Parts
346	Metal Forgings and Stampings	391	Jewelry, Silverware, and Plated Ware
347	Coating, Engraving, and Allied Services	393	Musical Instruments
348	Ordnance and Accessories, Except Vehicles and Guided Missiles	394	Dolls, Toys, Games and Sporting and Athletic
349	Miscellaneous Fabricated Metal Products	395	Pens, Pencils, and Other Artists' Materials
351	Engines and Turbines	396	Costume Jewelry, Costume Novelties, Buttons, and Miscellaneous Notions, Ecept Precious Metal
352	Farm and Garden Machinery and Equipment	399	Miscellaneous Manufacturing Industries
353	Construction, Mining, and Materials Handling		

Table A5 - Descriptive Statistics*

Occupation	Share in National Employment§	Descriptive Statistics			
		Obs.	Mean	Std. Dev.	% zero obs.
White Collar					
Management Occupations	***55.8***	***502***	***3.88***	***2.62***	***2.0***
Chief executives	55.2	831	47.29	15.34	*0.2*
Advert., MKTG, prom., P.R. and sales man.	67.1	831	10.65	5.95	*7.3*
Administrative services managers	41.0	831	2.38	1.84	*16.1*
Financial managers	66.0	831	7.75	3.39	*5.9*
Human resources managers	54.1	831	3.78	2.19	*10.0*
Industrial production managers	91.4	831	16.24	7.25	*4.6*
Purchasing managers	73.6	831	2.68	1.63	*12.4*
Transp,, storage, and distrib. man.	41.5	831	1.08	1.78	*46.6*
Construction managers	8.8	831	0.19	1.26	*85.7*
Engineering managers	73.7	831	7.66	7.79	*15.4*
Medical and health services managers	6.8	831	0.10	1.14	*94.0*
Prop., real est., and comm.. assoc. man.	82.5	831	0.20	2.33	*95.0*
Business and Financial Operations Occupations	***54.6***	***502***	***0.74***	***0.83***	***3.2***
Buyers and purchasing agents	72.5	783	31.35	14.56	*3.7*
Compliance officers	21.8	783	1.07	3.07	*72.5*
Cost estimators	33.9	783	9.40	12.70	*28.6*
Human res., train. and lab. rel. spec.	38.9	783	12.12	9.63	*20.2*
Management analysts	59.8	783	2.91	8.22	*69.7*
Accountants and auditors	63.9	783	41.84	17.83	*1.0*
Budget analysts	32.0	783	1.31	2.71	*64.9*
Computer and Mathematical Occupations	***59.3***	***502***	***0.64***	***3.05***	***10.6***
Computer programmers	66.3	717	37.27	21.72	*6.6*
Computer support specialists	55.8	717	24.46	14.45	*9.2*
Computer systems analysts	56.6	717	31.47	21.89	*17.9*
Database administrators	56.8	717	6.80	6.88	*33.5*
Architecture and Engineering Occupations	***76.8***	***502***	***1.14***	***1.66***	***6.8***
Aerospace engineers	74.8	730	1.10	7.04	*89.6*
Agricultural engineers	47.2	730	0.20	1.42	*95.2*
Civil engineers	53.6	730	1.36	5.37	*77.0*
Computer hardware engineers	72.4	730	3.28	11.12	*67.4*
Industrial engineers	78.6	730	34.38	25.23	*5.8*
Marine engineers and naval architects	53.5	730	0.17	2.39	*97.3*
Materials engineers	86.3	730	4.05	8.70	*51.5*
Mechanical engineers	82.6	730	23.05	17.20	*14.8*
Mining and geological engineers	41.6	730	0.14	1.18	*95.9*
Petroleum engineers	12.7	730	0.33	2.74	*95.6*
Drafters	81.3	730	8.23	12.64	*35.2*
Engineering technicians, except drafters	87.3	730	23.71	17.25	*12.3*
Life, Physical, and Social Science Occupations	***14.9***	***502***	***0.27***	***0.69***	***21.9***
Life scientists	28.6	563	6.84	18.57	*76.2*
Physical scientists	37.6	563	27.02	24.73	*30.6*
Market and survey researchers	10.2	563	45.95	32.06	*57.2*
Life, physical, and social science technicians	9.9	563	20.19	33.65	*15.5*
Legal Occupations	***75.8***	***502***	***0.31***	***3.25***	***73.5***
Lawyers					
Sales and Related Occupations	***85.8***	***502***	***1.21***	***2.36***	***4.4***
Cashiers, except gaming	82.5	772	1.51	7.67	*79.9*
Parts salespersons	93.1	772	0.19	1.05	*90.8*
Retail salespersons	95.9	772	5.47	10.05	*45.6*
Advertising sales agents	35.2	772	0.92	3.84	*88.2*

* Wage bill or cost shares (in %) for all variables excluding the explanatory ones.
§ Share of national employment accounted for by the industries included in the sample.

Table A5 - Descriptive Statistics* (cont.)

Occupation	Share in National Employment§	Descriptive Statistics			
		Obs.	Mean	Std. Dev.	% zero obs.
White Collar					
Sales representatives	86.6	772	82.98	17.86	*0.1*
Demonstrators and product promoters	62.6	772	0.43	1.47	*78.9*
Sales engineers	80.0	772	7.44	11.15	*45.1*
Telemarketers	35.1	772	1.06	5.01	*82.4*
Office and Administrative Support Occupations	***54.8***	***502***	***2.49***	***2.12***	***2.2***
First-line supervisors/managers	49.9	778	9.82	4.29	*4.5*
Switchboard operators, including answering service	32.1	778	0.75	0.80	*24.7*
Financial clerks	50.5	778	17.71	5.93	*1.3*
Information and record clerks	47.1	778	0.65	1.40	*35.2*
Order, receptionist and information clerks	40.6	778	6.17	3.51	*6.4*
Material rec., sched., dispatc., and distrib. workers	75.2	778	34.36	11.37	*0.1*
Weighers, measurers, checkers, and samplers, recordkeeping	57.1	778	1.63	2.14	*29.1*
Executive secretaries and administrative assistants	86.7	778	14.25	7.23	*2.8*
Other office and administrative support workers	40.0	778	14.57	6.75	*1.8*
Statistical assistants	43.8	778	0.09	0.45	*81.0*
Blue Collar (Major Groups Only)					
Building and grounds cleaning and maintenance occupations	14.4	502	0.13	0.17	5.0
Construction and extraction occupations	42.7	502	0.72	3.53	12.6
Installation, maintenance, and repair occupations	33.8	502	0.57	0.54	7.0
Production occupations	82.3	502	8.96	6.88	2.6
Transportation and material moving occupations	46.9	502	1.77	1.77	2.8
Other Inputs					
Energy	-	502	2.49	3.34	0.0
Non energy material	-	502	74.67	12.82	0.0
Explanatory Variables					
Service offshoring	-	836	3.75	8.00	-
Material offshoring	-	833	16.27	11.05	-
Share of high-tech capital	-	859	6.16	6.69	-
lnK	-	859	8.60	1.83	-
lnY	-	864	9.69	1.68	-

* Wage bill or cost shares (in %) for all variables excluding the explanatory ones.

§ Share of national employment accounted for by the industries included in the sample.