Service Offshoring and White-Collar Employment*

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Abstract

This paper empirically studies the effects of service offshoring on white-collar employment, using data for more than one hundred U.S. occupations. A model of firm behavior based on separability allows to derive the labor demand elasticity with respect to service offshoring for each occupation. Estimation is performed with Quasi-Maximum Likelihood, to account for high degrees of censoring in the employment variable. The estimated elasticities are then related to proxies for the skill level and the degree of tradability of the occupations. Results show that service offshoring increases high skilled employment and decreases medium and low skilled employment. Within each skill group, however, service offshoring penalizes tradable occupations and benefits non-tradable occupations.

JEL codes: F1.

Keywords: Occupations; Skills; Tradability; Separability; Quasi-Maximum Likelihood.

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1 Introduction

In this paper, I study the effects of service offshoring on white-collar employment. In particular, I use a highly detailed data set containing information on wages and number of employees for more than one hundred U.S. occupations to analyze how service offshoring affects employment across jobs characterized by different skill levels and degrees of tradability.

Service offshoring has become a phenomenon in recent years. The rapid improvements in Information and Communication Technologies (ICT) have in fact eased the exchanges of services across national borders, and opened up new opportunities for firms to globalize their operations (Freund and Weinhold, 2002; Lipsey, 2006). Both anecdotal evidence (Unctad, 2004a) and official statistics (Unctad, 2004b; Oecd, 2007) suggest that the range of service activities relocated abroad by U.S. and European firms have rapidly expanded over the last decade. Consequently, some authors have started referring to service offshoring as "The Next Industrial Revolution" (Blinder, 2006), while academic research and media attention have increasingly been directed to figure out its possible consequences for the developed countries (Amiti and Wei, 2005; Mankiw and Swagel, 2006).

One of the most debated, yet probably least understood issues is the effects on the white-collar workers. 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", which pay high wages and require high skill levels (Kirkegaard, 2004). Second, they have generally been shielded from offshoring in the past (Feenstra and Hanson, 2003; Crinò, 2008a). For these reasons, understanding how white-collar employment responds to service offshoring has become a major goal for international trade economists.

Service offshoring entails the relocation of narrow activities, each performed by a specific occupation. This implies that different occupations may in principle show different responses to service offshoring. The first likely determinant of heterogeneity is represented by differences in skill levels: according to standard factor proportion arguments, in fact, the developed countries should specialize in the most skill-intensive service activities and offshore the others; as a result, service offshoring should shift the composition of white-collar employment away from the least skilled occupations and towards the most skilled occupations (Bhagwati et al., 2004; Deardorff, 2005; Markusen, 2005). The second possible determinant of heterogeneity is instead represented by differences in tradability characteristics, because the occupations whose activities are more tradable should be less costly to offshore, and thus more likely to be relocated abroad, holding fixed the skill level (Grossman and Rossi-Hansberg, 2008).

The main contribution of this paper is to investigate the role of skills and tradability characteristics jointly from an empirical perspective. To this purpose, I use employment and wage data for 112 U.S. occupations (58 of which are white-collar) coming from the Occupational Employment Statistics and covering 144 industries between 1997 and 2006. I match these data with a proxy for service offshoring at the industry-level, defined as the share of imported private services in total non-energy input purchases and based on Input-Output Accounts and service import data from the Bureau of Economic Analysis. For each white-collar occupation, I measure the skill level with data from the Occupational Employment Statistics and from the 2004 Public Use Microdata Series (Ruggles et al., 2008), and the degree of tradability by using the O*NET data set to construct quantitative indices of the following job characteristics: involvement in routine cognitive tasks, dependence on ICT, and degree of face-to-face contact.

The empirical analysis based on these data works in two phases. First, I derive and estimate the labor demand elasticity with respect to service offshoring for all the white-collar occupations. Then, I relate these elasticities to the proxies for skills and tradability. Results show that service offshoring is skill-biased, because it increases employment in high skilled occupations and decreases employment in medium and low skilled occupations. However, for a given skill level, service offshoring penalizes the occupations with strong tradability characteristics and benefits the others.

The high level of occupational detail poses two methodological issues in the first phase of the analysis. First, firm technology has to be modelled in such a way that guarantees tractable derivation of labor 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 firm behavior that uses mild restrictions on the relationship among occupations. Following Fuss (1977), the model assumes that the firm technology is separable in groups of homogeneous occupations. This assumption makes the derivation of labor demand functions tractable even for high numbers of occupations, because it allows the firm optimization process to be consistently solved in two separate stages: in the first stage, firms choose the optimal mix of occupations within each group; in the second stage, they choose the optimal employment of each group. I propose an extension of the original model, in which service offshoring is allowed to affect the demand for each occupation at both stages of the optimization process. Separability has been widely used in consumption theory to derive demand functions 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 a small number of labor inputs.[1] The model presented in this paper integrates 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 al. (2005). This estimator is designed to provide consistent estimates of the parameters in the presence of censoring and panel data. The modification proposed in this paper may be useful for applications to panel data set of moderate cross-sectional dimension, which are typical of studies based on industry-level data.

Exploiting the estimated parameters, I compute the labor demand elasticity with respect to service offshoring for all the white-collar occupations and run the second phase of the analysis. I use three different approaches. First, I compare the occupations with negative and positive elasticities in terms of skill levels and average values of the indices of tradability characteristics. I find a higher concentration of positive elasticities among the high skilled occupations and of negative elasticities among the medium and low skilled occupations; at the same time, I find that the occupations with negative elasticities have more pronounced tradability characteristics than those with positive elasticities, independent of the skill level. Second, I regress the elasticities on the proxies for skills and tradability, thereby conditioning the effect of each variable on the other occupational attributes. I find that high skilled occupations are the most likely to show a positive elasticity, i.e. to grow with service offshoring; yet, holding fixed the skill level, occupations with stronger tradability characteristics are more likely to show a negative elasticity, i.e. to be offshored. Third, I run a counterfactual experiment aiming to show what the composition of white-

[1] See, among others, Feenstra and Hanson (1996, 1999, 2003), Morrison and Siegel (2001), Ekholm and Hakkala (2005), Hijzen et al. (2005) and Crinò (2007b).

collar employment would have been if service offshoring had remained constant at the 1997 level. I find that high skilled employment would have been lower, while medium and low skilled employment would have been higher; at the same time, in all skill groups, employment in more tradable occupations would have been higher, while employment in less tradable occupations would have been lower. Hence, service offshoring has changed the composition of white-collar employment by favoring high skilled occupations relative to medium and low skilled occupations, and less tradable occupations relative to more tradable occupations.

These results support the existing theoretical predictions and 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 the developed countries.[2] Although the white-collar workers represent the most skilled fraction of the labor force, the negative employment effects of service offshoring are concentrated on occupations with the lowest levels of education, whereas high skilled occupations benefit from it. Second, the heterogeneous behavior of occupations with different degrees of tradability suggests that service offshoring is likely to induce a change in the composition of educational demand towards the programs that prepare workers to perform less tradable jobs; in this sense, the findings of this paper are in line with the argument in Blinder (2006). Finally, the results also suggest that traditional trade theories should combine the usual classification of labor into broad skill groups with a parallel classification emphasizing the tradable/non-tradable nature of specific occupations.

This paper aims to contribute to a growing empirical literature on the consequences of service offshoring for the developed countries' labor markets. First, it is related to the recent work by Amiti and Wei (2005, 2006b), who find that service offshoring has only small negative effects on total domestic employment.[3] This paper suggests that one reason for this is the high heterogeneity in the response of specific occupations: since employment grows in some of them but shrinks in others, the overall effects of service offshoring may end up being small. Second, the paper is related to a large set of studies that aim to predict the number of workers at risk of service offshoring on the basis of the tradability attributes of

[2] This concern has mostly been expressed in the media and in the political talks that accompanied the 2004 U.S. Presidential election. See Blinder (2006) and Mankiw and Swagel (2006) for a detailed summary of the debate.

[3] See also Hijzen et al. (2007) and Liu and Trefler (2008) for two studies using detailed data at the firm- and worker-level.

their jobs.[4] Unlike those studies, this paper does not predict future offshorability, but analyzes how skills and tradability characteristics have shaped the effects of service offshoring *so far*. Finally, the paper is related to the recent work by Becker et al. (2007), who use detailed data at the plant- and worker-level to study how offshoring by German multinationals has changed the composition of domestic employment along three dimensions: occupations, tasks and skills. This paper makes an attempt to interact those three dimensions, with the aim of studying how the change in occupational employment depends on the interplay between skills and tasks.[5]

The remainder of the paper is organized as follows: Section (2) illustrates the data and Section (3) provides some preliminary evidence; Section (4) describes the theoretical model and Section (5) explains the estimation strategy; Section (6) presents the results, whose main implications are discussed in Section (7); Section (8) briefly concludes.

2 Data

This section presents the most salient aspects of the two variables of interest: service offshoring and white-collar employment.[6] The data span the period 1997-2006 and cover 144 industries, of which 135 are in manufacturing and 9 in the service sector. The industrial classification is SIC87: manufacturing industries are defined at the 3-digit level, while service industries are more aggregated, in order to reach a common classification across the variables. The complete list of industries, with their SIC code, is reported in Appendix Table A1.

2.1 Service Offshoring

Service offshoring is proxied by the share of imported private services in total non-energy input purchases. This proxy has originally been proposed by Amiti and Wei (2005, 2006a,b), who extended to services the

[4]Bardhan and Kroll (2003), Jensen and Kletzer (2005, 2008), Kroll (2005), Van Welsum and Vickery (2005) and Blinder (2006, 2007).

[5]A parallel literature, both theoretical and empirical, analyzes the effects of service offshoring on aggregate welfare and productivity in the developed countries. With a few exceptions (e.g., Samuelson, 2004), this literature suggests that service offshoring boosts the productivity of domestic inputs and raises national welfare. See Mann (2003), Amiti and Wei (2006a,b), Olsen (2006) and Crinò (2008b) for empirical contributions, and Bhagwati et al. (2004), Deardorff (2005), Markusen (2005), Antras et al. (2006, 2008), Baldwin and Robert-Nicoud (2007) and Rodriguez Clare (2007) for theoretical models.

[6]Further details on these variables and on the other regressors used in the econometric analysis can be found in the web appendix available at http://crino.iae-csic.org/.

indicator developed by Feenstra and Hanson (1996, 1999) to measure the offshoring of intermediate inputs (material offshoring). The idea underlying this measure is the following: the output of service activities relocated abroad has to be imported back in the U.S., in order to enter the production process together with other inputs; hence, the more intense is service offshoring, the higher will be the share of total inputs accounted for by imported services.

The main problem in constructing this proxy is that official data on imported services at the industry-level either lack, or are too coarse to be used in the econometric analyses. The same problem typically arises when constructing proxies for material offshoring. A by now large literature, pioneered by Feenstra and Hanson (1996, 1999), has therefore proposed to estimate these figures, by combining two sources of data: imports at the *economy-wide* level and Input-Output accounts. I will follow this literature in constructing the main proxy for service offshoring used in the paper.

From the Bureau of Economic Analysis (BEA), I retrieve the economy-wide time series of affiliated and unaffiliated imports of thirteen private services: IM_{st} will denote the imports of service s in year t.[7] From the Input-Output accounts, I gather the *1997 Import Matrix*, which contains, only for that year, detailed information on service (and material) imports for all U.S. industries. Using this information, I compute the share of each industry j in the 1997 economy-wide level of imports of the thirteen private services (ϑ_{js}^{97}). I maintain the assumption that these shares have remained constant between 1997 and 2006, and multiply them by IM_{st}. This gives an estimate of the imports of each service for all industries in every year. I finally sum these estimates across the thirteen private services, and obtain the total value of service imports for all industries in every year ($IMPS_{jt}$). Formally,

$$IMPS_{jt} = \sum_{s=1}^{13} \vartheta_{js}^{97} * IM_{st}.$$

Because the 1997 Import Matrix uses the 6-digit NAICS classification, these estimates are converted into

[7] The private services are: finance, insurance, telecommunications, computer and information, operational leasing, research and development, management and consulting, accounting and bookkeeping, advertising, architecture and engineering, legal services, installation and maintenance, other business services. Data come from *U.S. International Services: Table 1 - Trade in Services, 1992-2006* and represent payments by U.S. residents to foreign residents. The bulk of exchanges in these services occur 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 the case in which U.S. firms hire foreign workers within the U.S.. This circumstance represents an example of service *outsourcing*, and is common to services that require the physical presence of the supplier in the foreign country (e.g., construction, transportation, etc.).

SIC codes using the concordance table of the Bureau of the Census.

The last step to obtain the proxy for service offshoring (SOS) consists in normalizing $IMPS$ with the total value of non-energy input purchases (NE):[8]

$$SOS_{jt} = \frac{IMPS_{jt}}{NE_{jt}}. \tag{1}$$

It should be noted that there may exist alternative normalizations for $IMPS$, like industry output or value added. Using inputs, however, makes easier to compare the results of the paper with those of the previous empirical studies on service offshoring and employment, which have used this normalization (see, in particular, Amiti and Wei, 2005, 2006b). As drawbacks, the use of inputs may be problematic for those industries that make large purchases of domestic services along with the foreign ones, as well as for those that substitute their own service production with imports: in this latter case, in fact, NE and $IMPS$ will rise by the same amount, and the change in service offshoring will be underestimated. Yet, previous studies have shown that the empirical behavior of the indicators normalized with inputs tends to be very similar to that of the indicators normalized with output and value added, both over time and across industries (Horgos, 2007); consistently, in my sample the correlation coefficient between SOS and an indicator normalized with output is equal to 0.96.

The main reason of concern about SOS is the use of estimated service imports at the numerator of (1), even though this practice is common to most of the previous empirical literature. The computation of $IMPS$ is indeed based on two assumptions that may be quite restrictive: first, the time variability only comes from the service imports at the economy-wide level; second, the industry variability is maintained constant as of 1997. To evaluate the consequences of these limitations for the results, I will use, whenever possible, a second proxy for service offshoring, which has the same expression as SOS but exploits the official data on industry-level service imports reported in the yearly Import Matrices of the BEA for the period 2002-2006. These data are classified in 3-digit NAICS codes; because it is not possible to map them into SIC codes, I construct a different sample with the NAICS classification.[9] Despite their

[8] NE includes input purchases from both domestic and foreign suppliers. Data come from the *Annual Survey of Manufactures* and from BEA (*Industry Economic Accounts – Supplemental Estimates*); also in this case, they are originally provided at the 6-digit NAICS level and then traced back to the SIC classification.

[9] This is made possible by the fact that also the employment data (presented below) are classified according to NAICS since 2002.

attractiveness, these data have some major limitations. The most important is that the industry detail is very limited: in my case, the matching with the employment variable leaves 28 industries, for a maximum of 140 observations. For this reason, I will not be able to use this measure as the preferred indicator of service offshoring.[10]

On average, SOS has increased from 2.6 percent in 1997 to 3.6 percent in 2006, a 38.5 percent rise.[11] Looking separately at manufacturing and services, SOS has increased from 25.4 to 32.6 percent in the service sector, and from 0.34 to 0.45 percent in the manufacturing sector. In order to have a sense of the quality of these numbers, I compare the manufacturing figures with those reported by Amiti and Wei (2006b). Despite some differences in the definition of the two proxies and in the structure of the two samples,[12] SOS is fairly close to the estimates of the authors: for instance, they report a value of 0.3 percent in 2000, while SOS equals 0.36 percent in that year. I also compare the indicator with the proxy based on official service import data. The latter ranges between 4.4 percent in 2002 and 4.6 percent in 2006. While these figures are slightly higher than the corresponding ones for SOS, the growth rate they imply (4.5 percent) matches that of SOS over the same time interval. The two proxies are also highly positively correlated, with a correlation coefficient equal to 0.81 over the whole sample.[13]

2.2 White-Collar Employment

Employment and wage data come from the Occupational Employment Statistics (OES), a large data set of the Bureau of Labor Statistics (BLS) containing industry-level information on about 800 occupations. Data are reported in the 3-digit SIC classification before 2002, and in the 5-digit NAICS classification afterwards. I convert all data into SIC codes using the conversion table of the Bureau of the Census.

As for the occupational coding, since 1999 the OES adopts the Standard Occupational Classification (SOC): occupations are assigned a 6-digit code and defined *minor occupations*; all the minor occupations with the same 2-digit code belong to a *major group* that identifies jobs with similar characteristics.

[10] Out of these 28 industries, 9 are in the service sector and coincide with those of the larger sample; this happens despite the use of a different classification, because the 9 service industries represent quite broad industrial aggregates as mentioned before. The remaining 19 industries cover a large fraction of the manufacturing sector.

[11] These numbers are weighted averages computed with the industry shares of non-energy input purchases as weights. Unweighted averages yield a similar picture, with SOS rising by 31.5 percent over the whole sample.

[12] Amiti and Wei include five service categories in their proxy, and their sample consists of all the 4-digit SIC manufacturing industries.

[13] To measure the correlation, I have computed SOS for the 28 NAICS industries for which official data on service imports are available; to this purpose, I have aggregated $IMPS$ and NE from 6-digit to 3-digit NAICS codes.

As an example, all the 6-digit managerial occupations belong to a 2-digit group called "management occupations". Data for earlier years are instead classified according to a system that was specific to the OES at that time. Only for about half of the occupations are there one-to-one matches or direct aggregations between the two coding systems. I exclude all occupations that do not represent productive inputs: examples are military and protective service occupations, and the full list is provided in the web appendix. Finally, I aggregate some of the remaining occupations to keep the dimension of the problem tractable. This yields a final number of 112 occupations belonging to thirteen major groups; out of these, eight are white-collar, for a total of 58 minor occupations (Appendix Table A2).

Since 2003, the OES data are released on a six-month basis instead of on a yearly basis. I use the May release, because the November one is not available for all years up to 2006.[14] Column (1) of Appendix Table A6 provides details about the coverage of the sample in 2006. I focus on the bottom of the table, which contains information on the major groups. The sample accounts for 55 to 88 percent of national employment in the eight white-collar groups, and for 8 to 79 percent in the five blue-collar groups.[15] Column (2) shows that the employment variable is often severely censored, especially for the minor occupations. In many cases, in fact, the fraction of zero observations in the sample exceeds 50 percent. The problem is typically less severe for the major groups, where zero observations account for about 10 percent of the sample.[16]

Having presented the employment data, I now turn to describe the proxies for skills and tradability characteristics that will be used later on in the analysis.

2.2.1 Skills

The OES provide two different measures of skills, both related to education. The first is the share of workers with at least a bachelor's degree, the second is the average degree of schooling or professional training required to perform the occupation. To the purpose of this paper, both measures present some limitations. The first proxy cannot be used to divide the occupations into homogeneous skill groups,

[14] Looking at the behavior of occupational wages and employment before and after 2003 does not seem to reveal significant breaks in the time series.

[15] The lowest shares among the blue-collar groups are found in "construction and extraction occupations" (8 percent) and in "building and grounds cleaning and maintenance occupations" (13 percent). The reason is that these occupations are highly concentrated in industries that are excluded from the sample, like hotels and restaurant and the construction sector.

[16] The only exception is "legal occupations". This group includes only one minor occupation, "lawyers".

because it is hard to define threshold values that distinguish high skilled occupations from medium and low skilled occupations. Therefore, this variable will only be used for some robustness checks; henceforth, it will be referred to as the *share of college graduate+*. The second measure can instead be used to classify the occupations, but the available detail of schooling degrees is limited: in particular, the schooling information is available if the occupation requires at least a bachelor's degree; otherwise, the main skills are represented by professional training, and there is no information about schooling. When using this measure, the occupations requiring at least a bachelor's degree will be defined as high skilled, while the others will be collected into a single group of medium-low skilled occupations; this classification will be referred to as the *skill classification based on BLS*.

In order to circumvent these limitations, I construct a third measure of skills and use it as the main proxy throughout the paper. Like the second OES measure, this is the average degree of schooling required to perform an occupation. Unlike that measure, however, this proxy offers a higher detail of schooling degrees, and therefore allows to classify the occupations into three, rather than two skill groups: high skilled, medium skilled and low skilled. To construct this proxy, I match the OES data with individual-level information from the 2004 5% extract of the Public Use Microdata Series (PUMS); in doing so, I exploit the fact that both sources use the SOC system to classify the occupations. PUMS contains information on the schooling degree of each individual, summarized into a discrete variable that ranges between 1 (no degree) and 16 (doctorate degree). I make the structure of the PUMS data set as close as possible to that of my sample, by excluding the self-employed (because they are not counted in the OES) and by keeping only the individuals working in the 144 industries; moreover, as standard in the labor economics literature, I focus on workers aged 18 to 64.[17] I then average the schooling degree across all individuals in the same occupation, using the PUMS sampling weights. The resulting variable (*schooling*) ranges from 9 (high school diploma) to 15 (professional school degree) across the 58 minor white-collar occupations. I define as high skilled the occupations requiring more than a bachelor's degree ($schooling > 12$), as medium skilled those requiring an associate degree in college ($schooling = 12$), and as low skilled those requiring lower degrees of schooling ($schooling < 12$). The three groups contain a similar number of occupations: 18 high skilled, 16 medium skilled, and 24 low skilled.[18]

[17] The main results of the paper do not depend on this selection (see Crinò, 2007a).

[18] I do not estimate the skill level for the major groups, because there is often high heterogeneity across the constituent

Appendix Table A3 reports the three measures of skills for the 58 minor white-collar occupations, which are ranked in decreasing order of *schooling*. All the occupations with *schooling* > 12 are classified as high skilled by the *skill classification based on BLS* and have very high values of the *share of college graduate+*, which ranges from 60 percent ("marine engineers") to 98 percent ("lawyers"). The three skill measures are highly consistent also for the occupations with *schooling* < 12. With the only exceptions of "cost estimators" and "property, real estate and community association managers", all these occupations fall in the medium-low skilled group of the *skill classification based on BLS* and their *share of college graduate+* is very low, ranging from 5 percent ("parts salespersons") to 50 percent ("sales representatives"). The picture is somewhat different for the occupations with *schooling* $= 12$, because ten of them would be classified as high skilled by the *skill classification based on BLS*. However, the *share of college graduate+* is broadly consistent with these occupations being medium skilled: this variable ranges in fact from 30 percent ("construction managers") to 75 percent ("budget analysts"), and these values fall approximately in between those of the other two skill groups.

2.2.2 Tradability and Other Occupational Characteristics

Previous studies seem to agree over three characteristics that contribute to making an occupation more tradable. First, the job should be routine, because this allows the tasks to be specified into simple instructions that can be taught without misunderstanding to foreign workers (Levy and Murname, 2006). Second, the job should produce impersonal services, which can be provided to the end users with little face-to-face contact (Blinder, 2006). Third, the job should be ICT-enabled, because this allows its services to be traded at low costs and high speed (Garner, 2004). In reality, an occupation may show all the three attributes jointly; perhaps more often, however, only one or two of them characterize a given job. Hence, I propose different proxies for each characteristic, along with an overall measure of tradability that accounts for all of them.

I mostly use information from O*NET 12.0, the latest update of the data set that replaced the Dictionary of Occupational Titles (DOT); in a few cases, discussed below, I will also exploit other sources. O*NET collects data on a wealth of job characteristics for 812 occupations, which are classified according to the SOC system. The information primarily comes from occupation analysts, and is meant to provide

minor occupations and this makes it hard to get a reliable indicator at the 2-digit SOC level.

firms and job seekers with a tool for identifying the relevant skills required by each job. The data set is organized into eleven Domain Files, each containing a large number of variables that describe a specific feature of the occupations.[19] The O*NET variables have an ordinal meaning, with higher numbers indicating a greater importance of the corresponding characteristic; hence, they can be used to rank the occupations.[20] I normalize the variables to have a common 0-1 scale, and then select a subset of them to construct the indices. I mostly use Principal Components Analysis (PCA) to get composite indices of several variables.[21] All indices have mean 0 and standard deviation 1, and higher values indicate a greater importance of the corresponding characteristic. I briefly present the indices below, leaving additional details to Appendix Table A4.

Three indices measure the importance of routine tasks; given the focus on white-collar jobs, they proxy for routine *cognitive* tasks. The first two (*routine cognitive 1* and *routine cognitive 2*) are based on previous work by Autor et al. (2003), who construct two different proxies using the DOT instead of O*NET. The first is a single variable measuring the "adaptability of an occupation to set limits, tolerances and standards" (STS), and represents the authors' preferred indicator. The second is a composite index, obtained by means of PCA on STS and three additional variables: "visual color discrimination", "importance of repeating the same tasks", "vocational preparation". *Routine cognitive 1* combines "visual color discrimination" and "importance of repeating the same tasks", which are present also in O*NET. *Routine cognitive 2* is instead a dummy equal to 1 if the occupation requires "adaptability to set limits, tolerances and standard". Because this information is not available in O*NET, I retrieve it from the DOT 1991; due to the change in occupational classification, data are available only for 44 occupations.[22] The third index (*routine cognitive 3*) is again based on O*NET, and obtained by combining three additional vari-

[19] The eleven Domain Files are: "abilities"; "education, training and experience"; "interests"; "job zones"; "knowledge"; "skills"; "tasks"; "work activities"; "work context"; "work styles"; "work values". They contain more than 275 job descriptors.

[20] As an example, the variable "getting information", contained in the Domain File "work activities", takes the minimum value of 1 if the occupation makes "regular use of the same types of information from a single source", and the maximum value of 7 if the occupation needs to get "new information from many sources, often by actively interacting with them". Because these ratings are produced by occupation analysts, they should not be systematically biased by differences in education levels across occupations, whereby more skilled workers overestimate the importance of some characteristics as compared to less skilled workers. At the same time, however, occupation analysts may tend to underestimate the changes in occupational attributes over time. This issue is particularly relevant when using time series of the O*NET variables, but should be less crucial in my case because I rely only on the last edition of the data set. See Spitz-Oener (2006) for a deeper discussion on this point.

[21] This approach is common to many other studies (see, e.g., Poletaev and Robinson, 2008). Following Autor et al. (2003), I always use the first factor when performing PCA.

[22] The occupational crosswalk between DOT and O*NET is available at www.xwalkcenter.org.

ables with those already included in *routine cognitive 1*: "getting information", "documenting/recording information", "inspecting equipment, structures and materials". The inclusion of these variables should provide a better proxy for cognitive activities.

Similarly, three indices proxy for the strength of face-to-face contact and for the personal nature of services. The first two are based on O*NET, the third is drawn from Blinder (2007). *Face-to-face 1* combines the frequency of "face-to-face interactions with individuals and groups" and the extent to which workers "perform for or work directly with the public". *Face-to-face 2* attempts to offer some more information on the personal nature of the services, by including two additional variables: the extent to which workers "deal with external customers" and the importance of "establishing and maintaining relationships". While probably good proxies, these indices are not perfect. On the one hand, the variables include a large arrays of on-the-job contacts, instead of being limited to those with the end users; on the other hand, they include many interactions by E-mail or on the phone, instead of being limited to those face-to-face. I therefore complement the two indices with a third one (*face-to-face 3*), which is based on previous work by Blinder (2007). The author ranks about 800 6-digit SOC occupations on a 0-100 scale, based on their offshorability degree. This index accounts for many attributes of an occupation, and therefore is not a specific measure of face-to-face contact and of the personal nature of services; yet, occupations that are less easily offshorable in Blinder's terminology are also likely to show such characteristics. I normalize the index to have mean 0 and standard deviation 1, and so that higher values indicate higher degrees of face-to-face contact.[23]

I measure the extent to which a job is ICT-enabled with a single O*NET variable: "interacting with computers"; the resulting index is called *interaction with PCs*.[24] I also construct an overall *tradability index*, by combining the variables included in *routine cognitive 3*, *face-to-face 2* and *interaction with PCs*. Finally, I compute two additional indicators measuring other occupational characteristics, namely the extent to which the occupations perform *non-routine cognitive* and *routine manual* tasks; these indicators

[23]Blinder (2007) ranks occupations according to the following criterion. First, he looks at whether the job must be performed at a work unit in the U.S.. If this is the case, the occupation is ranked as non-offshorable. If this is not the case, the author judges whether one of the following conditions holds: either the worker need not be physically close to any work unit or the whole work unit can be moved abroad. The author uses the information in O*NET to this purpose.

[24]I have also experimented with other variables contained in the Tools and Technologies supplement of O*NET. These are dummies for whether the workers must use the phone, or a vast list of Internet technologies, to successfully carry out their jobs. These variables perform similarly to *interaction with PCs* in regressions like those discussed in Section (6.2), but their dichotomous nature does not allow to rank the occupations. I therefore do not discuss them in the rest of the paper; results are available from the author upon request.

will be used in some robustness checks of the main results.[25]

How well do the indices proxy for tradability features? Appendix Table A5 reports the values of all indicators for the 58 minor white-collar occupations, which are ranked in decreasing order of the *tradability index*. The ranking is broadly consistent with commonsense. The ten most tradable occupations, in fact, include "database administrators", "drafters", "computer support specialists", "computer programmers", "statistical assistants", and some engineering jobs. The ten least tradable occupations, instead, comprise "cashiers", "chief executives", "lawyers", "demonstrators and product promoters", "parts salespersons" and "retail salespersons". Probably more surprising is the presence of "switchboard operators" among the least tradable occupations; notice, however, that this SOC code includes not only call center employees, but also other types of answering service workers (e.g., receptionists), whose jobs are perhaps less likely to show marked tradability features. Panel a) of Table 1 reports the average values of the indices for the two groups of tradable and non-tradable occupations recently identified by the BLS; that classification considers a number of additional characteristics that may be responsible for tradability, along with those explicitly measured in this paper.[26] Notice that the *tradability index* is substantially higher for the tradable occupations. The latter perform more routine cognitive tasks, require less face-to-face contact and depend significantly more on ICT. Overall, this suggests that the indices describe fairly well some of the main occupational attributes that may be responsible for tradability.

What is the relationship between tradability and skills? This question is addressed in Panel b) of Table 1, which reports the average values of the indices for each skill group. Interestingly, results show that tradability is monotonically increasing in skills.[27] The reason is that high skilled occupations interact more with computers, require less face-to-face contact and perform more routine cognitive tasks. This latter result, however, deserves a better qualification. Notice, in fact, that high skilled occupations also perform more non-routine cognitive activities: hence, high skilled jobs are more involved in all types of

[25] *Non-routine cognitive* includes the following O*NET variables: "analyzing data or information", "developing objectives and strategies", "mathematical reasoning", "processing information", "thinking creatively". *Routine manual* includes "finger dexterity" and "manual dexterity".

[26] Tradable occupations have been identified by a team of occupation experts, based on the following characteristics: the job can be carried out at long distance, is ICT-enabled, does not require knowledge of social issues or industrial organization, produces outputs that are modular in nature. The full methodological note is available in *Occupational Projections and Training Data, 2006-2007 Edition* (Chap. 2, pp. 12-14). The tradable occupations in my sample are: "computer programmers", "computer support specialists", "aerospace engineers", "computer hardware engineers", "marine engineers", "materials engineers", "mechanical engineers", "switchboard operators".

[27] See also Blinder (2007) and Jensen and Kletzer (2008) on this point.

cognitive tasks, both routine and non-routine. They are instead substantially less involved in routine manual tasks.

2.2.3 Stylized Facts

I close this section with a few stylized facts about the employment changes occurred between 1997 and 2006. These are reported in Table 2 for all minor occupations and major groups, for the high, medium and low skilled groups, and for the occupations with *tradability index* above and below the median value of -0.08 (defined as tradable and non-tradable for brevity). Total white-collar employment has declined by 2.5 percent over the ten years, and about 615,000 jobs have been lost.[28] Among the major groups, employment has decreased in "management occupations", "computer and mathematical occupations", "architecture and engineering occupations", "office and administrative support occupations", and increased in the others. Overall, high skilled employment has risen by 25 percent, medium skilled employment has fallen by 30 percent, low skilled employment has increased by a tiny 1.5 percent.[29] Finally, tradable occupations have experienced a large employment decrease (-14 percent), while non-tradable occupations a slight increase (+1 percent).

3 Preliminary Evidence

I now move to the main goal of the paper, that is to test whether the increase in service offshoring has been accompanied by a systematic change in the domestic composition of white-collar employment, across occupations with different skill levels and tradability characteristics. This section presents some preliminary evidence suggesting that this has indeed been the case.

I will base the tests on the following assumption: service offshoring has become a feasible option for firms, due, among other factors, to the rapid improvements in ICT; as a consequence, firms have modified their international allocation of labor, and accordingly changed their domestic demand for some service

[28] Although apparently high in absolute terms, this number does not seem as impressive if compared with 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.

[29] Other studies have provided direct or indirect evidence of similar trends by skill level (Mann, 2003; Kirkegaard, 2004; Jensen and Kletzer, 2005; Feenstra, 2007). These employment changes also show that the U.S. labor market has polarized over the last decade, as the medium skilled workers have lost a substantial share of total employment. See Spitz-Oener (2006), Goos and Manning (2007) and Autor et al. (2008) on this point.

occupations. I will thus estimate alternative variants of occupation-specific labor demand functions, and allow them to experience parallel shifts as a result of service offshoring. I will then interpret a negative relationship between service offshoring and occupational employment as evidence that the demand for that occupation has shifted inward, and viceversa for a positive relationship.

However, this is not the only mechanism that may be at work. An alternative possibility is that the domestic supply of some occupations has changed, leading firms to resort more heavily to offshoring. For instance, a lower supply of computer programmers may have induced firms to hire more of these workers abroad: the observed relationship between service offshoring and occupational employment would then be negative, exactly as in the case of an inward shift in labor demand. What changes between the two scenarios is the behavior of relative wages: an inward shift in labor demand would in fact be associated to a relative wage decline, while a lower supply would bring about a relative wage increase. I will first present some suggestive evidence that labor demand shifts have been stronger than labor supply shifts over the last decade, and then relate the labor demand shifts to service offshoring.

Previous studies with individual-level data suggest that the recent behavior of U.S. occupational wages reflects changes in labor demand.[30] To see if also my data are consistent with this explanation, I present some simple correlations between the changes in relative occupational wages and employment: a positive correlation would suggest that shifts in labor demand have outweighed those in labor supply. I pool all the yearly observations for the 58 minor white-collar occupations and run the following regression:

$$\Delta \ln \left(\frac{w^i_{n,t}}{\overline{w}_t} \right) = b_0 + b_1 \Delta \left(\frac{L^i_{n,t}}{\overline{L}_t} \right) + e^i_{n,t}, \tag{2}$$

where L^i_n and w^i_n are the number of employees and the wage in the n-th minor occupation of the i-th major group, $\overline{L}$ is total white-collar employment, $\overline{w}$ is the average white-collar wage and e^i_n is a white-noise error term; finally, Δ indicates the first-difference operator.[31] Panel a) of Table 3 reports the first set of

[30] For instance, Kambourov and Manovskii (2008a) have shown that a large fraction of the increase in (within-group) wage inequality in the U.S. can be explained by the change in the demand for the services of specific occupations, together with the rise in the variance of productivity shocks. See also Kambourov and Manovskii (2008b) for additional evidence on the recent changes in occupational wages in the U.S..

[31] I exclude observations for which the changes in relative wages and employment fall in the highest or lowest 0.5 percentile of the sample distribution, as these are extreme changes as compared to sample averages. In the case of relative wages the mean change is 0.3 percent, while the highest and lowest 0.5 percentiles are equal to 12.0 and -11.0 percent, respectively. In the case of relative employment, the mean change is close to zero, while the two percentiles are equal to 0.82 and -0.86 percentage points.

results. In column (1), I estimate a model without time effects and find that b_1 is positive and statistically significant. In column (2), I include a full set of time dummies and again find that b_1 is significantly greater than zero. Hence, changes in relative employment and wages are positively correlated in the sample.

In Panel b), I make an attempt to disentangle demand and supply shifts from the observed correlation, by conditioning equation (2) to a proxy for the changes in occupational supply. I use yearly data on the number of completion rates in post-secondary degrees, which are available in the Integrated Post-secondary Education Data System administered by the National Center for Education Statistics. These data are reported at the 6-digit level of the Classification of Instructional Program, and thanks to the high detail can be matched with the employment data for the white-collar occupations, thereby providing a proxy for the number of new labor market entrants in each occupation every year.[32] I normalize the number of degrees for each occupation by the total number of degrees for all the white-collar occupations, and include this variable (in first-differences) in equation (2). The coefficient b_1 remains positive and significant, and actually becomes larger. The coefficient on the proxy for occupational supply has always the expected negative sign, but is very small and imprecisely estimated. This suggests that the observed correlation between changes in relative wages and employment has mostly resulted from labor demand shifts, while labor supply shifts have been weak. In Panel c) and d), I re-estimate the model separately for, respectively, the three skill groups and the occupations with *tradability index* above and below the median. Notice that the coefficients have the same sign and (approximately) the same size as those obtained on the whole sample, although b_1 is imprecisely estimated for the high skilled group and for the non-tradable occupations. Hence, the previous evidence seems largely confirmed across occupations with different skill levels and tradability characteristics.

I now move to relate the labor demand shifts with service offshoring. I present here the results from a simple log-linear specification of a short-run (conditional) labor demand function, estimated separately for each minor occupation and for each major group. This model has been used by the previous empirical studies on service offshoring, in particular by Amiti and Wei (2005, 2006b). The baseline specifications

[32] I am able to match 36 occupations between 1997 and 2003 and 50 afterwards, so that the total number of observations slightly drops.

have the following expressions:

$$\ln L^i_{n,jt} = b_0 + b_1 \ln w^i_{n,jt} + b_2 \ln y_{jt} + b_3 \ln k_{jt} + b_4 SOS_{jt} + \mathbf{b'\Omega}_{jt} + e^i_{n,jt} \quad \forall\ n \text{ and } \forall i$$

$$\ln L^i_{jt} = b_0 + b_1 \ln w^i_{jt} + b_2 \ln y_{jt} + b_3 \ln k_{jt} + b_4 SOS_{jt} + \mathbf{b'\Omega}_{jt} + e^i_{jt} \quad \forall i, \tag{3}$$

where L^i_n and w^i_n are again the number of employees and the wage in the n-th minor occupation of the i-th major group, L^i and w^i are total employment and average wage in major group i, y is real output (real value of shipments), k is capital stock, e^i_n and e^i are white-noise disturbances, and $\mathbf{\Omega}$ is a vector of control variables that may determine parallel shifts in the demand functions, similarly to SOS. These are: a proxy for material offshoring (MOS), defined as the share of imported intermediate inputs in total non-energy input purchases, and computed as in (1) using economy-wide commodity imports from NBER (Feenstra et al., 2002) and the International Trade Commission;[33] a proxy for technological progress ($TECH$), defined as the share of computer and software equipment in total capital stock; a proxy for industry openness ($OPEN$), defined as the log of imports plus exports over total shipments.[34] MOS controls for the fact that some white-collar jobs may be relocated abroad as a result of the offshoring of intermediate inputs. $TECH$ accounts for the well known effects of technological progress, which are unevenly faced by occupations with different skill levels (Berman et al., 1994) and different tasks (Autor et al., 2003). $OPEN$ controls for other phenomena linked to globalization and potentially correlated with service offshoring, like movements in the exchange rate, foreign demand shocks, etc. (Baily and Lawrence, 2004). I allow the occupation wage to vary across industries in order to account for imperfect labor mobility and inter-industry differences in wage setting institutions like unions, and use a short-run specification (i.e., conditioned on the capital stock) to make the results comparable with those of the structural model illustrated in Section (4).[35] Finally, I include time and 2-digit industry dummies.

The baseline results are reported in Table 4 (Panel a)) for the minor occupations, and in Table 5 (Panel a)) for the major groups. Both tables show the estimates of b_4, the labor demand elasticity

[33] See Campa and Goldberg (1997), Feenstra (1998), Hummels et al. (1998), Hummels et al. (2001) for studies assessing the quantitative importance of material offshoring.

[34] Descriptive statistics on these variables are in Appendix Table A7.

[35] The occupation wages are normalized to 1 in 2000, as in the structural model presented below.

with respect to service offshoring; standard errors are corrected for clustering within 2-digit industries. Starting from Table 4, two-thirds of the elasticities are significant at conventional levels; in terms of signs, thirty-four are negative and twenty-four positive. Turning to Table 5, five elasticities are positive and three negative; overall, four of them are statistically different from zero. In Panel b), the models are re-estimated including linear and quadratic industry-specific time trends in place of the time dummies: this attempts to account for the fact that SOS may just be capturing an overall trend in the economy-wide service imports, because all of its time variability comes from that source. In only one case do the elasticities change sign ("mining and geological engineers"); otherwise, they are remarkably close to those from the baseline model. Panel c) excludes the wage from the regressors, to check that the results do not crucially depend on the assumption of industry-specific wages.[36] All elasticities maintain the same sign as in the baseline model; moreover, size and significance are virtually unchanged. Finally, Panel d) includes the log price of energy among the regressors, to control for other macroeconomic shocks (above all the change in oil prices) that cannot be measured at the industry-level. Reassuringly, the elasticities show no single change in sign, and the point estimates are very similar to those from the baseline specification.

In the bottom of Table 5, I re-estimate the four models using the proxy for service offshoring based on official data on service imports. I am able to use this variable only for the major groups, because for the minor occupations censoring is much more severe and the log transformation leaves with too few observations to identify the parameters. Elasticities are generally less precisely estimated than those obtained with SOS, mostly due to the much smaller sample size. Notice, however, that the pattern of signs is consistent across the two proxies: in fact, only one elasticity switches sign when using the official data ("sales and related occupations"). Moreover, the estimates remain broadly stable across the four specifications of the model. Although limited to the major groups, this evidence suggests that the main pattern of results is not driven by measurement error in the proxy for service offshoring.[37]

I now compare the occupations with positive and negative elasticities in terms of skills and tradability characteristics. I use the baseline elasticities from Table 4 and report the results in Table 6. The comparison is conducted on the whole sample of minor occupations (Panel a)) and across skill groups (Panel b)-d)). The frequency of positive and negative elasticities differs across skill levels (column (1)): in fact,

[36] In this specification, wages are assumed to vary only over time, and their effects are captured by the time dummies.
[37] In these specifications, MOS is replaced with an equivalent indicator using official data on imported intermediate inputs at the industry-level.

positive elasticities prevail in the high skilled group, where they represent 56 percent of the occupations, while negative elasticities prevail in the medium and low skilled groups, where they respectively account for 69 and 63 percent of all occupations. At the same time, the occupations with negative elasticities have more pronounced tradability characteristics: they show in fact a substantially higher value of the *tradability index* (column (2)), are more involved in routine cognitive tasks (columns (3)-(5)), depend more on ICT (column (6)), and require lower degrees of face-to-face contact, at least according to two out of three indices (columns (7)-(9)). More importantly, the same evidence holds, with few exceptions, across skill groups. Hence, the majority of low and medium skilled occupations are offshored, while the majority of high skilled occupations are retained domestically. Within skill groups, the occupations that are offshored are more tradable than those remaining in the U.S..

The log-linear approach in (3) is highly appealing, because is computationally simple and the labor demand elasticities with respect to service offshoring coincide with a single parameter. Yet, this approach suffers from one major limitation: due to the high degree of censoring in the employment variable, the log transformation causes significant losses of observations. This has two consequences. First, the estimated parameters may be inconsistent. Second, the available number of observations is sometimes too small to identify all the cross-wage elasticities. This has forced me to set them equal to zero, implicitly excluding any relationship among occupations. With a high level of detail in the employment variable, such an assumption is far too restrictive. Hence, the evidence discussed in this section should only be taken as suggestive. The next section will present a model of firm behavior that overcomes the main limitation of the log-linear approach.

4 A Model of Firm 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 condition the firm optimization process on service offshoring. The model is based on two assumptions. First, the technology is separable in groups of minor occupations. Second, service offshoring acts as a shift-factor affecting the position of the technological frontier.

Separability allows to impose only mild restrictions on the relationship among occupations. Under this assumption, in fact, changes in the employment of an occupation do not affect the marginal rate of technical substitution between any other pairs of occupations in a different group. Hence, the relationship among the occupations in the same group is unrestricted, while the relationship among the occupations in different groups is restricted in the following way: if the occupations of a group become relatively more expensive, firms will substitute away from them and raise *proportionally* the demand for all occupations in another group. At the same time, separability keeps the derivation of labor demand functions tractable even for high numbers of occupations, because it allows to break down the firm optimization process in two separate stages, each involving a moderate number of variables: in the first stage, firms choose the optimal mix of occupations within each group, while in the second stage they choose the optimal employment of all groups. This procedure, known as Two-Stage Optimization (TSO), is said to be *consistent* if it yields the same labor demand functions as those obtained with single-stage optimization.[38]

While separability is likely to hold when working with detailed occupations (Weiss, 1977), an important issue is how the occupations are grouped. In my case, it seems natural to follow the hierarchical structure of the OES, and group the minor occupations into the corresponding 2-digit SOC major groups. On the one hand, each major group identifies a set of occupations that perform homogeneous jobs and differ substantially from those in the other major groups. On the other hand, this grouping is likely to be orthogonal to the two occupational attributes that are of interest for this paper: skills and tradability characteristics. I therefore assume that the firm technology is separable in the 13 2-digit SOC major groups.[39]

The second assumption of the model, namely that service offshoring acts as a shift-factor, implies that TSO takes place for any level of this variable. The resulting labor demand functions will thus be conditioned upon service offshoring and will shift parallel when the latter changes: this allows to derive labor demand elasticities with respect to service offshoring for all occupations. A crucial issue with this assumption, however, is that the variability of service offshoring may not be exogenous with respect to the firm optimization process. First, service offshoring is a choice variable for firms, which

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

[39] The separability assumption could in principle be tested (see, among others, Woodland, 1978, Moschini, 1992, Diewert and Wales, 1995, and Koebel, 2006). 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.

may be determined together with the optimal composition of employment. Second, unobserved industry heterogeneity and time varying shocks could simultaneously affect the level of service offshoring and the occupational composition of employment. Both issues could be effectively dealt with during estimation, by using an Instrumental Variables approach. The latter is however unfeasible in my case due to the complex nature of the empirical model. As a consequence, I am forced to assume, as in most of the previous literature, that the optimal level of service offshoring has been already chosen by firms when they optimize over employment, i.e. it is predetermined.[40] I will instead attempt to deal explicitly with the simultaneity bias arising from unobserved industry heterogeneity and time varying shocks.

4.1 The Model

4.1.1 Primal and Dual Representation of the Technology

I assume that the short-run production function of the representative firm in each industry depends on a quasi-fixed input (capital, k) and on the following variable inputs: labor (L), energy and non-energy materials (collected into the vector $\boldsymbol{\delta}$ with generic entry δ^r).[41] The labor input consists of minor occupations (indexed by the subscript n) that belong to different major groups (indexed by the superscript i): L_n^i will therefore indicate the number of employees in the n-th minor occupation of the i-th major group. I also assume that a set of shift-factors, including service offshoring and other control variables, determine the position of the technological frontier. Without loss of generality, I collect k and the shift-factors into the vector $\mathbf{z}$, with generic entry z^u. The production function, then, has the form

$$y = f\left(L_1^1, ..., L_n^i, ..., L_N^I, \boldsymbol{\delta}', \mathbf{z}'\right), \tag{4}$$

where y is real output. I assume that (4) is twice differentiable and strictly quasi-concave, exhibits positive marginal products of all inputs and satisfies the Hicksian stability conditions. I also assume that (4) is separable in the major occupational groups, and precisely, that it has the following alternative

[40] This assumption is implicitly maintained by all the studies using OLS estimators to test the effects of offshoring on labor demand. See Hijzen et al. (2005) for an example.

[41] I am forced to use a short-run representation of the technology by the lack of information on the price of capital. This representation allows the cost function (presented below) to depend on the level of the capital stock, which can be observed (Berman et al., 1994).

representation:

$$y = f\left(L^1, ..., L^i, ..., L^I, \boldsymbol{\delta}', \mathbf{z}'\right), \tag{5}$$

where

$$L^i = L(L_1^i, ..., L_N^i, \mathbf{z}') \ \ \forall i \tag{6}$$

are linearly homogeneous aggregator functions (quantity indices) for the minor occupations in each major group.[42] It can be shown that, given this technology, TSO conditioned upon $\mathbf{z}$ is consistent. The following Lemma states this result and provides the dual representation of (5) and (6).

Lemma 1 *If the production function is of the form (5) and (6), TSO conditioned upon* $\mathbf{z}$ *is consistent and yields the short-run cost function*

$$C_{SR} = C(w^1, ..., w^i, ..., w^I, \mathbf{p}', y, \mathbf{z}'), \tag{7}$$

where $\mathbf{p}$ *is a vector containing the prices of the non-labor inputs and*

$$w^i = w(w_1^i, ..., w_N^i, \mathbf{z}') \ \ \forall i \tag{8}$$

are linearly homogeneous aggregator functions (wage indices) for the wages of the minor occupations in each major group. Each wage index represents the minimum unitary expenditure in the corresponding major group.

Proof. See Appendix (9.1.1). ■

By Lemma 1, the optimal labor demand functions can be retrieved from (7) and (8) in two stages. First, by applying Shephard's lemma to (8) one obtains the demand functions for the minor occupations that minimize the unitary expenditure in each major group. Then, by applying Shephard's lemma to (7) one obtains the demand functions for the major groups that minimize total costs.

[42] Assuming that the quantity indices are linearly homogeneous ensures that the product between them and the wage indices (w^i, introduced below) equals total expenditure in the major groups. For details, see Gorman (1959), Green (1964), Berndt and Christensen (1973), Fuss (1977) and Blackorby et al. (1978).

Being conditioned upon $\mathbf{z}$, these functions will experience parallel shifts when one of its arguments changes. It is therefore possible to derive formulas for the labor demand elasticity with respect to service offshoring for all occupations. Notice that a change in service offshoring will affect both stages of the optimization process: that is, firms will first re-optimize the employment mix within each major group, and then re-adjust the level of employment of all groups; this latter effect will then translate proportionally to all the constituent minor occupations. Hence, for the generic minor occupation n, the final expression of the labor demand elasticity with respect to service offshoring will be

$$\varkappa_{n,SOS} = \xi^{i}_{n,SOS} + sh^{i}_{n} \cdot \rho^{i}_{SOS}, \tag{9}$$

where $\xi^{i}_{n,SOS}$ measures the percent change induced by service offshoring in the employment of n, holding fixed the employment of major group i; sh^{i}_{n} is the share of occupation n in the wage bill of major group i; and ρ^{i}_{SOS} measures the percent change induced by service offshoring in the employment of major group i.

As such, ρ^{i}_{SOS} is the labor demand elasticity with respect to service offshoring for the i-th major group. Its expression is equal to the combination of two terms: the first depends on the presence of service offshoring as an independent argument of the cost function (7), while the second works through the changes induced by service offshoring in all the wage aggregators (8). Formally,

$$\rho^{i}_{SOS} = \frac{\partial \log L^{i}}{\partial SOS} + \left[\frac{\partial \log L^{i}}{\partial \log w^{i}} \cdot \frac{\partial w}{\partial SOS} + \sum_{q \neq i} \frac{\partial \log L^{i}}{\partial \log w^{q}} \cdot \frac{\partial w}{\partial SOS} \right]. \tag{10}$$

4.1.2 Functional Forms

I follow Fuss (1977) and Moschini (1992) and specify a Flexible and Separable Translog (FAST) model for equations (7) and (8). The FAST model offers a non-nested framework in which separability can be combined with the flexible nature of the translog: in this way, imposing separability does not cause loss of flexibility.[43] Under FAST, the short-run cost function in (7) has the following form:

$$\begin{aligned}
\ln C_{SR,jt} &= \ln \alpha_0 + \sum_{i=1}^{I} \alpha_i \ln w_{jt}^i + \sum_{r=1}^{R} \alpha_r \ln p_{jt}^r + \alpha_y \ln y_{jt} + \sum_{u=1}^{U} \alpha_u z_{jt}^u + \\
&+ \frac{1}{2} \sum_{i=1}^{I} \sum_{q=1}^{Q} \alpha_{iq} \ln w_{jt}^i \ln w_{jt}^q + \frac{1}{2} \sum_{r=1}^{R} \sum_{w=1}^{W} \alpha_{rw} \ln p_{jt}^r \ln p_{jt}^w + \sum_{i=1}^{I} \sum_{r=1}^{R} \alpha_{ir} \ln w_{jt}^i \ln p_{jt}^r + \\
&+ \frac{1}{2} \alpha_{yy} (\ln y_{jt})^2 + \frac{1}{2} \sum_{u=1}^{U} \sum_{v=1}^{V} \alpha_{uv} z_{jt}^u z_{jt}^v + \sum_{u=1}^{U} \alpha_{u\,\mathrm{y}} z_{jt}^u \ln y_{jt} + \sum_{i=1}^{I} \alpha_{iy} \ln w_{jt}^i \ln y_{jt} + \\
&+ \sum_{i=1}^{I} \sum_{u=1}^{U} \alpha_{iu} \ln w_{jt}^i z_{jt}^u + \sum_{r=1}^{R} \alpha_{ry} \ln p_{jt}^r \ln y_{jt} + \sum_{r=1}^{R} \sum_{u=1}^{U} \alpha_{ru} \ln p_{jt}^r z_{jt}^u. \qquad (11)
\end{aligned}$$

The aggregators in (8) are instead represented by

$$\ln w_{jt}^i = \sum_{n=1}^{N} \beta_n \ln w_{n,jt}^i + \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{M} \beta_{nm} \ln w_{n,jt}^i \ln w_{m,jt}^i + \sum_{n=1}^{N} \sum_{u=1}^{U} \beta_{nu} \ln w_{n,jt}^i z_{jt}^u \quad \forall i. \qquad (12)$$

Following Fuss (1977), it can be shown that this representation yields exact Tornqvist-Theil indices for the wages of the minor occupations in each major group.[44] This result will be exploited in Section (5.2).

Lemma 2 *Given* $\mathbf{z}$ *a vector of shift-factors and quasi-fixed inputs, equation (12) corresponds to the Tornqvist-Theil index for the wages of the minor occupations in each major group.*

Proof. See Appendix (9.1.2). ■

With equations (11) and (12) at hand, I now derive the optimal labor demand functions. Applying Shephard's Lemma to (12) and exploiting standard translog results yield I systems of demand equations of the form

$$sh_{n,jt}^i = \beta_n + \sum_{m=1}^{M} \beta_{nm} \ln w_{m,jt}^i + \sum_{u=1}^{U} \beta_{nu} z_{jt}^u \qquad \forall\ n \text{ and } \forall i, \qquad (13)$$

[43] See instead Berndt and Christensen (1974), Blackorby et al. (1977) and Denny and Fuss (1977) for cases in which imposing separability on a translog cost function leads to the loss of flexibility.

[44] See also Diewert (1976) on this point.

where sh_n^i is the share of occupation n in the wage bill of major group i. Similarly, applying Shephard's Lemma to (11) yields the following system of demand equations:

$$SH_{jt}^{i(r)} = \alpha_{i(r)} + \sum_{i=1}^{I} \alpha_{iq(ir)} \ln w_{jt}^i + \sum_{r=1}^{R} \alpha_{ir(rw)} \ln p_{jt}^r + \alpha_{iy(ry)} \ln y_{jt} + \sum_{u=1}^{U} \alpha_{iu(ru)} z_{jt}^u \qquad \forall i \text{ and } \forall r, \tag{14}$$

where $SH^{i(r)}$ is the share of major group i (non-labor input r) in total variable costs.[45]

Estimation of (13) and (14) is computationally feasible, because each system contains a moderate number of equations.[46] The estimated parameters can then be used to compute the labor demand elasticities with respect to service offshoring for the minor occupations and for the major groups. This requires to specialize equations (9) and (10) to the translog case. The first term of (9), $\xi_{n,SOS}^i$, has the following expression:[47]

$$\xi_{n,SOS}^i = \frac{\beta_{n,SOS}}{sh_n^i}. \tag{15}$$

The expression for ρ_{SOS}^i, instead, is

$$\rho_{SOS}^i = \frac{\alpha_{i,SOS}}{SH^i} + \left(\frac{\alpha_{ii}}{SH^i} + SH^i - 1\right) \cdot \left(\sum_{n=1}^{N} \beta_{n,SOS} \ln w_n^i\right) + \sum_{q \neq i} \left(\frac{\alpha_{iq}}{SH^i} + SH^q\right) \cdot \left(\sum_{n=1}^{N} \beta_{n,SOS} \ln w_n^q\right), \tag{16}$$

where $\alpha_{i,SOS}/SH^i$ corresponds to the first addendum of (10), $\left(\frac{\alpha_{ii}}{SH^i} + SH^i - 1\right)$ and $\left(\frac{\alpha_{iq}}{SH^i} + SH^q\right)$ are the translog formulas for, respectively, the own- and cross-price elasticities of demand for major group i, and $\left(\sum_{n=1}^{N} \beta_{n,SOS} \ln w_n^{i(q)}\right)$ are the changes induced by service offshoring in the wage aggregators.

Summing up, this section has presented a model of firm behavior that yields formulas for the labor demand elasticity with respect to service offshoring for each minor occupation and each major group, while allowing for a flexible relationship among occupations. To this purpose, the model exploits separability

[45] Linear homogeneity in prices and symmetry imply the following restrictions on the parameters of (11):
$\sum_{i=1}^{I} \alpha_i + \sum_{r=1}^{R} \alpha_r = 1$; $\sum_{i=1}^{I} \alpha_{iq} = \sum_{q=1}^{Q} \alpha_{qi} = 0$; $\sum_{r=1}^{R} \alpha_{rw} = \sum_{w=1}^{W} \alpha_{wr} = 0$; $\sum_{i=1}^{I} \alpha_{ir} = 0$; $\sum_{r=1}^{R} \alpha_{ir} = 0$;
$\sum_{i=1}^{I} \alpha_{iy} = 0$; $\sum_{r=1}^{R} \alpha_{ry} = 0$; $\sum_{i=1}^{I} \alpha_{iu} = 0$; $\sum_{r=1}^{R} \alpha_{ru} = 0; \alpha_{iq} = \alpha_{qi}; \alpha_{rw} = \alpha_{wr}; \alpha_{uv} = \alpha_{vu}$.
The same properties imply the following restrictions on the parameters of (12): $\sum_{n=1}^{N} \beta_n = 1$; $\sum_{n=1}^{N} \beta_{nm} = \sum_{m=1}^{N} \beta_{mn} = 0$; $\sum_{n=1}^{N} \beta_{nu} = 0; \beta_{nm} = \beta_{mn}$.

[46] The largest system in (13) is composed of twelve equations (minor occupations). The system in (14) contains fifteen equations (thirteen major groups and two non-labor inputs).

[47] The detailed derivation can be found in Ekholm and Hakkala (2005). Industry and time subscripts are omitted to save on notation.

and TSO, and assumes that service offshoring acts as a shift-factor. The first stage of the optimization process has been characterized with I systems of labor demand functions, and the second stage with just one system. Each system contains a moderate number of equations, which makes estimation tractable.

5 Estimation Strategy

The stochastic version of (13) and (14) is

$$sh^i_{n,jt} = \beta_n + \sum_{m=1}^{M} \beta_{nm} \ln w^i_{m,jt} + \sum_{u=1}^{U} \beta_{nu} z^u_{jt} + \varepsilon^i_{n,jt} + c_j \tag{17}$$

$$SH^{i(r)}_{jt} = \alpha_{i(r)} + \sum_{i=1}^{I} \alpha_{iq(ir)} \ln w^i_{jt} + \sum_{r=1}^{R} \alpha_{ir(rw)} \ln p^r_{jt} + \alpha_{iy(ry)} \ln y_{jt} + \sum_{u=1}^{U} \alpha_{iu(ru)} z^u_{jt} + \epsilon^i_{jt} + c_j. \tag{18}$$

The term c_j is an industry-specific component accounting for individual heterogeneity, which will be discussed in Section (5.1). Instead, ε^i_n and ϵ^i are idiosyncratic disturbances with the following properties:

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

Property 2a $E(\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}') = \Gamma = \Gamma_\varepsilon \otimes I_{JT}$, where $\Gamma_\varepsilon = [\sigma^{nm}_\varepsilon]$, I_{JT} is the identity matrix of order JT, n and m refer to two generic equations from (17).[48]

Property 2b $E(\boldsymbol{\epsilon}\boldsymbol{\epsilon}') = \Sigma = \Sigma_\epsilon \otimes I_{JT}$, where $\Sigma_\epsilon = [\sigma^{iq}_\epsilon]$, i and q refer to two generic equations from (18).

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

Property 4 $\begin{pmatrix} \boldsymbol{\epsilon} \\ \boldsymbol{\varepsilon} \end{pmatrix} \sim N\left(\mathbf{0}, \begin{bmatrix} \Sigma_\epsilon & \Psi_{\epsilon\varepsilon} \\ \Psi_{\epsilon\varepsilon} & \Gamma_\varepsilon \end{bmatrix} \otimes I_{JT}\right)$, where $\Psi_{\epsilon\varepsilon} = [\sigma^{in}_{\epsilon\varepsilon}]$.

These properties imply that the idiosyncratic disturbances are jointly normally distributed with mean 0, and correlated both across the equations of each system and across the two stages of the FAST model.[49]

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

[49] Cross-stage error correlation may seem inconsistent with the separability assumption: some authors have indeed argued that, due to separability, the 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 separability; rather, in order to obtain block-recursivity, one would need to impose restrictive assumptions on the variance-covariance matrix of the error terms.

Estimation of (17) and (18) is complicated by the high degree of censoring of the dependent variables, which would make SUR estimates inconsistent. Censoring can arise from either corner solutions or designated technologies. Because estimation under designated technologies is unfeasible with a large number of occupations, I assume that censoring arises from corner solutions.[50]

Under the assumption of corner solutions, three alternative estimation approaches are available. This paper relies on the panel data version of the Amemiya's (1974) Tobit model proposed by Meyerhoefer et al. (2005).[51] 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; as a result, parameter estimates are inconsistent. This issue is known as "incidental parameters problem" (Neyman and Scott, 1948). Meyerhoefer et al. (2005) have however shown that the Amemiya's Tobit model can be easily extended to panel data, by exploiting Quasi-Maximum Likelihood Estimation (QMLE) results.[52] The next section will present a different treatment of QMLE, which may be useful when the cross-sectional dimension of the panel is moderately small, as is usually the case in studies using industry-level data.[53]

[50] Designated technologies do not use some of the inputs. Estimation under this assumption would be unfeasible in my case, because it should be performed separately on all of the observed combinations of occupations. If the technologies were designated, my estimation strategy would overestimate the labor demand elasticities, but the extent of overestimation should be limited and the pattern of signs should be preserved. As shown by Bousquet and Ladoux (2006), in fact, designated technologies yield lower price elasticities with the same sign as those estimated under corner solutions. *Ceteris paribus*, this would translate into lower values for $\varkappa_{n,SOS}$ and ρ^{i}_{SOS}, because both depend on the changes induced by service offshoring in the wage aggregators (see, for instance, equations (9) and (10)); in Crinò (2007a), I show however that these latter terms are typically small. At the same time, designated technologies would yield lower values for both $\beta_{n,SOS}/sh^{i}_{n}$ and $\alpha_{i,SOS}/SH^{i}$, because estimation would not account for those cases in which an occupation either starts or ceases to be employed after the rise in service offshoring. Yet, because such cases represent a tiny fraction of the sample observations (about 4 percent across all occupations), also this second effect should be small.

[51] 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.

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

[53] There may be other solutions to the "incidental parameters problem". In a parametric framework like that required by QMLE, Becker and Muendler (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, Honoré (1992) has shown that individual heterogeneity can be wiped out by an appropriate "trimming" of the distribution of the dependent variable. The way QMLE treats individual heterogeneity, however, makes it particularly suited for the analysis in this paper.

5.1 Quasi-Maximum Likelihood Estimation

QMLE works in two steps. In the first step, a conditional 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 (e.g., symmetry and linear homogeneity in prices) 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-equation context can be generalized to a multi-equation framework.

The treatment of QMLE in this paper differs from that in Meyerhoefer et al. (2005) at both steps. In the first step, the main difference is in the specification of the distribution of c_j. In the second step, the main difference is in the correction of the variance-covariance matrix. 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 (17) and (18) that c_j appears in the systems of equations at both stages of the FAST 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). Therefore, c_j is assumed to have conditional distribution depending on the subset of regressors that appear at both stages of the model. Specifically, the conditional distribution of c_j is represented by a linear projection of the latter on the group means of the shift-factors and quasi-fixed inputs (indicated with a "bar"):

$$c_j = \sum_{u=1}^{U} \lambda_u \bar{z}_j^u + \eta_j, \tag{19}$$

where the λ's are parameters to be estimated and η is a projection error uncorrelated with all the explanatory variables and satisfying $\eta \sim N(0, \sigma_\eta^2)$ and $E(\eta_j \epsilon_{jt}^i) = E(\eta_j \varepsilon_{n,jt}^i) = 0 \; \forall j, i, n, t$.[54]

The specified distribution of c_j has to be integrated out from the joint density function of each system of equations. This simply requires substituting (19) into (17) and (18). Substitution yields the following reduced-form versions of the systems:

$$sh_{n,jt}^i = \beta_n + \sum_{m=1}^{M} \beta_{nm} \ln w_{m,jt}^i + \sum_{u=1}^{U} \beta_{nu} z_{jt}^u + \sum_{u=1}^{U} \lambda_u \overline{z}_j^u + \tau_{n,jt}^i \tag{20}$$

$$SH_{jt}^{i(r)} = \alpha_{i(r)} + \sum_{i=1}^{I} \alpha_{iq(ir)} \ln w_{jt}^i + \sum_{r=1}^{R} \alpha_{ir(rw)} \ln p_{jt}^r + \alpha_{iy(ry)} \ln y_{jt} + \sum_{u=1}^{U} \alpha_{iu(ru)} z_{jt}^u + \sum_{u=1}^{U} \lambda_u \overline{z}_j^u + \varpi_{jt}^i, \tag{21}$$

where $\tau_n^i = \varepsilon_n^i + \eta$ and $\varpi^i = \epsilon^i + \eta$, with $\tau_n^i \sim N(0, \sigma_\tau^2)$ and $\varpi^i \sim N(0, \sigma_\varpi^2)$. Notice one important implication of this approach: the shift-factors and quasi-fixed inputs are uncorrelated with both τ_n^i and ϖ^i. The group means of these variables account for their potential correlation with the error term, as in fixed-effect estimation. This eliminates the potential simultaneity bias of service offshoring arising from unobserved industry heterogeneity. Since each equation in the systems (20) and (21) contains the same regressors and industry heterogeneity has been integrated out, equation-by-equation pooled Tobit estimation yields consistent and $\sqrt{J}$-asymptotically normal estimates of the reduced-form parameters (Wooldridge, 2002).

In the second step of QMLE, cross-equation restrictions are imposed on the reduced-form parameters by means of MDE. I focus the exposition of MDE on the generic system in (20); MDE on (21) will proceed along the same lines. Collect the reduced-form parameters from (20) into the vector $\mathbf{\Pi}$ of dimension $\Upsilon \times 1$, with $\Upsilon = N \cdot (N + 2U + 2)$. N is the number of occupations in each equation and the number of equations in the system, while U is the number of shift-factors and quasi-fixed inputs; the constant term and the error variance σ_τ^2 justify the 2 additional parameters. The total number of restrictions to be imposed is $N(N-1)/2 + (N+U+1) + (N-1)U$, where $N(N-1)/2$ are the symmetry restrictions, $N+U+1$ are the homogeneity restrictions, and $(N-1)U$ are the restrictions needed to make the conditional distribution of c_j constant across equations. Given the linear nature of these restrictions, the mapping between $\mathbf{\Pi}$ and the structural (restricted) parameters $\boldsymbol{\beta}^*$ will be $\mathbf{\Pi} = H\boldsymbol{\beta}^*$, where H is the matrix of restrictions and has

[54] The formulation in (19) has originally been proposed by Mundlak (1978).

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:

$$\widehat{\boldsymbol{\beta}}^* = \arg\min_{\boldsymbol{\beta}^*}[\widehat{\boldsymbol{\Pi}} - \mathbf{H}\boldsymbol{\beta}^*]'\widehat{\boldsymbol{\Xi}}^{-1}[\widehat{\boldsymbol{\Pi}} - \mathbf{H}\boldsymbol{\beta}^*], \tag{22}$$

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

$\widehat{\boldsymbol{\Xi}}$ has to be corrected to account for the fact that $\widehat{\boldsymbol{\Pi}}$ has been obtained using the marginal, rather than the joint distributions of the dependent variables. This does not allow to account for two types of correlation in the scores of the joint likelihood function of (20). First, the scores are correlated across equations, 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 $\iota_{jt}(\widehat{\boldsymbol{\Pi}}_n)$ the score of the observation-specific Tobit log-likelihood function for the n-th equation. Also define the following two matrices: $\widehat{\mathbf{A}} = diag\begin{bmatrix} \widehat{\mathbf{A}}_1 & ,..., & \widehat{\mathbf{A}}_n & ,..., & \widehat{\mathbf{A}}_N \end{bmatrix}$, where $\widehat{\mathbf{A}}_n = J^{-1}\sum_{j=1}^{J}\sum_{t=1}^{T}\iota_{jt}(\widehat{\boldsymbol{\Pi}}_n)\iota_{jt}(\widehat{\boldsymbol{\Pi}}_n)'$, and $\widehat{\mathbf{B}} = J^{-1}\sum_{j=1}^{J}\sum_{t=1}^{T}\widehat{\boldsymbol{\Phi}}_{jt}\widehat{\boldsymbol{\Phi}}'_{jt}$, where $\widehat{\boldsymbol{\Phi}}_{jt} = [\begin{matrix} \iota_{jt}(\widehat{\boldsymbol{\Pi}}_1) & ... & \iota_{jt}(\widehat{\boldsymbol{\Pi}}_n) & ... & \iota_{jt}(\widehat{\boldsymbol{\Pi}}_N) \end{matrix}]$. The final expression for $\widehat{\boldsymbol{\Xi}}$ will be:

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

The matrix $\widehat{\mathbf{B}}$ accounts for both serial correlation in the scores of each equation and correlation among the scores of different equations.

Meyerhoefer et al. (2005) specify a different distribution for c_j, which depends on all the lags and leads of all the regressors (as in Chamberlain, 1980, 1982). This implies that the estimation of $\widehat{\boldsymbol{\Pi}}$ has to be performed cross-section by cross-section on each equation separately. The formulation in (19) 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.[55]

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

5.2 Instrumenting the Wage Indices at the Second Stage of the FAST Model

In estimating the second stage of the FAST model (system (21)), the log wage of major group i could be computed as a Tornqvist-Theil index of the observed log wages of the corresponding minor occupations. The index would be equal to $\ln w^i_{jt} = \sum_n 0.5(sh^i_{n,j0} + sh^i_{n,jt}) \ln w^i_{n,jt}$, where the subscript 0 indicates a base year of normalization in which all wages are set up to 1 (2000 in my case). Unfortunately, this formulation would imply the endogeneity of $\ln w^i$, because sh^i_n would appear both as explained variable at the first stage of the FAST model and as explanatory variable at the second (Fuss, 1977; Edgerton et al., 1996). By Lemma 2, however, the formulation of the aggregators in (12) yields exact Tornqvist-Theil indices without making use of sh^i_n. 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 (21).

6 Results

I start from a model including the same shift-factors as the baseline log-linear specification in (3): SOS, MOS, $TECH$, $OPEN$ and time dummies.[56] Panel a) of Table 7 reports the labor demand elasticities with respect to service offshoring for the minor occupations ($\varkappa_{n,SOS}$); Panel a) of Table 8 reports those for the major groups (ρ^i_{SOS}); the other panels of both tables contain results from alternative specifications, which will be discussed in Section (6.3.1). Elasticities are evaluated at the sample median and standard errors are obtained with 100 bootstrap replications. About 80 percent of the elasticities (46 out of 58) are significant for the minor occupations, and about 63 percent (5 out of 8) are so for the major groups. Not surprisingly, the size of the QMLE elasticities differs (sometimes substantially) from that of their log-linear counterparts. This happens because the log-linear model excludes any relationship among the occupations, and may produce inconsistent estimates due to the high degree of censoring in the employment variable. With very few exceptions, however, the elasticities maintain the same sign across the two estimation methods. Precisely, for the major groups there is no single change in sign. For the minor occupations, six elasticities switch sign; yet, the total number of positive and negative elasticities remains equal to twenty-four and thirty-four, respectively.

Before commenting on these results, I check the regularity conditions on the cost function in (11), in

[56] Descriptive statistics on the dependent variables (sh^i_n and $SH^{i(r)}$) are shown in Appendix Table A6 (columns (3)-(4)).

order to make sure that the elasticities are consistent with the restrictions implied by economic theory. This is particularly important when working with aggregators of detailed inputs, because those restrictions may not hold on the aggregates (Koebel, 2002). As standard with translog-type models, linear homogeneity in prices and symmetry have been imposed on the parameters and therefore hold by construction. The theoretical properties to be tested are instead monotonicity and concavity. Monotonicity holds if the predicted values of $SH^{i(r)}$ are non-negative for each industry in each time period; while these results are not reported 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 the test on the median value of the price elasticities.[57] Results reported in Appendix Table A8 show that all principle minors are indeed negative.

6.1 Skills, Tradability and Service Offshoring: Unconditional Results

I now move to study how the elasticities relate to the skill level and the tradability characteristics of the occupations. I start by simply comparing the occupations with positive and negative elasticities. Results are reported in Table 9. Column (1) shows that positive elasticities prevail in the high skilled group, where they account for 61 percent of the occupations; negative elasticities prevail instead in the medium and low skilled groups, where they respectively account for 63 and 71 percent of the occupations. The *tradability index* reported in column (2) is higher for the occupations with negative elasticities; the latter perform more routine cognitive tasks (columns (3)-(5)), interact more with PCs (column (6)), and require less face-to-face contact (columns (7)-(9)). More importantly, the occupations with negative elasticities have stronger tradability characteristics in all skill groups: the *tradability index* is in fact higher for these occupations independent of their skill level. A similar picture emerges for all indices of routine cognitive tasks, for *interaction with PCs*, and for two out of three indices of face-to-face contact. Hence, QMLE results confirm, and probably strengthen, the main picture emerged before from the log-linear estimates: the majority of low and medium skilled occupations are offshored, while the majority of high skilled occupations are retained domestically; within skill groups, the occupations that are offshored are more

[57] 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 this property at specific points, like the sample mean or median (see, among others, Hijzen et al., 2005).

tradable than those remaining in the U.S..

6.2 Conditional Results

In this section, I analyze more structurally the joint role of skills and tradability characteristics, by conditioning the effect of each variable on the other occupational attributes. Define with $DPOS_n$ a dummy equal to 1 if $\varkappa_{n,SOS} > 0$ and zero otherwise. I estimate the following model over the 58 minor occupations:

$$DPOS_n = b_0 + \mathbf{b}'\digamma_n + e_n, \tag{23}$$

where e_n is a white-noise disturbance and $\digamma_n$ is a vector of occupational characteristics including skills and tradability. The elements of the vector $\mathbf{b}$ measure the effect of each variable on the probability of observing a positive labor demand elasticity with respect to service offshoring, conditional on the other regressors.

The main results are reported in Table 10. The upper part of the table shows the estimates from a Linear Probability Model, while the bottom part reports the marginal effects from Probit. Because the main results are consistent across estimators, I comment on the marginal effects. In column (1), I only include the high and medium skilled dummies among the regressors. The marginal effect of the high skilled dummy is positive, significant and large, implying that the probability of a positive demand elasticity is higher for this group by approximately 0.32. The marginal effect of the medium skilled dummy is instead small and insignificant. This suggests that high skilled occupations are the most likely to grow with service offshoring.

Column (2) provides evidence on the interplay between skills and tradability characteristics, by including the *tradability index* among the regressors. The marginal effect of this variable is negative and precisely estimated: controlling for the skill level, occupations with stronger tradability attributes are more likely to show a negative demand elasticity, i.e. they are more likely to be offshored. The point estimate implies that a one standard deviation increase in the *tradability index* raises the probability of a negative elasticity by about 0.12. At the same time, the marginal effect of the high skilled dummy is still positive and significant; it is also much larger than before, suggesting that not accounting for tradability characteristics may lead to a downward bias in the point estimate. This happens because, as shown before, the high skilled occupations have the highest values of the *tradability index*, so that, when this variable is not included among the regressors, its effect is captured by the high skilled dummy. Finally, the marginal effect of the medium skilled indicator remains positive and insignificant. Summing up, high skilled occupations are the most likely to grow with service offshoring; at given skill level, stronger tradability characteristics raise the risk that an occupation be offshored.

Next, I study the three tradability characteristics separately. I start from routine cognitive tasks in columns (3)-(5). Notice that the marginal effects of all indices are negative and statistically significant: holding fixed the skill level, occupations performing more routine cognitive tasks are more likely to be offshored. Interestingly, service offshoring acts similarly to technical change, which has been shown to substitute for routine cognitive tasks (Autor et al., 2003; Spitz-Oener, 2006). Hence, the two phenomena may reinforce each other, as recently suggested by Levy and Murname (2006). Turning to ICT-dependence (column (6)), the marginal effect of *interaction with PCs* is negative and significant, implying that ICT-enabled jobs are more likely to be relocated abroad, once controlling for the skill level. As for face-to-face contact (column (7)-(9)), all marginal effects are statistically insignificant, which probably suggests that the occupations requiring more face-to-face interaction and producing more personal services are not more likely to be offshored. Finally, the marginal effect of the high skilled dummy is positive and precisely estimated in all specifications, while the marginal effect of the medium skilled indicator is always insignificant. In columns (10)-(12), I report results from a model including all the indices of tradability characteristics jointly; I show the estimates obtained with *face-to-face 2*, because the other indicators of face-to-face interaction yield virtually the same results. The previous findings are confirmed.

6.3 Robustness Checks

I devote this section to some robustness checks of the previous results. The main concerns will be that: 1) the estimated elasticities do not crucially depend on the specification of the FAST model; 2) the effects of skills and tradability characteristics are robust across alternative versions of equation (23).

6.3.1 Alternative Specifications of the FAST Model

QMLE elasticities are complex non-linear combinations of the parameters, which in turn are estimated with a non-linear algorithm: this may raise concerns about the stability of the estimates across different specifications of the FAST model. Moreover, the baseline specification considered so far may be omitting some important variables that are correlated with both service offshoring and occupational employment: unobserved shocks to these variables may thus spuriously drive the baseline elasticities. I now try to account for these issues.

In Panel b) of Tables 7 and 8, I replace industry openness with export intensity (log of exports over total shipments) and import penetration (log of imports over apparent consumption). These variables control for two international factors that are correlated with service offshoring, namely firm participation in foreign markets and competition from foreign countries. Notice that all elasticities maintain the same sign for the major groups, while five switch sign for the minor occupations.

In Panel c), I use a broader proxy for technological progress, namely the share of high-tech capital in total capital stock.[58] This measure controls for the effects of other high technologies, which may impact on occupational demand and be highly correlated with service offshoring: one example is accounting equipment, which may directly substitute for domestic accountants but also facilitate more offshoring of accounting services. As compared with the baseline specification, only one elasticity changes sign for the major groups, while four do so for the minor occupations.

Finally, in Panel d) I try to account for other technological shocks that may ease the recourse to service offshoring and lead firms to modify the occupational structure of labor demand. The sudden and rapid fall in the price of ICT has probably been the strongest of these shocks over the last decade. A cheaper access to ICT reduces the costs of coordinating service activities across national borders and makes service offshoring more convenient *ceteris paribus*. At the same time, it also leads firms to expand domestic employment in occupations that complement with those technologies. These effects are only partly captured by $TECH$, because that variable evolves as a result of past investment decisions, while these shocks may lead firms to modify offshoring and employment today in the expectation of cheaper

[58] High-tech capital includes computer and peripheral equipment, software, communications, photocopy and related equipment, office and accounting equipment. This definition has been used, among others, by Berman et al. (1994).

investments in the near future. I use the BEA data on computer prices as a proxy for the price of ICT. Because these data are not available at the industry-level, I interact the economy-wide time series with the average share of computer and software equipment in total capital stock between 1987 and 1996: in this way, more computerized industries are allowed to be more exposed to the change in computer prices. After adding this variable to the baseline model, only one elasticity changes sign for the major groups, while seven are affected for the minor occupations.

Overall, these robustness checks suggest that the previous results may not be severely affected by model misspecifications. The next section will provide more robust evidence in that sense.

6.3.2 Further Conditional Results

Table 11 presents some sensitivity tests of the conditional results. For the sake of space, only the Probit marginal effects are reported. I start by checking that the previous findings are robust with respect to the use of different dependent variables in equation (23). Panel a) excludes the baseline elasticities that are not precisely estimated: hence, $DPOS_n = 1$ if $\varkappa_{n,SOS}$ is greater than zero *and* this difference is significant at conventional levels; similarly, $DPOS_n = 0$ if $\varkappa_{n,SOS}$ is significantly negative. Results are virtually unchanged, suggesting that the main findings are not driven by the insignificant elasticities. Panel b) excludes the elasticities that change sign across the four models presented in Table 7. Also in this case, the main evidence is largely unaffected. Finally, Panel c) uses $\varkappa_{n,SOS}$ as the dependent variable, rather than the dichotomous indicator $DPOS_n$. This allows to exploit the entire variability of the elasticities, instead of collapsing it into a binary variable. Results are obtained with a robust estimation procedure that smooths the effect of extreme values in the dependent variable.[59] As expected, the point estimates are lower than before, because they measure the effect of each variable on the absolute size of the elasticities. Yet, the main pattern of results is preserved.

Having verified that the results are robust to the use of alternative dependent variables in (23), I will keep the original definition of $DPOS_n$ in the remaining sensitivity tests, which aim to check whether the main findings are robust to the use of different proxies for skills and to the inclusion of controls for other occupational characteristics. Panel d) uses a dummy equal to 1 for the occupations defined as high skilled by the *skill classification based on BLS*, while Panel e) uses the *share of college graduate+*. In

[59] I have used the `rreg` routine in Stata 10.0. OLS produce similar, although less precise results.

both cases, the proxies for skills are positive and very precisely estimated, suggesting that the previous evidence is not driven by the way I measure the skill content of the occupations. Panel f) includes instead controls for other occupational characteristics, namely the *non-routine cognitive* and *routine manual* indices, the log wage of each occupation and a full set of major group dummies.[60] As shown before, the indices of non-routine cognitive and of routine manual tasks are highly correlated with the tradability characteristics and the skill level of the occupations, and previous studies have suggested that these job attributes may independently affect the offshoring strategies of firms;[61] the occupation wage may be an additional determinant of offshoring, because firms may prefer to hire foreign workers in occupations with high wage differentials relative to the U.S. (Bardhan and Kroll, 2003); finally, the major group dummies control for any other unobserved occupational attributes that are constant across similar jobs. While all variables have the expected sign (positive for *non-routine cognitive*, negative for *routine manual* and the occupation wage), their marginal effects are often insignificant. Instead, the skill dummies and the indices of tradability characteristics behave similarly to the previous specifications.[62]

Next, I check the robustness of the findings with respect to the use of an alternative definition of tradability. I construct a dummy equal to 1 for the tradable occupations of the BLS, and include it in equation (23) together with the skill indicators. Results are reported in column (1) of Table 12. Reassuringly, the marginal effect of the BLS tradable dummy is negative and precisely estimated, while the results for the skilled dummies are essentially unaffected. A very similar picture emerges from column (2), which includes the full set of controls for other occupational characteristics. Hence, the previous findings are not driven by the way I measure tradability. The remaining columns of Table 12 include the BLS tradable dummy together with the indices of tradability characteristics. Interestingly, the marginal effects of the latter are remarkably close to those reported in Panel f) of Table 11; instead, the marginal effect of the BLS tradable dummy almost halves and is no longer precisely estimated. This probably

[60] I define four dummies for whether the occupation belongs to one of the following groups: 1) "management occupations", "business and financial operations occupations"; 2) "architecture and engineering occupations", "legal occupations"; 3) "computer and mathematical occupations", "life, physical and social science occupations"; 4) "sales and related occupations", "office and administrative support occupations". I use the last group as the omitted category. I have also experimented with dummies for the 2-digit SOC groups: results are consistent with those reported in Panel f), but the marginal effects are less precisely estimated.

[61] For instance, Becker et al. (2007) find that offshoring is associated with a rise in the content of non-routine tasks performed by domestic plants in Germany.

[62] Results in column (3) are from a Linear Probability Model, because in that specification some of the major group dummies are perfect predictors of the labor demand elasticities.

suggests that the three characteristics considered in this paper are the most important for determining tradability, so that, once they are accounted for, the other characteristics loose relevance.

Finally, in Table 13 I cross-classify the occupations by skill and tradability group. For instance, I define as "high skilled non-tradable" the occupations belonging to the high skilled group and having *tradability index* below the median. Following this definition, I construct six skill-tradability dummies and then regress $DPOS_n$ on four of them, using the entire low skill group as the omitted category: the parameters will thus measure the difference in the probability of a positive elasticity with respect to the low skilled occupations. Column (1) reports results from a baseline model, while column (2) includes the controls for other occupational characteristics; results are consistent across the two models, although the point estimates are somewhat lower in column (2). Interestingly, the coefficients of the skill dummies obtained from the previous specifications (see, in particular, column (1) of Table 10) are roughly in between those reported in Table 13. This confirms that the average effects of skills mask substantial heterogeneity between more and less tradable occupations.

To sum up, the previous findings suggest that differences in skills and tradability characteristics across occupations are important to understand the effects of service offshoring on white-collar employment. The next section reports evidence on how service offshoring may have changed the composition of white-collar employment over the last decade.

6.4 Counterfactual Experiment

I use the baseline elasticities reported in Table 7 to simulate a counterfactual world in which service offshoring has remained constant at the 1997 level, while the other explanatory variables have evolved regularly. I compute the employment share of each skill-tradability group under that scenario and subtract it from the actual share. A positive number will thus measure the contribution of service offshoring in shifting the composition of employment towards that group.

The main results are reported in the upper part of Table 14, which uses the skill classification based on PUMS. Starting from column (1), the employment share of high skilled occupations has risen by 0.35 percentage points with service offshoring; by contrast, the shares of medium and low skilled occupations have respectively declined by 0.33 and 0.02 percentage points. In terms of absolute changes (unreported), high skilled employment has increased by 2.11 percent, while medium and low skilled employment have fallen by 2.84 and 0.75 percent, respectively; overall, total white-collar employment has declined by 0.72 percent.[63] Although not large, these numbers confirm that service offshoring is skill-biased. This is consistent with anecdotal evidence reported, among others, by Bhagwati et al. (2004), who suggest that in recent years U.S. firms have increasingly focused on high skill-intensive service activities and offshored the others. Notice, however, that this result pertains only to white-collar employment, as this paper does not analyze the implications of service offshoring for the white- to blue-collar employment ratio: because total white-collar employment has declined with service offshoring, that ratio may have declined as well.[64]

I now decompose the overall changes in the employment shares of the three skill groups across occupations with stronger and weaker tradability characteristics. As before, I use the median value of the *tradability index* to divide the occupations into two groups, defined as tradable and non-tradable for brevity. Results are reported in column (2) and (3) of Table 14. Notice that the overall changes discussed before mask a modification in the composition of employment against the tradable occupations and in favor of the non-tradable occupations, which is particularly clear in the medium and low skilled groups.

The bottom part of Table 14 re-runs the experiment with the *skill classification based on BLS*. Using a different aggregation of occupations does not alter the main findings: the high skilled share of white-collar employment has in fact increased with service offshoring, while in each skill group the composition of employment has changed against the occupations with stronger tradability characteristics, and in favor of those with less pronounced tradability attributes.

7 Discussion

I now discuss some of the implications of these results. 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 the developed countries. Indeed, *on average*, white-collar workers are employed in jobs that require high levels of education and pay high wages.

[63] I caution that these numbers should only be taken as suggestive. The simulation exercise is based on the assumption that the labor demand elasticities are constant along the growth path of service offshoring; in the translog case, instead, the elasticities measure local effects, so that such an assumption may be too restrictive.

[64] In a recent paper on the U.K., Geishecker and Gorg (2008) report additional evidence that service offshoring is skill-biased, by showing that it reduces the real wages of low and medium skilled workers and boosts those of high skilled employees.

Needless to say, however, there is a lot of heterogeneity among the white-collar workers, because some of them are very highly educated, while some others less. This paper suggests that service offshoring lowers employment in the least skilled occupations, while actually boosting it in the most skilled. Overall, this evidence seems at odds with the above concern.

The paper also shows, however, that the employment responses to service offshoring differ markedly across occupations with the same skill level, but different tradability characteristics. Consistent with Blinder (2006), this suggests that service offshoring will affect not only the level, but also the composition of educational demand. Along with a generic stimulus to acquire further education, service offshoring is likely to bring about a shift in educational demand towards the programs and degrees that allow workers to qualify for less tradable jobs.[65]

Another important message of the above results is that the traditional classifications of labor into skill groups should be combined with information on the tradability characteristics of the occupations, in order to capture the complex effects of service offshoring. This is true for both empirical and theoretical studies. So far, theoretical contributions have generally kept the two dimensions separate. A first set of models have adopted traditional definitions of skills, but given less weight to differences in tradability attributes across occupations (Bhagwati et al., 2004; Deardorff, 2005; Markusen, 2005). A second set of models have instead stressed the role of tradability characteristics, but given less weight to differences in skill levels (Grossman and Rossi-Hansberg, 2008). The former literature suggests that developed countries will increasingly specialize in high skill-intensive activities, as service offshoring rises.[66] The latter literature predicts instead that non-tradable activities will be retained domestically and will complement with more tradable jobs relocated 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, 2008).

[65] This is consistent with the recent "convexification" of the U.S. wage profile, characterized by growing inequality between the top and the middle of the wage distribution, and declining inequality between the middle and the bottom of the wage distribution (Lemieux, 2007). Binelli (2008) has in fact shown that the "convexification" may result from an increased demand for skills that raises the incentives to invest in education, provided that higher and intermediate education are complementary and that the supply of intermediate education increases more than the supply of higher education. She has also provided evidence of a similar convexification in a number of Latin American countries.

[66] See also Trefler (2005a,b) on this point.

8 Conclusion and Lines for Further Research

In this paper, I have studied the effects of service offshoring on white-collar employment. I have first derived and estimated the labor demand elasticity with respect to service offshoring for a large number of U.S. white-collar occupations, and then related these elasticities to proxies for the skill level and the tradability characteristics of each occupation. I found evidence that service offshoring is skill-biased, but also that, at given skill level, it penalizes tradable occupations and benefits non-tradable occupations.

These results raise a number of questions, which may represent promising avenues for future research. First: Are these findings consistent with the recent experience of other developed countries? Service offshoring has been growing rapidly also in Western Europe; because the European labor market differs from the U.S., the employment responses to service offshoring may not be the same on the two sides of the Atlantic. Second: What is the long-run relationship between service offshoring and white-collar employment? In the long-run, service offshoring may affect firm efficiency, influence the level of domestic investment, impact on the scale of operations, and indirectly lead firms to modify their employment decisions. These effects may strengthen the short-run evidence discussed in this paper, for instance because capital complements with more skilled labor (Griliches, 1969) and scale may be skill-biased (Epifani and Gancia, 2006). Finally: What are the effects of service offshoring on individual workers? 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). These issues cannot be studied with industry-level data, but the increasing availability of matched employer-employee data sets should make this line of research practicable soon.

9 Appendix

9.1 Proofs

9.1.1 Lemma 1

Assume that the firm technology is of the form (5) and (6). By separability, total costs can be minimized in two stages. In the first stage, firms only look at the wages of the minor occupations in each major group and choose the employment mix that yields, for any level of employment, the minimum expenditure in that group. Formally,

$$E^i = E(w_1^i, ..., w_N^i, L^i, \mathbf{z'}) = \min_{L_1^i,...,L_N^i} [\sum_n w_n^i L_n^i \quad \text{s.t.} \quad L^i = L(L_1^i, ..., L_N^i, \mathbf{z'})], \tag{24}$$

where E^i denotes expenditure in major group i. The linear homogeneity of L^i implies that $E^i = L^i \cdot w^i$, where $w^i = w(w_1^i, ..., w_N^i, \mathbf{z'})$ is a linearly homogeneous wage aggregator measuring unitary expenditure in major group i. Once the first stage has been solved, firms choose the employment of each major group and the amount of the non-labor inputs that minimize total costs for any level of output:

$$\begin{aligned} C_{SR}(w^1, ..., w^i, ..., w^I, \mathbf{p'}, y, \mathbf{z'}) &= \min_{L^1,...,L^I,\boldsymbol{\delta'}} [\sum_i E^i + \mathbf{p'}\boldsymbol{\delta} \quad \text{s.t.} \quad y = f(L^1, ..., L^i, ..., L^I, \boldsymbol{\delta'}, \mathbf{z'})] = \\ &= \min_{L^1,...,L^I,\boldsymbol{\delta'}} [\sum_i L^i \cdot w^i + \mathbf{p'}\boldsymbol{\delta} \quad \text{s.t.} \quad y = f(L^1, ..., L^i, ..., L^I, \boldsymbol{\delta'}, \mathbf{z'})]. \end{aligned} \tag{25}$$

Hence, the dual representation of (5) and (6) is the short-run cost function in (7) and (8).

Using (24) into (25) yields:

$$\begin{aligned} C_{SR}(w^1, ..., w^i, ..., w^I, \mathbf{p'}, y, \mathbf{z'}) &= \min_{L_1^1,...,L_N^I,\boldsymbol{\delta'}} [\sum_i \sum_n w_n^i L_n^i + \mathbf{p'}\boldsymbol{\delta} \quad \text{s.t.} \quad y = f\left(L_1^1, ..., L_n^i, ..., L_N^I, \boldsymbol{\delta'}, \mathbf{z'}\right)] = \\ &= C_{SR}(w_1^1, ..., w_n^i, ..., w_N^I, \mathbf{p'}, y, \mathbf{z'}). \end{aligned}$$

Hence, the cost function in (7) and (8) is equivalent to a cost function obtained by minimizing total costs in one single stage. This implies that the labor demand functions derived in two stages coincide with those derived in one stage, and therefore that TSO conditioned upon $\mathbf{z}$ is consistent.

9.1.2 Lemma 2

The Tornqvist-Theil index for the wages of the minor occupations in major group i is:

$$\ln w_{jt}^i - \ln w_{j0}^i = \sum_n 0.5(sh_{n,j0}^i + sh_{n,jt}^i)(\ln w_{n,jt}^i + \ln w_{n,j0}^i), \tag{26}$$

where the subscript 0 indicates the base year of normalization (2000), in which all wages are set up to 1. This normalization implies that $\ln w_{j0}^i = \ln w_{n,j0}^i = 0$; moreover, from equation (13) it also implies that

$sh^i_{n,j0} = \beta_n + \sum_{u=1}^{U} \beta_{nu} z^u_{jt}$. Substituting back into equation (26) yields:

$$\ln w^i_{jt} = \sum_n 0.5 \left(\beta_n + \sum_{u=1}^{U} \beta_{nu} z^u_{jt} + sh^i_{n,jt} \right) \ln w^i_{n,jt}. \tag{27}$$

Substituting equation (13) into equation (27) yields

$$\ln w^i_{jt} = \sum_n 0.5 \left(\beta_n + \sum_{u=1}^{U} \beta_{nu} z^u_{jt} + \beta_n + \sum_{m=1}^{M} \beta_{nm} \ln w^i_{m,jt} + \sum_{u=1}^{U} \beta_{nu} z^u_{jt} \right) \ln w^i_{n,jt};$$

finally, rearranging terms gives

$$\ln w^i_{jt} = \sum_{n=1}^{N} \beta_n \ln w^i_{n,jt} + \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{M} \beta_{nm} \ln w^i_{n,jt} \ln w^i_{m,jt} + \sum_{n=1}^{N} \sum_{u=1}^{U} \beta_{nu} \ln w^i_{n,jt} z^u_{jt}.$$

Hence, in the presence of shift-factors and quasi-fixed inputs, equation (12) corresponds to the Tornqvist-Theil index for the wages of the minor occupations in each major group.

References

[1] Amemiya, T., 1974, "Multivariate Regression and Simultaneous Equation Models when the Dependent Variables are Truncated Normal," *Econometrica*, 42(6), pp. 999-1012

[2] Amiti, M. and S.J. Wei, 2005, "Fear of Service Outsourcing: Is It Justified?," *Economic Policy*, 20(42), pp. 308-347

[3] Amiti, M. and S.J. Wei, 2006a, "Service Offshoring and Productivity: Evidence from the United States," *NBER Working Paper 11926*

[4] Amiti, M. and S.J. Wei, 2006b, "Service Offshoring, Productivity and Employment: Evidence from the U.S.," *CEPR Working Paper 5475*

[5] Antras, P., L. Garicano and E. Rossi-Hansberg, 2006, "Offshoring in a Knowledge Economy," *The Quarterly Journal of Economics*, 121(1), pp. 31-77

[6] Antras, P., L. Garicano and E. Rossi-Hansberg, 2008, "Organizing Offshoring: Middle Managers and Communication Costs," in E. Helpman, D. Marin and T. Verdier, eds., *The Organization of Firms in a Global Economy*, Cambridge, MA: Harvard University Press

[7] Autor, D., F. Levy and R. Murname, 2003, "The Skill Content of Recent Technological Change: An Empirical Exploration”, *The Quarterly Journal of Economics*, 118(4), pp. 1279-1333

[8] Autor, D., L.F. Katz and M.S. Kearney, 2008, "Trends in U.S. Wage Inequality: Re-Assessing the Revisionists," *The Review of Economics and Statistics*, 90(2), pp. 300-323

[9] Baily, M.N. and D. Farrell, 2004, “Exploding the Myths of Offshoring,” *McKinsey Quarterly*, April 2004

[10] Baily, M.N. and R.Z. Lawrence, 2004, "What Happened to the Great U.S. Job Machine? The Role of Trade and Electronic Offshoring," *Brookings Papers on Economic Activity*, 2004(2), pp. 211-270

[11] Baldwin, R. and F. Robert-Nicoud, 2007, "Offshoring: General Equilibrium Effects on Wages, Production and Trade," *NBER Working Paper 12991*

[12] Bardhan, A.D. and C. Kroll, 2003, "The New Wave of Outsourcing," *Fisher Center for Real Estate and Urban Economics, Working Paper 1103*

[13] Bartelsman, E.J. and W. Gray, 1996, "The NBER Manufacturing Productivity Database," *NBER Technical Working Paper 205*

[14] Becker, S.O., K. Ekholm and M. Muendler, 2007, "Offshoring and the Onshore Composition of Occupations, Tasks and Skills," *Mimeo*

[15] Becker, S.O. and M. Muendler, 2006, "Margins of Multinational Labor Substitution," *UCSD Department of Economics, Discussion Paper 2006-04*

[16] Berman, E., J. Bound and Z. Griliches, 1994, "Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures," *The Quarterly Journal of Economics*, 109(2), pp. 367-397

[17] Berndt, E.R. and L.R. Christensen, 1973, "The Internal Structure of Functional Relationships: Separability, Substitution, and Aggregation, *The Review of Economic Studies,* 40(3), pp. 403-410

[18] Berndt, E.R. and L.R. Christensen, 1974, "Testing for the Existence of a Consistent Aggregate Index of Labor Inputs," *The American Economic Review*, 64(3), pp. 391-404

[19] Bhagwati, J., A. Panagariya and T.N. Srinivasan, 2004, "The Muddles over Outsourcing," *The Journal of Economic Perspectives*, 18(4), pp. 93-114

[20] Bieri, J. and A. de Janvri, 1972, "Empirical Analysis of Demand Under Consumer Budgeting," *Monograph 30*, Giannini Foundation, University of California Berkeley

[21] Binelli, C., 2008, "Wage Inequality and Education Choices in Latin America: A General Equilibrium Approach," *Mimeo*

[22] Blackorby, C., D. Primont and R.R. Russell, 1977, "On Testing Separability Restrictions with Flexible Functional Forms," *Journal of Econometrics*, 5(2), pp. 195-209

[23] Blackorby, C., D. Primont and R.R. Russell, 1978, *Duality, Separability and Functional Structure: Theory and Economic Applications*, New York: Elsevier/North Holland

[24] Blinder, A.S., 2006, "Offshoring: The Next Industrial Revolution?," *Foreign Affairs*, March/April 2006, pp. 113-128

[25] Blinder, A.S., 2007, "How Many U.S. Jobs Might Be Offshorable?," *CEPS Working Paper 142*

[26] Bousquet, A. and N. Ladoux, 2006, "Flexible versus Designated Technologies and Interfuel Substitution," *Energy Economics*, 28(4), pp. 426-443

[27] Campa, J. and L.S. Goldberg, 1997, "The Evolving External Orientation of Manufacturing Industries: Evidence from Four Countries," *Federal Reserve Bank of New York - Economic Policy Review*, 3(2), pp. 53-81

[28] Chakir, R., A. Bousquet and N. Ladoux, 2004, "Modeling Corner Solutions with Panel Data: Application to the Industrial Energy Demand in France," *Empirical Economics*, 29(1), pp. 193-208

[29] Chamberlain, G., 1980, "Panel Data," in Z. Griliches and M. Intriligator, eds., *Handbook of Econometrics*, vol. 2, pp. 1247-1318, Amsterdam: North-Holland

[30] Chamberlain, G., 1982, "Multivariate Regression Models for Panel Data," *Journal of Econometrics*, 18(1), pp. 5-46

[31] Crinò, R., 2007a, "Service Offshoring and White-Collar Employment," *CESifo Working Paper 2040*

[32] Crinò, R. 2007b, "Skill-Biased Effects of Service Offshoring in Western Europe," *CESPRI Working Paper 205*

[33] Crinò, R., 2008a, "Offshoring, Multinationals and Labour Market: A Review of the Empirical Literature," *Journal of Economic Surveys*, forthcoming

[34] Crinò, R., 2008b, "Service Offshoring and Productivity in Western Europe," *CESPRI Working Paper 220*

[35] Deardorff, A.V., 2005, "A Trade Theorist's Take on Skilled-Labor Outsourcing," *International Review of Economics and Finance*, 14(3), pp. 259-271

[36] Denny, M. and M. Fuss, 1977, "The Use of Approximation Analysis to Test for Separability and the Existence of Consistent Aggregates," *The American Economic Review,* 67(3), pp. 404-418

[37] Denny, M., M. Fuss and L. Waverman, 1982, "Substitution Possibilities for Energy: Evidence from U.S. and Canadian Manufacturing Industries," in E. R. Berndt and B. C. Field, eds., *Modelling and Measuring Natural Resource Substitution*, Cambridge, MA: The MIT Press

[38] Diewert, W.E., 1976, "Exact and Superlative Index Numbers," *Journal of Econometrics*, 4(2), pp. 115-145

[39] Diewert, W.E. and T.J. Wales, 1995, "Flexible Functional Forms and Test of Homogeneous Separability," *Journal of Econometrics*, 67(2), pp. 259-302

[40] Edgerton, D.L., 1993, "On the Estimation of Separable Demand Models," *Journal of Agricultural and Resource Economics*, 18(2), pp. 141-146

[41] Edgerton, D.L., 1997, "Weak Separability and the Estimation of Elasticities in Multistage Demand System," *American Journal of Agricultural Economics*, 79(1), pp. 62-79

[42] Edgerton, D.L., B. Assarson, A. Hummelmose, I.P. Laurila, K. Rickertsen and P.H. Vale, 1996, *The Econometrics of Demand Systems with Applications to Food Demand in the Nordic Countries*, Dordrecht: Kluwer Academic Publishers

[43] Ekholm, K. and K. Hakkala, 2005, "The Effect of Offshoring on Labor Demand: Evidence from Sweden," *CEPR Working Paper 5648*

[44] Epifani, P. and G. Gancia, 2006, "Increasing Returns, Imperfect Competition, and Factor Prices," *The Review of Economics and Statistics*, 88(4), pp. 583-598

[45] Feenstra, R.C., 1998, "Integration of Trade and Disintegration of Production in the Global Economy," *The Journal of Economic Perspectives*, 12(4), pp. 31-50

[46] Feenstra, R.C., 2007, "Globalization and Its Impact on Labor," paper presented as the Global Economy Lecture, Vienna Institute for International Economics Studies

[47] Feenstra, R.C. and G.H. Hanson, 1996, "Globalization, Outsourcing and Wage Inequality," *The American Economic Review*, 86(2), pp. 240-245

[48] Feenstra, R.C. and G.H. Hanson, 1999, "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979-1990," *The Quarterly Journal of Economics*, 114(3), pp. 907-940

[49] Feenstra, R.C. and G.H. Hanson, 2003, "Global Production Sharing and Rising Inequality: A Survey of Trade and Wages," in K. Choi and J. Harrigan, eds., *Handbook of International Economics*, pp. 146-185, Basil Blackwell

[50] Feenstra, R.C., J. Romalis and P.K. Schott, 2002, "U.S. Imports, Exports, and Tariff Data, 1989-2001," *NBER Working Paper 9387*

[51] Freund, C. and D. Weinhold, 2002, "The Internet and International Trade in Services," *The American Economic Review, Papers and Proceedings*, 92(2), pp. 236-240

[52] Fuss, M.A., 1977, "The Demand for Energy in Canadian Manufacturing: An Example of the Estimation of Production Structures with Many Inputs," *Journal of Econometrics,* 5(1), pp. 89-116

[53] Garner, A.C., 2004, "Offshoring in the Service Sector: Economic Impact and Policy Issues," *Federal Reserve Bank of Kansas City - Economic Review*, 2004(3), pp. 5-37

[54] Geishecker, I. and H. Gorg, 2008, "Service Offshoring and Wages: Evidence from Micro Data," *IZA Discussion Paper 3593*

[55] Goos, M. and A. Manning, 2007, "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain," *The Review of Economics and Statistics*, 89(1), pp. 118-133

[56] Gorman, W.M., 1959, "Separable Utility and Aggregation," *Econometrica*, 27(3), pp. 469-481

[57] Green, H.A.J., 1964, *Aggregation in Economic Analysis: An Introductory Survey*, Princeton, New Jersey: Princeton University Press.

[58] Griliches, Z., 1969, "Capital-Skill Complementarity," *The Review of Economics and Statistics*, 51(4), pp. 465-468

[59] Grossman, G.M. and E. Rossi-Hansberg, 2008, "Trading Tasks: A Simple Theory of Offshoring," *The American Economic Review*, forthcoming

[60] Heckman, J.J., 1979, "Sample Selection Bias as a Specification Error," *Econometrica*, 47(1), pp. 153-161

[61] Hijzen, A., H. Gorg and R.C. Hine, 2005, "International Outsourcing and the Skill Structure of Labour Demand in the United Kingdom," *The Economic Journal*, 115(506), pp. 860-878

[62] Hijzen, A., M. Pisu, R. Upward and P. Wright, 2007, "Employment, Job Turnover, and the Trade in Producer Services: Firm-Level Evidence," *GEP Research Paper 2007/37*

[63] Honoré, B.E., 1992, "Trimmed Lad and Least Squares Estimation of Truncated and Censored Regression Models with Fixed Effects," *Econometrica*, 60(3), pp. 533-565

[64] Horgos, D., 2007, "Labor Market Effects of International Outsourcing: How Measurement Matters," *Helmut Schmidt University, Department of Economics, Discussion Paper 62*

[65] Hsiao, C., 2003, *Analysis of Panel Data*, Cambridge: Cambridge University Press

[66] Hummels, D., J. Ishii and K.M. Yi, 2001, "The Nature and Growth of Vertical Specialization in World Trade," *Journal of International Economics*, 54(1), pp. 75-96

[67] Hummels, D., D. Rapoport and K.M. Yi, 1998, "Vertical Specialization and the Changing Nature of World Trade," *Federal Reserve Bank of New York - Economic Policy Review*, 4(2), pp. 79-99

[68] Jacobson, L.S., R. LaLonde and D.G. Sullivan, 1993, "Earnings Losses of Displaced Workers," *The American Economic Review*, 83(4), pp. 685-709

[69] Jakubson, G., 1988, "The Sensitivity of Labor Supply Parameter Estimates to Unobserved Individual Effects: Fixed and Random Effects Estimates in a Nonlinear Model Using Panel Data," *Journal of Labor Economics*, 6(3), pp. 302-329

[70] Jensen, B.J. and L. Kletzer, 2005, "Tradeable Services: Understanding the Scope and Impact of Services Offshoring," in L. Brainard and S.M. Collins, eds., *Offshoring White-Collar Work - The Issues and the Implications,* pp. 73-133, Washington, D.C.: Brookings Trade Forum 2005

[71] Jensen, B.J. and L. Kletzer, 2008, "Measuring Tradeable Services and the Task Content of Offshorable Services Jobs," in K. Abraham, M. Harper and J. Spletzer, eds., *Labor in the New Economy*, Chicago: University of Chicago Press

[72] Kambourov, G. and I. Manovskii, 2008a, "Occupational Mobility and Wage Inequality," *The Review of Economic Studies*, forthcoming

[73] Kambourov, G. and I. Manovskii, 2008b, "Rising Occupational and Industrial Mobility in the United States: 1968-97," *International Economic Review*, 49(1), pp. 41-79

[74] Kirkegaard, J.F., 2004, "Outsourcing - Stains on the White-Collar?," *Mimeo*

[75] Kletzer, L.G., 1998, "Job Displacement," *The Journal of Economic Perspectives*, 12(1), pp. 115-136

[76] Koebel, B.M., 2002, "Can Aggregation across Goods Be Achieved by Neglecting the Problem? Property Inheritance and Aggregation Bias," *International Economic Review*, 43(1), pp. 223-255

[77] Koebel, B.M., 2006, "Exports and Labor Demand: Searching for Functional Structure in Multi-Output Multi-Skill Technologies," *Journal of Business and Economic Statistics*, 24(1), pp. 91-103

[78] Kroll, C.A., 2005, "State and Metropolitan Area Impacts of the Offshore Outsourcing of Business Services and IT," *Fisher Center for Real Estate and Urban Economics, Working Paper 293*

[79] La France, J.T., 1991, "When is Expenditure 'Exogenous' in Separable Demand Models," *Western Journal of Agricultural Economics*, 16(1), pp. 49-62

[80] Lee, L.F. and M.M. Pitt, 1986, "Microeconometric Demand Systems with Binding Nonnegativity Constraints: The Dual Approach," *Econometrica*, 54(5), pp. 1237-1242

[81] Lemieux, T., 2007, "The Changing Nature of Wage Inequality," *NBER Working Paper 13523*

[82] Levy, F. and R. Murname, 2006, "How Computerized Work and Globalization Shape Human Skill Demands," *Mimeo*

[83] Lipsey, R.E., 2006, "Measuring International Trade in Services," *NBER Working Paper 12271*

[84] Liu, R. and D. Trefler, 2008, "Much Ado About Nothing: American Jobs and the Rise of Service Outsourcing to China and India," *NBER Working Paper 14061*

[85] Mankiw, G.N. and P. Swagel, 2006, "The Politics and Economics of Offshore Outsourcing," *Journal of Monetary Economics*, 53(5), pp. 1027-1056

[86] Mann, C.L., 2003, "Globalization of IT Services and White-Collar Jobs: The Next Wave of Productivity Growth," *Peterson Institute for International Economics, Policy Brief 03-11*

[87] Markusen, J., 2005, "Modeling the Offshoring of White-Collar Services: From Comparative Advantage to the New Theories of Trade and FDI," in L. Brainard and S.M. Collins, eds., *Offshoring White-Collar Work - The Issues and the Implications,* pp. 1-34, Washington, D.C.: Brookings Trade Forum 2005

[88] Markusen, J. and B. Strand, 2008, "Trade in Business Services in General Equilibrium," *CEPR Working Paper 6080*

[89] Meyerhoefer, C.D., 2002, "The Econometrics of Non-Standard Structural Demand Modelling: Applications to Transition Country Data," *Ph.D. Dissertation*, Cornell University

[90] Meyerhoefer, C.D., C.K. Ranney and D.E. Sahn, 2005, "Consistent Estimation of Censored Demand Systems Using Panel Data," *American Journal of Agricultural Economics*, 87(3), pp. 660-672

[91] Morrison, C. and D. Siegel, 2001, "The Impacts of Technology, Trade and Outsourcing on Employment and Labor Composition," *The Scandinavian Journal of Economics*, 103(2), pp. 241-264

[92] Moschini, G., 1992, "A Non-Nested Test of Separability for Flexible Functional Forms," *The Review of Economics and Statistics*, 74(2), pp. 365-369

[93] Mundlak, Y., 1978, "On the Pooling of Time Series and Cross-Section Data," *Econometrica*, 46(1), pp. 69-85

[94] Neyman, J. and E.L. Scott, 1948, "Consistent Estimates Based on Partially Consistent Observations," *Econometrica*, 16(1), pp. 1-32

[95] Oecd, 2007, *Offshoring and Employment: Trends and Impacts*, Paris and Washington, D.C.: OECD

[96] Olsen, K.B., 2006, "Productivity Impacts of Offshoring and Outsourcing: A Review," *OECD Directorate for Science, Technology and Industry, Working Paper 2006/1*

[97] Poletaev, M. and C. Robinson, 2008, "Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000," *Journal of Labor Economics*, 26(3), pp. 387-420

[98] Rodriguez Clare, A., 2007, "Offshoring in a Ricardian World," *NBER Working Paper 13203*

[99] Ruggles, S., M. Sobek, T. Alexander, C.A. Fitch, R. Goeken, P.K. Hall, M. King and C. Ronnander, 2008, *Integrated Public Use Microdata Series: Version 4.0* [Machine-readable database], Minneapolis, MN: Minnesota Population Center [producer and distributor]. Available at: http://usa.ipums.org/usa/

[100] Samuelson, P.A., 2004, "Where Ricardo and Mill Rebut and Confirm Arguments of Mainstream Economists Supporting Globalization," *The Journal of Economic Perspectives*, 18(3), pp. 135-146

[101] Spitz-Oener, A., 2006, "Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure," *Journal of Labor Economics*, 24(2), pp. 235-270

[102] Trefler, D., 2005a, "Offshoring: Threats and Opportunities," in L. Brainard and S.M. Collins, eds., *Offshoring White-Collar Work - The Issues and the Implications,* pp. 35-73, Washington, D.C.: Brookings Trade Forum 2005

[103] Trefler, D., 2005b, "Policy Responses to the New Offshoring: Think Globally, Invest Locally," paper prepared for Industry Canada's Roundtable on Offshoring, March 30, 2005

[104] Unctad, 2004a, "Service Offshoring Takes Off in Europe: In Search of Improved Competitiveness," New York and Geneva: United Nations

[105] Unctad, 2004b, *World Investment Report: The Shift Towards Services*, New York and Geneva: United Nations

[106] Van Welsum, D. and G. Vickery, 2005, "Potential Off-Shoring of ICT-Intensive Occupations," in *Enhancing the Performance of the Services Sector*, pp. 187-213, Paris and Washington, D.C.: OECD

[107] Wales, T.J. and A.D. Woodland, 1983, "Estimation of Consumer Demand Systems with Binding Non-Negativity Constraints," *Journal of Econometrics*, 21(3), pp. 263-285

[108] Weiss, R.D., 1977, "Elasticities of Substitution among Capital and Occupations in U.S. Manufacturing," *Journal of the American Statistical Association,* 72(360), pp. 764-771

[109] White, H., 1982, "Maximum Likelihood Estimation of Misspecified Models," *Econometrica*, 50(1), pp. 1-25

[110] Woodland, A.D., 1978, "On Testing Weak Separability," *Journal of Econometrics,* 8(3), pp. 383-398

[111] Woodland, A.D., 1993, "A Micro-Econometric Analysis of the Industrial Demand for Energy in NSW," *Energy Journal*, 14(2), pp. 57-89

[112] Wooldridge, J.M., 2002, *Econometric Analysis of Cross-Section and Panel Data*, Cambridge, MA: MIT Press

[113] Yen, S.T. and B.H. Lin, 2006, "A Sample Selection Approach to Censored Demand Systems," *American Journal of Agricultural Economics*, 88(3), pp. 742-749

Table 1 - Indices of Tradability and Other Occupational Characteristics

	a) Averages by BLS tradability group		*b) Averages by skill group*		
	Tradable	Non-tradable	High	Medium	Low
Tradability index	0.689	-0.110	0.615	-0.051	-0.428
Routine cognitive 1	0.409	-0.065	0.696	-0.132	-0.434
Routine cognitive 2	1.000	0.703	0.875	0.333	0.842
Routine cognitive 3	0.316	-0.051	0.653	-0.054	-0.454
Interaction with PCs	0.714	-0.114	0.340	0.177	-0.373
Face-to-face 1	-0.662	0.106	-0.504	-0.076	0.429
Face-to-face 2	-0.873	0.140	-0.564	0.282	0.235
Face-to-face 3	-0.801	0.128	0.018	-0.114	0.062
Non-routine cognitive	-0.413	0.066	0.655	0.216	-0.635
Routine manual	0.070	-0.011	-0.314	-0.138	0.328

Panel a) reports average values of the indices for the groups of tradable and non-tradable occupations identified by the BLS. Panel b) reports averages by skill group: high skilled occupations require at least a bachelor's degree, medium skilled occupations an associate degree in college, low skilled occupations lower degrees of schooling; the skill classification is based on PUMS (see the first column of Appendix Table A3). All indices except *routine cognitive 2* have mean 0 and standard deviation 1, and are normalized so that higher values indicate higher levels of the corresponding characteristic; *routine cognitive 2* is a dummy equal to 1 if the occupation requires to attain set limits, tolerances and standards. See Appendix Tables A4 and A5 for details.

Table 2 - Employment Changes, 1997-2006

Minor occupation(SOC code)	#	%
Total white-collar employment	***-615,327***	***-2.5***
High skilled	***520,169***	***24.6***
Lawyers(230000)	79,742	24.2
Petroleum engineers(172171)	388	19.5
Life scientists(191000)	34,135	77.1
Physical scientists(192000)	43,698	51.2
Materials engineers(172131)	2,631	19.1
Sales engineers(419031)	-12,522	-17.6
Computer hardw engin(172061)	-177,027	-77.7
Accountants and auditors(132011)	122,502	20.8
MKT and survey researchers(193020)	131,586	431.6
Management analysts(131111)	242,831	445.9
Engineering managers(119041)	-93,881	-39.6
Mining and geolog engin(172151)	690	58.0
Industrial engineers(172110)	67,029	57.8
Aerospace engineers(172011)	40,105	116.6
Mechanical engineers(172141)	-1,837	-1.0
Marine engineers(172121)	1,430	60.3
Civil engineers(172051)	39,972	43.0
Agricultural engineers(172021)	-1,303	-46.0
Medium skilled	***-1,399,756***	***-30.1***
Medic and health serv manag(119111)	7,556	159.1
Chief executives(111011)	-1,071,645	-50.3
Budget analysts(132031)	-3,631	-16.6
Purchasing managers(113061)	-99,326	-66.8
Administr serv manag(113011)	-81,932	-48.4
Construction managers(119021)	-5,771	-24.6
Database administrators(151061)	3,461	6.2
Computer system analysts(151051)	-44,545	-13.1
Computer support specialists(151041)	-23,687	-8.0
Computer programmers(151021)	-133,098	-32.7
Human resources manag(113040)	-52,737	-42.8
Adv, MKTG, prom, PR and sales manag(112000)	87,180	27.9
Compliance officers(131041)	41,924	386.4
Hum resources, training and lab rel spec(131070)	49,044	34.2
Advert sales agents(413011)	27,079	71.3
Financial managers(113031)	-99,628	-23.3

Minor occupation(SOC code)	#	%
Low skilled	***264,260***	***1.5***
Cost estimators(131051)	-537	-0.9
Life, phys and soc scien technicians(194000)	-17,337	-13.5
Buyers and purch agents(131020)	48,458	19.0
Exec secretaries and admin assistants(436011)	318,495	34.1
Sales representatives(414010)	346,843	26.4
Statistical assistants(439111)	-9,610	-63.8
Drafters(173010)	-31,988	-15.7
Engineering technicians(173020)	-217,977	-42.6
First line superv of off and admin workers(431011)	-211,293	-25.0
Indust prod manag(113051)	-66,007	-32.3
Prop, real est, and comm assoc manag(119141)	-11,930	-8.7
Order, receptionists and record clerks(434100)	-184,945	-25.4
Other off and admin support workers(439000)	-297,015	-16.3
Demonstrat and prod promoters(419011)	-9,685	-13.4
Financial clerks(433000)	91,218	6.6
Retail salespers(412031)	368,055	9.6
Transp, stor, and distrib, manag(113071)	7,818	26.7
Parts salespers(412022)	-60,892	-21.7
Info and record clerks(434000)	-192,705	-57.2
Switchboard operators(432011)	-42,071	-44.3
Telemarketers(419041)	-199,052	-64.2
Mat record, sched, dispatch workers(435000)	489,724	27.9
Weighers, measurers, checkers(435111)	7,423	20.6
Cashiers(412011)	139,269	4.8
Tradable occupations	***-739,441***	***-13.8***
Non-tradable occupations	***124,114***	***0.6***

Major group(SOC Code)	#	%
Management occupations(110000)	-1,480,302	-37.5
Business and financial operations occupations(130000)	500,591	44.1
Computer and mathematical occupations(150000)	-197,869	-18.0
Architecture and engineering occupations(170000)	-277,887	-20.0
Life, physical, and social science occupations(190000)	192,082	66.6
Legal occupations(230000)	79,742	24.2
Sales and related occupations(410000)	599,095	6.8
Office and administrative support occupations(430000)	-30,779	-0.4

Source: Author's calculations based on the Occupational Employment Statistics. Tradable occupations are those with *tradability index* above the median.

Table 3 - Demand and Supply Shifts

Depend Variable: Log Relative Occupational Wage

	a) Baseline		*b) Conditioning on occupational supply*	
	(1)	(2)	(1)	(2)
Relative occupational employment	0.018*	0.019**	0.021*	0.026**
	[0.009]	[0.009]	[0.012]	[0.012]
Proxy for occupational supply			-0.004	-0.001
			[0.003]	[0.003]
Time dummies	NO	YES	NO	YES
Obs.	512	512	352	352

	c) Estimates by skill group			*d) Estimates by tradability group*	
	High	Medium	Low	Tradable	Non-tradable
Relative occupational employment	0.040	0.037*	0.028*	0.039*	0.020
	[0.057]	[0.019]	[0.017]	[0.021]	[0.014]
Proxy for occupational supply	-0.000	-0.003	-0.010**	-0.000	-0.000
	[0.005]	[0.005]	[0.004]	[0.005]	[0.004]
Time dummies	YES	YES	YES	YES	YES
Obs.	127	97	128	194	158

OLS regressions with robust standard errors in brackets. ***, **, *: significant at 1, 5 and 10 percent level, respectively. *Relative occupational employment* is the occupation share of total white-collar employment. *Proxy for occupational supply* is the number of completion rates in post-secondary degrees in each occupation, relative to the total across all white-collar occupations. Tradable and non-tradable occupations are defined as in Table 2. All variables are in first-differences.

Table 4 - Labor Demand Elasticities with Respect to Service Offshoring: Log-Linear Estimates for the Minor Occupations

Dependent Variable: Log Employment in Each Minor Occupation

Minor occupation(SOC code)	*a) Baseline*		*b) Using linear and quadratic time trends - No time dummies*		*c) Excluding occupation wage*		*d) Controlling for energy prices*	
	Elast.	Std. Err.	Elast.	Std. Err.	Elast.	Std. Err.	Elast.	Std. Err.
High skilled								
Lawyers(230000)	0.068	0.036 *	0.062	0.035	0.068	0.036 *	0.068	0.037 *
Petroleum engineers(172171)	-0.021	0.004 ***	-0.020	0.003 ***	-0.027	0.008 **	-0.020	0.001 ***
Life scientists(191000)	0.133	0.067 *	0.130	0.065 *	0.123	0.077	0.140	0.064 *
Physical scientists(192000)	0.254	0.022 ***	0.251	0.022 ***	0.254	0.022 ***	0.256	0.022 ***
Materials engineers(172131)	-0.028	0.006 ***	-0.027	0.006 ***	-0.030	0.005 ***	-0.028	0.006 ***
Sales engineers(419031)	-0.038	0.003 ***	-0.038	0.003 ***	-0.043	0.003 ***	-0.038	0.003 ***
Computer hardw engin(172061)	-0.035	0.005 ***	-0.034	0.005 ***	-0.036	0.006 ***	-0.035	0.005 ***
Accountants and auditors(132011)	0.045	0.010 ***	0.045	0.010 ***	0.044	0.010 ***	0.045	0.010 ***
MKT and survey researchers(193020)	0.003	0.003	0.002	0.003	0.003	0.003	0.002	0.003
Management analysts(131111)	0.003	0.003	0.002	0.003	0.003	0.003	0.002	0.003
Engineering managers(119041)	-0.041	0.002 ***	-0.042	0.002 ***	-0.042	0.002 ***	-0.042	0.002 ***
Mining and geolog engin(172151)	0.090	0.094	-0.068	0.121	0.182	0.098	0.121	0.228
Industrial engineers(172110)	0.007	0.061	0.011	0.056	0.007	0.061	0.000	0.063
Aerospace engineers(172011)	0.142	0.015 ***	0.133	0.013 ***	0.141	0.018 ***	0.121	0.018 ***
Mechanical engineers(172141)	-0.058	0.002 ***	-0.058	0.002 ***	-0.060	0.002 ***	-0.058	0.002 ***
Marine engineers(172121)	0.027	0.067	0.105	0.106	0.093	0.015 ***	0.084	0.134
Civil engineers(172051)	-0.073	0.005 ***	-0.074	0.005 ***	-0.071	0.004 ***	-0.073	0.005 ***
Agricultural engineers(172021)	-0.114	0.134	-0.116	0.138	-0.119	0.133	-0.255	0.186
Medium skilled								
Medic and health serv manag(119111)	-0.009	0.001 ***	-0.009	0.001 ***	-0.008	0.001 ***	-0.009	0.001 ***
Chief executives(111011)	0.003	0.002	0.003	0.002	0.003	0.002	0.003	0.002
Budget analysts(132031)	-0.003	0.002	-0.003	0.002	-0.003	0.002	-0.003	0.002
Purchasing managers(113061)	-0.020	0.002 ***	-0.020	0.002 ***	-0.019	0.001 ***	-0.020	0.002 ***
Administr serv manag(113011)	0.006	0.012	0.005	0.012	0.006	0.012	0.005	0.012
Construction managers(119021)	-0.054	0.007 ***	-0.055	0.007 ***	-0.054	0.007 ***	-0.055	0.006 ***
Database administrators(151061)	-0.038	0.018 **	-0.041	0.017 **	-0.039	0.018 **	-0.040	0.018 **
Computer system analysts(151051)	-0.054	0.011 ***	-0.053	0.011 ***	-0.048	0.012 ***	-0.056	0.011 ***
Computer support specialists(151041)	-0.050	0.011 ***	-0.048	0.011 ***	-0.049	0.011 ***	-0.051	0.011 ***
Computer programmers(151021)	-0.093	0.013 ***	-0.094	0.013 ***	-0.092	0.013 ***	-0.095	0.013 ***
Human resources manag(113040)	-0.003	0.001 **	-0.003	0.001 **	-0.003	0.001 **	-0.003	0.001 ***
Adv, MKTG, prom, PR and sales manag(112000)	0.003	0.002	0.003	0.002	0.003	0.002	0.002	0.002
Compliance officers(131041)	-0.009	0.019	-0.014	0.018	-0.016	0.019	-0.006	0.019
Hum resources, training and lab rel spec(131070)	0.003	0.001 *	0.003	0.001 *	0.003	0.001 *	0.003	0.001 *
Advert sales agents(413011)	-0.029	0.010 **	-0.028	0.010 **	-0.025	0.010 **	-0.029	0.010 **
Financial managers(113031)	0.016	0.001 ***	0.015	0.001 ***	0.015	0.001 ***	0.015	0.001 ***
Low skilled								
Cost estimators(131051)	-0.026	0.003 ***	-0.025	0.003 ***	-0.026	0.003 ***	-0.026	0.003 ***
Life, phys and soc scien technicians(194000)	0.269	0.033 ***	0.270	0.033 ***	0.279	0.034 ***	0.270	0.032 ***
Buyers and purch agents(131020)	-0.009	0.002 ***	-0.009	0.002 ***	-0.009	0.002 ***	-0.009	0.002 ***
Exec secretaries and admin assistants(436011)	0.002	0.001	0.002	0.001	0.002	0.001	0.002	0.001
Sales representatives(414010)	-0.036	0.001 ***	-0.036	0.001 ***	-0.036	0.001 ***	-0.036	0.002 ***
Statistical assistants(439111)	0.012	0.003 ***	0.011	0.003 ***	0.011	0.003 ***	0.012	0.003 ***
Drafters(173010)	-0.029	0.004 ***	-0.027	0.004 ***	-0.029	0.003 ***	-0.030	0.004 ***
Engineering technicians(173020)	-0.071	0.001 ***	-0.071	0.001 ***	-0.071	0.001 ***	-0.072	0.001 ***
First line superv of off and admin workers(431011)	-0.012	0.030	-0.008	0.030	-0.013	0.031	-0.013	0.029
Indust prod manag(113051)	-0.045	0.001 ***	-0.045	0.001 ***	-0.045	0.002 ***	-0.045	0.001 ***
Prop, real est, and comm assoc manag(119141)	0.007	0.011	0.007	0.009	0.008	0.013	0.006	0.006
Order, receptionists and record clerks(434100)	-0.030	0.036	-0.025	0.036	-0.035	0.035	-0.032	0.035
Other off and admin support workers(439000)	-0.022	0.039	-0.015	0.039	-0.022	0.039	-0.024	0.038
Demonstrat and prod promoters(419011)	-0.036	0.009 ***	-0.037	0.009 ***	-0.033	0.008 ***	-0.035	0.009 ***
Financial clerks(433000)	0.005	0.002 ***	0.005	0.002 ***	0.005	0.002 ***	0.005	0.002 ***
Retail salespers(412031)	0.015	0.030	0.012	0.031	0.016	0.029	0.016	0.030
Transp, stor, and distrib, manag(113071)	-0.050	0.002 ***	-0.049	0.002 ***	-0.050	0.002 ***	-0.050	0.002 ***
Parts salespers(412022)	-0.225	0.193	-0.264	0.116 **	-0.225	0.193	-0.224	0.192
Info and record clerks(434000)	0.019	0.002 ***	0.019	0.002 ***	0.019	0.002 ***	0.019	0.002 ***
Switchboard operators(432011)	-0.007	0.034	-0.016	0.036	-0.007	0.034	-0.002	0.033
Telemarketers(419041)	0.007	0.004 *	0.006	0.004	0.007	0.004 *	0.007	0.004 *
Mat record, sched, dispatch workers(435000)	-0.025	0.031	-0.024	0.030	-0.026	0.035	-0.026	0.031
Weighers, measurers, checkers(435111)	-0.017	0.003 ***	-0.016	0.003 ***	-0.016	0.003 ***	-0.017	0.003 ***
Cashiers(412011)	0.013	0.003 ***	0.013	0.003 ***	0.014	0.004 ***	0.013	0.003 ***

OLS regressions with standard errors corrected for clustering within 2-digit industries. ***, **, *: significant at 1, 5 and 10 percent level, respectively. The baseline model also includes log occupational wage, material offshoring, proxy for technological progress, trade openness, log output, log capital, time and 2-digit industry dummies.

Table 5 - Labor Demand Elasticities with Respect to Service Offshoring: Log-Linear Estimates for the Major Groups

Dependent Variable: Log Employment in Each Major Group

Major group(SOC Code)	*a) Baseline*			*b) Using linear and quadratic time trends - No time dummies*			*c) Excluding occupation wage*			*d) Controlling for energy prices*		
	Elast.	Std. Err.		Elast.	Std. Err.		Elast.	Std. Err.		Elast.	Std. Err.	
				Using estimated industry-level service imports								
Management occupations(110000)	0.002	0.002		0.002	0.002		0.002	0.002		0.002	0.002	
Business and financial operations occupations(130000)	0.007	0.014		0.008	0.014		0.010	0.013		0.007	0.014	
Computer and mathematical occupations(150000)	-0.074	0.011	***	-0.072	0.011	***	-0.068	0.010	***	-0.073	0.011	***
Architecture and engineering occupations(170000)	0.015	0.018		0.019	0.016		0.016	0.017		0.014	0.018	
Life, physical, and social science occupations(190000)	0.124	0.017	***	0.121	0.016	***	0.123	0.017	***	0.123	0.017	***
Legal occupations(230000)	0.068	0.036	*	0.062	0.035		0.068	0.036	*	0.068	0.037	*
Sales and related occupations(410000)	-0.007	0.002	***	-0.007	0.002	***	-0.005	0.002	***	-0.007	0.002	***
Office and administrative support occupations(430000)	-0.019	0.033		-0.016	0.032		-0.021	0.034		-0.020	0.032	
				Using official industry-level service imports								
Management occupations(110000)	0.332	0.292		0.322	0.285		0.345	0.305		0.299	0.185	
Business and financial operations occupations(130000)	0.027	0.058		0.029	0.060		0.034	0.060		0.025	0.062	
Computer and mathematical occupations(150000)	-0.089	0.107		-0.069	0.098		-0.104	0.130		-0.069	0.111	
Architecture and engineering occupations(170000)	0.965	0.842		0.960	0.828		1.436	1.114		0.966	0.861	
Life, physical, and social science occupations(190000)	0.285	0.124	**	0.271	0.106	**	0.298	0.118	**	0.363	0.123	***
Legal occupations(230000)	0.010	0.096		-0.014	0.089		0.004	0.095		0.142	0.151	
Sales and related occupations(410000)	0.047	0.108		0.045	0.104		-0.073	0.023	***	0.074	0.131	
Office and administrative support occupations(430000)	-0.012	0.018		-0.012	0.020		-0.011	0.019		-0.010	0.020	

See notes to Table 4.

Table 6 - Skills, Tradability and Service Offshoring: Preliminary Evidence

	Frequency	*Tradability index*	*Routine cognitive 1*	*Routine cognitive 2*	*Routine cognitive 3*	*Interaction with PCs*	*Face-to-face 1*	*Face-to-face 2*	*Face-to-face 3*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
a)					*All minor occupations*				
Negative elast.	58.62	0.11	0.22	0.87	0.20	0.06	-0.05	-0.10	0.04
Positive elast.	41.38	-0.15	-0.32	0.62	-0.28	-0.08	0.07	0.15	-0.06
b)					*High skilled*				
Negative elast.	44.44	0.85	1.33	1.00	1.20	0.46	-0.72	-0.80	0.30
Positive elast.	55.56	0.43	0.19	0.78	0.22	0.24	-0.33	-0.38	-0.21
c)					*Medium skilled*				
Negative elast.	68.75	0.26	-0.09	0.75	-0.01	0.40	-0.30	-0.05	-0.18
Positive elast.	31.25	-0.73	-0.22	0.00	-0.16	-0.32	0.42	1.01	0.02
d)					*Low skilled*				
Negative elast.	62.50	-0.40	-0.14	0.83	-0.19	-0.42	0.50	0.23	0.06
Positive elast.	37.50	-0.47	-0.93	0.86	-0.90	-0.30	0.31	0.25	0.07

Results based on the elasticities in Table 4, Panel a). Column 1 reports the frequency of positive and negative elasticities, both on the whole sample of minor occupations and across skill groups. The remaining columns report average values of the indices of tradability characteristics.

Table 7 - Labor Demand Elasticities with Respect to Service Offshoring: QMLE Estimates for the Minor Occupations

Dependent Variables: Wage Bill Shares of the Minor Occupations and Variable-Cost Shares of the Major Groups and of the Non-Labor Inputs

Minor occupation(SOC code)	*a) Baseline*			*b) Using export intensity and import penetration instead of openess*			*c) Using high-tech share of capital stock instead of computer and software share*			*d) Controlling for ICT prices*		
	Elast.	Std. Err.		Elast.	Std. Err.		Elast.	Std. Err.		Elast.	Std. Err.	
High skilled												
Lawyers(230000)	0.068	0.031	**	0.031	0.015	**	0.127	0.055	**	0.038	0.022	*
Petroleum engineers(172171)	0.217	0.103	**	0.196	0.116	*	0.305	0.179	*	0.078	0.044	*
Life scientists(191000)	0.044	0.023	*	0.052	0.020	***	0.068	0.037	*	0.068	0.036	*
Physical scientists(192000)	0.013	0.004	***	0.027	0.010	***	0.025	0.013	*	0.027	0.014	*
Materials engineers(172131)	-0.035	0.017	**	0.030	0.018		-0.079	0.026	***	-0.177	0.030	***
Sales engineers(419031)	-0.101	0.036	***	-0.090	0.031	***	-0.099	0.011	***	-0.090	0.020	***
Computer hardw engin(172061)	-0.053	0.014	***	-0.008	0.003	***	-0.012	0.004	***	-0.178	0.031	***
Accountants and auditors(132011)	0.051	0.025	**	0.044	0.010	***	0.051	0.021	**	0.070	0.039	*
MKT and survey researchers(193020)	0.068	0.038	*	0.070	0.017	***	0.112	0.049	**	0.142	0.078	*
Management analysts(131111)	0.062	0.032	*	0.094	0.030	***	0.043	0.011	***	0.019	0.007	***
Engineering managers(119041)	-0.035	0.017	**	-0.028	0.013	**	-0.033	0.014	**	-0.048	0.019	**
Mining and geolog engin(172151)	0.086	0.041	**	0.070	0.034	**	0.011	0.005	**	0.139	0.062	**
Industrial engineers(172110)	0.059	0.240		0.043	0.256		0.053	0.295		0.033	0.288	
Aerospace engineers(172011)	0.628	0.129	***	-0.120	0.027	***	0.399	0.081	***	0.743	0.153	***
Mechanical engineers(172141)	-0.008	0.132		-0.003	0.139		0.008	0.170		-0.035	0.164	
Marine engineers(172121)	1.981	0.407	***	1.468	0.301	***	0.796	0.164	***	3.027	0.622	***
Civil engineers(172051)	-0.050	0.015	***	-0.029	0.016	*	-0.038	0.011	***	-0.282	0.058	***
Agricultural engineers(172021)	-0.200	0.190		-0.036	0.108		-0.233	0.356		0.093	0.144	
Medium skilled												
Medic and health serv manag(119111)	-0.458	0.165	***	-0.848	0.306	***	-0.190	0.069	***	-0.056	0.020	***
Chief executives(111011)	0.030	0.014	**	0.026	0.013	**	0.032	0.011	***	0.024	0.011	**
Budget analysts(132031)	-0.026	0.013	**	-0.039	0.009	***	-0.016	0.003	***	0.005	0.002	**
Purchasing managers(113061)	-0.009	0.005	*	-0.002	0.001	**	-0.007	0.002	***	-0.020	0.007	***
Administr serv manag(113011)	0.045	0.004	***	0.042	0.004	***	0.042	0.004	***	0.048	0.006	***
Construction managers(119021)	-0.147	0.020	***	-0.292	0.040	***	-0.281	0.038	***	-0.143	0.019	***
Database administrators(151061)	-0.051	0.021	**	-0.013	0.005	**	-0.292	0.132	**	-0.023	0.014	*
Computer system analysts(151051)	-0.353	0.142	**	-0.209	0.055	***	-1.446	0.573	**	-0.163	0.079	**
Computer support specialists(151041)	-0.313	0.184	*	-0.202	0.068	***	-1.264	0.489	***	-0.149	0.081	*
Computer programmers(151021)	-0.451	0.119	***	-0.279	0.066	***	-1.830	0.708	***	-0.191	0.087	**
Human resources manag(113040)	0.008	0.004	**	0.003	0.001	***	0.007	0.003	**	0.013	0.007	*
Adv, MKTG, prom, PR and sales manag(112000)	0.000	0.018		0.003	0.018		0.002	0.018		-0.010	0.024	
Compliance officers(131041)	-0.010	0.005	*	-0.022	0.011	*	-0.001	0.012		-0.003	0.002	*
Hum resources, training and lab rel spec(131070)	0.009	0.005	*	0.007	0.002	***	0.006	0.003	*	0.012	0.006	**
Advert sales agents(413011)	-0.036	0.006	***	0.034	0.006	***	0.153	0.024	***	0.071	0.011	***
Financial managers(113031)	0.033	0.012	***	0.033	0.012	***	0.034	0.012	***	0.027	0.016	*
Low skilled												
Cost estimators(131051)	-0.012	0.007	*	-0.006	0.003	**	-0.003	0.001	***	-0.021	0.011	*
Life, phys and soc scien technicians(194000)	0.009	0.004	**	0.014	0.005	***	0.032	0.012	***	0.043	0.027	
Buyers and purch agents(131020)	0.022	0.010	**	0.017	0.010	*	0.024	0.014	*	0.033	0.018	*
Exec secretaries and admin assistants(436011)	-0.027	0.099		-0.052	0.102		-0.037	0.078		-0.031	0.084	
Sales representatives(414010)	-0.008	0.260		-0.014	0.226		0.003	0.342		-0.003	0.167	
Statistical assistants(439111)	0.345	0.018	***	0.327	0.016	***	0.267	0.014	***	0.623	0.031	***
Drafters(173010)	-0.125	0.036	***	-0.115	0.043	***	-0.076	0.044	*	-0.085	0.041	**
Engineering technicians(173020)	-0.012	0.005	**	-0.008	0.004	**	0.004	0.149		-0.038	0.023	
First line superv of off and admin workers(431011)	-0.007	0.070		-0.014	0.073		-0.009	0.055		0.001	0.060	
Indust prod manag(113051)	-0.005	0.029		-0.002	0.027		-0.002	0.028		-0.013	0.037	
Prop, real est, and comm assoc manag(119141)	0.135	0.044	***	0.152	0.050	***	0.143	0.047	***	0.191	0.062	***
Order, receptionists and record clerks(434100)	-0.032	0.041		-0.046	0.042		-0.031	0.032		-0.023	0.034	
Other off and admin support workers(439000)	-0.019	0.089		-0.037	0.091		-0.026	0.069		-0.028	0.075	
Demonstrat and prod promoters(419011)	-0.041	0.003	***	0.016	0.003	***	-0.127	0.009	***	0.001	0.002	
Financial clerks(433000)	-0.049	0.129		-0.071	0.132		-0.060	0.101		-0.047	0.109	
Retail salespers(412031)	0.028	0.003	***	0.042	0.021	**	0.017	0.004	***	0.039	0.019	**
Transp, stor, and distrib, manag(113071)	-0.005	0.002	**	0.005	0.002	**	-0.020	0.003	***	-0.010	0.003	***
Parts salespers(412022)	-0.588	0.086	***	-0.481	0.070	***	-0.409	0.060	***	-0.158	0.023	***
Info and record clerks(434000)	-0.013	0.005	**	-0.026	0.006	***	-0.017	0.004	***	0.054	0.005	***
Switchboard operators(432011)	-0.025	0.008	***	-0.035	0.008	***	-0.007	0.004	*	-0.006	0.003	**
Telemarketers(419041)	0.811	0.099	***	0.882	0.108	***	0.872	0.107	***	0.820	0.100	***
Mat record, sched, dispatch workers(435000)	-0.111	0.254		-0.162	0.260		-0.115	0.196		-0.089	0.215	
Weighers, measurers, checkers(435111)	-0.060	0.023	***	-0.045	0.020	**	-0.069	0.021	***	-0.101	0.025	***
Cashiers(412011)	0.368	0.074	***	0.419	0.080	***	0.207	0.040	***	0.391	0.074	***

Quasi-Maximum Likelihood estimates with bootstrapped standard errors based on 100 replications. Elasticities are evaluated at the median of the sample. ***, **, *: significant at 1, 5 and 10 percent level, respectively. The baseline model also includes log occupational wages, material offshoring, proxy for technological progress, trade openness, log capital, time dummies, log output and price of energy and non-energy materials (only at the second stage). *Export intensity* is log exports over total shipments; *import penetration* is log imports over apparent consumption; *high-tech capital* includes computer and peripheral equipment, software, communications, photocopy and related equipment, office and accounting equipment; *ICT prices* are the product between the economy-wide time series of computer prices and the average capital share of computer and software equipment in each industry between 1987 and 1996.

Table 8 - Labor Demand Elasticities with Respect to Service Offshoring: QMLE Estimates for the Major Groups

Dependent Variables: Wage Bill Shares of the Minor Occupations and Variable-Cost Shares of the Major Groups and of the Non-Labor Inputs

Major group(SOC code)	*a) Baseline*			*b) Using export intensity and import penetration instead of openess*			*c) Using high-tech share of capital stock instead of computer and software share*			*d) Controlling for ICT prices*		
	Elast.	Std. Err.		Elast.	Std. Err.		Elast.	Std. Err.		Elast.	Std. Err.	
Management occupations(110000)	0.048	0.023	**	0.043	0.013	***	0.056	0.027	**	0.027	0.012	**
Business and financial operations occupations(130000)	0.106	0.798		0.094	0.553		0.106	1.155		0.137	0.558	
Computer and mathematical occupations(150000)	-1.337	0.302	***	-0.810	0.167	***	-5.400	2.093	***	-0.595	0.228	***
Architecture and engineering occupations(170000)	0.125	0.062	**	0.073	0.024	***	0.119	0.055	**	0.041	0.023	*
Life, physical, and social science occupations(190000)	0.080	0.030	***	0.100	0.036	***	0.158	0.043	***	0.201	0.114	*
Legal occupations(230000)	0.068	0.031	**	0.031	0.015	**	0.127	0.055	**	0.038	0.022	*
Sales and related occupations(410000)	-0.009	0.317		-0.009	0.267		0.006	0.410		0.004	0.198	
Office and administrative support occupations(430000)	-0.261	0.705		-0.402	0.723		-0.293	0.546		-0.229	0.594	

See notes to Table 7.

Table 9 - Skills, Tradability and Service Offshoring: Unconditional Results

	Frequency	*Tradability index*	*Routine cognitive 1*	*Routine cognitive 2*	*Routine cognitive 3*	*Interaction with PCs*	*Face-to-face 1*	*Face-to-face 2*	*Face-to-face 3*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
a)					*All minor occupations*				
Negative elast.	58.62	0.09	0.04	0.92	0.07	0.14	-0.05	-0.04	0.01
Positive elast.	41.38	-0.13	-0.06	0.55	-0.09	-0.20	0.08	0.06	-0.01
b)					*High skilled*				
Negative elast.	38.89	0.78	1.34	1.00	1.21	0.58	-0.65	-0.64	0.16
Positive elast.	61.11	0.51	0.29	0.80	0.30	0.19	-0.41	-0.52	-0.07
c)					*Medium skilled*				
Negative elast.	62.50	0.32	-0.12	0.75	0.02	0.43	-0.37	-0.13	-0.18
Positive elast.	37.50	-0.67	-0.15	0.00	-0.18	-0.24	0.42	0.97	-0.01
d)					*Low skilled*				
Negative elast.	70.83	-0.33	-0.40	0.93	-0.38	-0.21	0.38	0.26	0.05
Positive elast.	29.17	-0.66	-0.52	0.60	-0.63	-0.76	0.54	0.17	0.09

Results based on the elasticities in Table 7, Panel a). See also note to Table 6.

Table 10 - Skills, Tradability and Service Offshoring: Conditional Results

Dependent Variable: Dummy for Positive QMLE Elasticities

OLS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
High skilled dummy	0.319**	0.467***	0.453***	0.381**	0.467***	0.416***	0.413**	0.388**	0.319**	0.607***	0.469***	0.589***
	[0.152]	[0.169]	[0.140]	[0.155]	[0.147]	[0.154]	[0.162]	[0.164]	[0.153]	[0.163]	[0.168]	[0.170]
Medium skilled dummy	0.083	0.137	0.119	-0.002	0.137	0.158	0.134	0.079	0.083	0.221	0.196	0.224
	[0.157]	[0.158]	[0.159]	[0.159]	[0.161]	[0.161]	[0.158]	[0.151]	[0.159]	[0.174]	[0.175]	[0.165]
Tradability index		-0.142*										
		[0.072]										
Routine cognitive 1			-0.119*							-0.153**		
			[0.062]							[0.064]		
Routine cognitive 2				-0.578***							-0.397*	
				[0.146]							[0.206]	
Routine cognitive 3					-0.133**							-0.148**
					[0.065]							[0.065]
Interaction with PCs						-0.136*				-0.165*	-0.188**	-0.148*
						[0.068]				[0.094]	[0.085]	[0.078]
Face-to-face 1							0.100					
							[0.076]					
Face-to-face 2								0.086		-0.004	-0.033	0.001
								[0.068]		[0.084]	[0.086]	[0.079]
Face-to-face 3									-0.003			
									[0.066]			
Probit marginal effects	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
High skilled dummy	0.319**	0.479***	0.488***	0.445***	0.494***	0.428***	0.418***	0.392**	0.319**	0.626***	0.613***	0.608***
	[0.149]	[0.173]	[0.154]	[0.167]	[0.160]	[0.157]	[0.162]	[0.161]	[0.149]	[0.164]	[0.193]	[0.177]
Medium skilled dummy	0.083	0.122	0.127	-0.057	0.138	0.153	0.130	0.068	0.083	0.193	0.212	0.201
	[0.154]	[0.152]	[0.153]	[0.210]	[0.157]	[0.163]	[0.156]	[0.145]	[0.154]	[0.159]	[0.257]	[0.154]
Tradability index		-0.123**										
		[0.057]										
Routine cognitive 1			-0.113*							-0.115**		
			[0.058]							[0.048]		
Routine cognitive 2				-0.654***							-0.500*	
				[0.172]							[0.293]	
Routine cognitive 3					-0.119**							-0.111**
					[0.055]							[0.048]
Interaction with PCs						-0.117**				-0.110*	-0.195**	-0.105*
						[0.056]				[0.060]	[0.092]	[0.058]
Face-to-face 1							0.087					
							[0.061]					
Face-to-face 2								0.080		0.007	-0.044	0.005
								[0.061]		[0.059]	[0.088]	[0.059]
Face-to-face 3									-0.002			
									[0.060]			
Obs.	58	58	58	44	58	58	58	58	58	58	44	58

OLS and Probit regressions with robust standard errors in brackets. ***, **, *: significant at 1, 5 and 10 percent level, respectively. Results based on the elasticities in Table 7, Panel a).

Table 11 - Conditional Results: Robustness Checks

Dependent Variable: Dummy for Positive QMLE Elasticities, Unless Otherwise Indicated

	a) Excluding insignificant elasticities				*b) Excluding unstable elasticities*				*c) Using elasticities as the dependent variable*			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
High skilled dummy	0.366*	0.590***	0.537**	0.547***	0.464**	0.563***	0.619***	0.598***	0.050**	0.073***	0.041**	0.102*
	[0.194]	[0.168]	[0.249]	[0.190]	[0.189]	[0.191]	[0.220]	[0.198]	[0.020]	[0.017]	[0.018]	[0.055]
Medium skilled dummy	-0.053	-0.008	0.166	0.029	0.060	0.124	0.172	0.172	0.015	0.032**	0.010	-0.066
	[0.182]	[0.182]	[0.304]	[0.184]	[0.184]	[0.203]	[0.275]	[0.199]	[0.019]	[0.016]	[0.024]	[0.051]
Tradability index	-0.136*				-0.148*				-0.019**			
	[0.073]				[0.076]				[0.008]			
Routine cognitive 1		-0.256***				-0.105				-0.020***		
		[0.090]				[0.077]				[0.007]		
Routine cognitive 2			-0.498*				-0.511*				-0.013	
			[0.260]				[0.273]				[0.023]	
Routine cognitive 3				-0.192**				-0.124*				-0.048**
				[0.079]				[0.069]				[0.022]
Interaction with PCs		-0.150	-0.319**	-0.150*		-0.161*	-0.260**	-0.157*		-0.032***	-0.024**	-0.041*
		[0.093]	[0.155]	[0.086]		[0.090]	[0.123]	[0.088]		[0.008]	[0.010]	[0.024]
Face-to-face 2		-0.039	-0.151	-0.041		-0.020	-0.114	-0.028		0.001	0.011	-0.003
		[0.091]	[0.146]	[0.089]		[0.098]	[0.134]	[0.091]		[0.008]	[0.010]	[0.024]
Obs.	46	46	34	46	45	45	36	45	58	58	44	58

	d) Using skill classification based on BLS				*e) Using share of college graduate+*				*f) Adding controls for other occup. charact.*			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
BLS high skilled dummy	0.341**	0.406***	0.533***	0.419***								
	[0.141]	[0.145]	[0.169]	[0.149]								
Share of college graduate+					0.008***	0.012***	0.012**	0.011***				
					[0.003]	[0.004]	[0.005]	[0.004]				
High skilled dummy									0.506**	0.590***	0.389*	0.573***
									[0.210]	[0.191]	[0.193]	[0.206]
Medium skilled dummy									0.003	0.122	0.146	-0.025
									[0.227]	[0.215]	[0.278]	[0.197]
Tradability index	-0.099*				-0.149*				-0.307**			
	[0.057]				[0.085]				[0.152]			
Routine cognitive 1		-0.087*				-0.210**				-0.127*		
		[0.050]				[0.087]				[0.070]		
Routine cognitive 2			-0.406*				-0.495***				-0.458**	
			[0.245]				[0.170]				[0.208]	
Routine cognitive 3				-0.094*				-0.182**				-0.282***
				[0.052]				[0.090]				[0.107]
Interaction with PCs		-0.126**	-0.194**	-0.117**		-0.212**	-0.335**	-0.189**		-0.185*	-0.228**	-0.259**
		[0.062]	[0.089]	[0.056]		[0.095]	[0.149]	[0.085]		[0.095]	[0.086]	[0.113]
Face-to-face 2		-0.023	-0.073	-0.021		-0.028	-0.073	-0.023		0.096	0.050	0.141
		[0.063]	[0.084]	[0.061]		[0.085]	[0.119]	[0.085]		[0.093]	[0.110]	[0.110]
Non-routine cognitive									0.232	0.175	0.238**	0.281
									[0.172]	[0.131]	[0.101]	[0.173]
Routine manual									-0.090	-0.045	-0.160**	-0.028
									[0.075]	[0.072]	[0.061]	[0.079]
Log wage									-0.648**	-0.470*	-0.780***	-0.439
									[0.301]	[0.271]	[0.275]	[0.300]
Obs.	58	58	44	58	58	58	44	58	58	58	44	58

Panel a) excludes the insignificant elasticities from the baseline model in Table 7. Panel b) excludes the elasticities that change sign across the four models in Table 7. Panel c) reports outlier-robust regressions using the absolute values of the baseline elasticities as the dependent variable. The *BLS high skilled dummy* used in Panel d) is equal to 1 if the occupation requires at least a bachelor's degree according to the BLS classification. The *share of college graduate+* used in Panel e) is the fraction of workers with at least a bachelor's degree. The *log wage* variable included in Panel f) is the logarithm of the average economy-wide wage of the occupation. Panel f) also controls for a full set of major group dummies; column (3) reports estimates from a Linear Probability Model, instead of marginal effects from Probit. See also notes to Table 10.

Table 12 - Conditional Results Using the BLS Tradability Classification

Dependent Variable: Dummy for Positive QMLE Elasticities

	(1)	(2)	(3)	(4)	(5)	(6)
High skilled dummy	0.417***	0.543**	0.532**	0.611***	0.404*	0.600***
	[0.151]	[0.214]	[0.209]	[0.191]	[0.210]	[0.201]
Medium skilled dummy	0.109	0.100	0.025	0.140	0.160	-0.015
	[0.158]	[0.219]	[0.241]	[0.225]	[0.293]	[0.206]
BLS tradable dummy	-0.238**	-0.202**	-0.158	-0.105	-0.048	-0.140
	[0.093]	[0.100]	[0.127]	[0.119]	[0.225]	[0.131]
Tradability index			-0.304**			
			[0.152]			
Routine cognitive 1				-0.132*		
				[0.073]		
Routine cognitive 2					-0.451**	
					[0.219]	
Routine cognitive 3						-0.294***
						[0.106]
Interaction with PCs				-0.180*	-0.222**	-0.258**
				[0.098]	[0.085]	[0.111]
Face-to-face 2				0.094	0.048	0.141
				[0.095]	[0.111]	[0.111]
Non-routine cognitive		0.024	0.211	0.159	0.220	0.265
		[0.109]	[0.184]	[0.145]	[0.136]	[0.185]
Routine manual		-0.128*	-0.096	-0.049	-0.162**	-0.028
		[0.073]	[0.075]	[0.073]	[0.062]	[0.078]
Log wage		-0.520**	-0.649**	-0.470*	-0.768**	-0.435
		[0.263]	[0.303]	[0.275]	[0.291]	[0.310]
Major group dummies	NO	YES	YES	YES	YES	YES
Obs.	58	58	58	58	44	58

The *BLS tradable dummy* takes value 1 if the occupation is defined as tradable by the BLS. Column (5) reports estimates from a Linear Probability Model, instead of marginal effects from Probit. See also notes to Tables 10 and 11.

Table 13 - Conditional Results Using the Classification of Occupations by Skill-Tradability Group

Dependent Variable: Dummy for Positive QMLE Elasticities

	Baseline	*Controlling for other occupational characteristics*
	(1)	(2)
High skilled non-tradable dummy	0.708***	0.556*
	[0.063]	[0.180]
High skilled tradable dummy	0.242**	0.275*
	[0.052]	[0.111]
Medium skilled non-tradable dummy	0.375**	0.315*
	[0.095]	[0.099]
Medium skilled tradable dummy	-0.292**	-0.451**
	[0.063]	[0.137]
Non-routine cognitive		0.066
		[0.040]
Routine manual		-0.078
		[0.128]
Log wage		-0.448
		[0.242]
Major group dummies	NO	YES
Obs.	58	58

OLS regressions with standard errors corrected for clustering within major groups in brackets. ***, **, *: significant at 1, 5 and 10 percent level, respectively. Results based on the elasticities in Table 7, Panel a). The *high skilled non-tradable dummy* is equal to 1 if the occupation requires at least a bachelor's degree and the *tradability index* is below the median value; the other dummies are defined accordingly.

Table 14 - Counterfactual Experiment

	Δ share of white-collar employment (percentage points)		
	(1)	(2)	(3)
	Total	NT occupations	T occupations
	Using the skill classification based on PUMS		
High skilled	0.346	0.172	0.174
Medium skilled	-0.331	0.163	-0.494
Low skilled	-0.015	0.005	-0.020
	Using the skill classification based on BLS		
High skilled	0.178	0.367	-0.189
Medium-low skilled	-0.178	-0.027	-0.151

The experiment uses the elasticities reported in Panel a) of Table 7 to simulate a counterfactual world in which service offshoring is assumed to have remained constant at the 1997 level. Column (1) reports the simulated changes in the share of each skill group in total white-collar employment. Columns (2) and (3) decompose these changes into the contribution of tradable and non-tradable occupations. A positive number indicates that the actual share is higher than it would have been in the constant-offshoring scenario.

Table A1 - Industries Used in the Analysis

Industry	Industry
Wholesale trade	Rubber and plastics footwear
Retail trade	Gaskets, packing, and sealing devices and rubber
Finance and insurance	Fabricated rubber products, not elsewhere classified
Real estate, rental and leasing	Miscellaneous plastics products
Legal services	Leather tanning and finishing
Computer systems design and related services	Boot and shoe cut stock and findings
Miscellaneous professional, scientific, and technical services	Footwear, except rubber
Management and public relations services	Leather gloves and mittens
Motion picture and sound recording industries	Luggage
Meat products	Handbags and other personal leather goods
Dairy products	Leather goods, not elsewhere classified
Canned, frozen, and preserved fruits, vegetables, and food specialties	Flat glass
Grain mill products	Glass and glassware, pressed or blown
Bakery products	Glass products, made of purchased glass
Sugar and confectionery products	Cement, hydraulic
Fats and oils	Structural clay products
Beverages	Pottery and related products
Miscellaneous food preparations and kindred	Concrete, gypsum, and plaster products
Cigarettes	Cut stone and stone products
Cigars	Abrasive, asbestos, and miscellaneous
Chewing and smoking tobacco and snuff	Steel works, blast furnaces, and rolling and finishing mills
Tobacco stemming and redrying	Iron and steel foundries
Broadwoven fabric mills, cotton	Primary smelting and refining of nonferrous metals
Broadwoven fabric mills, manmade fiber and silk	Secondary smelting and refining of nonferrous metals
Broadwoven fabric mills, wool (including dyeing and finishing)	Rolling, drawing, and extruding of nonferrous metals
Narrow fabric and other smallwares mills cotton, wool, silk, and manmade fiber	Nonferrous foundries (castings)
Knitting mills	Miscellaneous primary metal products
Dyeing and finishing textiles, except wool fabrics	Metal cans and shipping containers
Carpets and rugs	Cutlery, handtools, and general hardware
Yarn and thread mills	Heating equipment, except electric and warm air; and plumbing fixtures
Miscellaneous textile goods	Fabricated structural metal products
Men's and boys' suits, coats, and overcoats	Screw machine products, and bolts, nuts, screws, rivets, and washers
Men's and boys' furnishings, work clothing, and allied garments	Metal forgings and stampings
Women's, misses', and juniors' outerwear	Coating, engraving, and allied services
Women's, misses', children's, and infants' undergarments	Ordnance and accessories, except vehicles and guided missiles
Hats, caps, and millinery	Miscellaneous fabricated metal products
Girls', children's, and infants' outerwear	Engines and turbines
Fur goods	Farm and garden machinery and equipment
Miscellaneous apparel and accessories	Construction, mining, and materials handling
Miscellaneous fabricated textile products	Metalworking machinery and equipment
Sawmills and planing mills, general	Special industry machinery, except metalworking
Millwork, veneer, plywood, and structural wood	General industrial machinery and equipment
Wood containers	Computer and office equipment
Wood buildings and mobile homes	Refrigeration and service industry machinery
Miscellaneous wood products	Miscellaneous industrial and commercial machinery and equipment
Household furniture	Electric transmission and distribution equipment
Office furniture	Electrical industrial apparatus
Public building and related furniture	Household appliances
Partitions, shelving, lockers, and office	Electric lighting and wiring equipment
Miscellaneous furniture and fixtures	Household audio and video equipment, and audio recordings
Pulp mills	Communications equipment
Paper mills	Electronic components and accessories
Paperboard mills	Miscellaneous electrical machinery, equipment, and supplies
Paperboard containers and boxes	Motor vehicles and motor vehicle equipment
Converted paper and paperboard products, except containers and boxes	Aircraft and parts
Books	Ship and boat building and repairing
Commercial printing	Railroad equipment
Manifold business forms	Motorcycles, bicycles, and parts
Blankbooks, looseleaf binders, and bookbinding	Guided missiles and space vehicles and parts
Service industries for the printing trade	Miscellaneous transportation equipment
Industrial inorganic chemicals	Search, detection, navigation, guidance, aeronautical, and nautical systems, instruments, and equipment
Plastics materials and synthetic resins, synthetic rubber, cellulosic and other manmade fibers, except glass	Laboratory apparatus and analytical, optical, measuring, and controlling instruments
Drugs	Surgical, medical, and dental instruments and supplies
Soap, detergents, and cleaning preparations; perfumes, cosmetics, and other toilet preparations	Ophthalmic goods
Paints, varnishes, lacquers, enamels, and allied products	Photographic equipment and supplies
Industrial organic chemicals	Watches, clocks, clockwork operated devices, and parts
Agricultural chemicals	Jewelry, silverware, and plated ware
Miscellaneous chemical products	Musical instruments
Petroleum refining	Dolls, toys, games and sporting and athletic
Asphalt paving and roofing materials	Pens, pencils, and other artists' materials
Miscellaneous products of petroleum and coal	Costume jewelry, costume novelties, buttons, and miscellaneous notions, except precious metal
Tires and inner tubes	Miscellaneous manufacturing industries

Table A2 - Minor Occupations and Major Groups Used in the Analysis

Occupation(SOC code)	Occupation(SOC code)
Management occupations(110000)	Order, receptionist and information clerks(434100)
Chief executives(111011)	Material recording, scheduling, dispatching, and distributing workers(435000)
Advertising, marketing, promotions, public relations and sales managers(112000)	Weighers, measurers, checkers, and samplers, recordkeeping(435111)
Administrative services managers(113011)	Executive secretaries and administrative assistants(436011)
Financial managers(113031)	Other office and administrative support workers(439000)
Human resources managers(113040)	Statistical assistants(439111)
Industrial production managers(113051)	***Construction and extraction occupations(470000)***
Purchasing managers(113061)	First-line supervisors/managers of construction trades and extraction workers(471011)
Transportation, storage, and distribution managers(113071)	Boilermakers(472011)
Construction managers(119021)	Brickmasons, blockmasons, and stonemasons(472020)
Engineering managers(119041)	Carpenters(472031)
Medical and health services managers(119111)	Cement masons and concrete finishers(472051)
Property, real estate, and community association managers(119141)	Paving, surfacing, and tamping equipment operators(472071)
Business and financial operations occupations(130000)	Electricians(472111)
Buyers and purchasing agents(131020)	Glaziers(472121)
Compliance officers, except agriculture, construction, health and safety, and transportation(131041)	Insulation workers(472130)
Cost estimators(131051)	Painters and paperhangers(472140)
Human resources, training and labor relations specialists(131070)	Plumbers, pipefitters, and steamfitters(472152)
Management analysts(131111)	Sheet metal workers(472211)
Accountants and auditors(132011)	Structural iron and steel workers(472221)
Budget analysts(132031)	Helpers, construction trades(473010)
Computer and mathematical occupations(150000)	***Installation, maintenance and repair occupations(490000)***
Computer programmers(151021)	First-line supervisors/managers of mechanics, installers, and repairers(491011)
Computer support specialists(151041)	Miscellaneous electrical and electronic equipment mechanics, installers, and repairers(492090)
Computer systems analysts(151051)	Aircraft mechanics and service technicians(493011)
Database administrators(151061)	Automotive body and related repairers(493021)
Architecture and engineering occupations(170000)	Bus and truck mechanics and diesel engine specialists(493031)
Aerospace engineers(172011)	Heavy vehicle and mobile equipment service technicians and mechanics(493040)
Agricultural engineers(172021)	Small engine mechanics(493050)
Civil engineers(172051)	Control and valve installers and repairers, except mechanical door(499012)
Computer hardware engineers(172061)	Heating, air conditioning, and refrigeration mechanics and installers(499021)
Industrial engineers, including health and safety(172110)	Home appliance repairers(499031)
Marine engineers and naval architects(172121)	Industrial machinery installation, repair, and maintenance workers(499040)
Materials engineers(172131)	Musical instrument repairers and tuners(499063)
Mechanical engineers(172141)	Miscellaneous installation, maintenance, and repair workers(499090)
Mining and geological engineers, including mining safety engineers(172151)	***Production occupations(510000)***
Petroleum engineers(172171)	First-line supervisors/managers of production and operating workers(511011)
Drafters(173010)	Assemblers and fabricators(512000)
Engineering technicians, except drafters(173020)	Food processing workers(513000)
Life, physical, and social science occupations(190000)	Metal workers and plastic workers(514000)
Life scientists(191000)	Tool and die makers, welders, cutters, solderers, and brazers(514100)
Physical scientists(192000)	Printing workers(515000)
Market and survey researchers(193020)	Textile, apparel, and furnishings workers(516000)
Life, physical, and social science technicians(194000)	Woodworkers(517000)
Legal occupations(230000)	Plant and system operators(518000)
Lawyers(230000)	Other production occupations(519000)
Building and grounds cleaning and maintenance occupations(370000)	Production workers, all other(519100)
Janitors and cleaners, except maids and housekeeping cleaners(372011)	***Transportation and material moving occupations(530000)***
Landscaping and groundskeeping workers(373011)	First-line supervisors/managers of helpers, laborers, and material movers, hand(531021)
Sales and related occupations(410000)	First-line supervisors/managers of transportation and material moving machine and vehicle operators(531031)
Cashiers, except gaming(412011)	Aircraft pilots and flight engineers(532010)
Parts salespersons(412022)	Driver/sales workers and truck drivers(533030)
Retail salespersons(412031)	Rail yard engineers, dinkey operators, and hostlers(534013)
Advertising sales agents(413011)	Railroad brake, signal, and switch operators(534021)
Sales representatives, wholesale and manufacturing(414010)	Transportation inspectors(536051)
Demonstrators and product promoters(419011)	Conveyor operators and tenders(537011)
Sales engineers(419031)	Crane and tower operators(537021)
Telemarketers(419041)	Excavating and loading machine and dragline operators(537032)
Office and administrative support occupations(430000)	Hoist and winch operators(537041)
First-line supervisors/managers of office and administrative support workers(431011)	Industrial truck and tractor operators(537051)
Switchboard operators, including answering service(432011)	Laborers and material movers, hand(537060)
Financial clerks(433000)	Tank car, truck, and ship loaders(537121)
Information and record clerks(434000)	

Table A3 - Skill Classifications

Minor occupation(SOC code)	*Schooling*	*Skill classification based on BLS*	*Share of college graduate+*
High skilled			
Lawyers(230000)	15	High skilled	97.9
Petroleum engineers(172171)	14	High skilled	82.0
Life scientists(191000)	14	High skilled	85.5
Physical scientists(192000)	14	High skilled	93.3
Materials engineers(172131)	13	High skilled	68.1
Sales engineers(419031)	13	High skilled	85.7
Computer hardw engin(172061)	13	High skilled	68.9
Accountants and auditors(132011)	13	High skilled	75.5
MKT and survey researchers(193020)	13	High skilled	78.8
Management analysts(131111)	13	High skilled	76.3
Engineering managers(119041)	13	High skilled	84.3
Mining and geolog engin(172151)	13	High skilled	80.7
Industrial engineers(172110)	13	High skilled	69.6
Aerospace engineers(172011)	13	High skilled	83.9
Mechanical engineers(172141)	13	High skilled	80.2
Marine engineers(172121)	13	High skilled	60.3
Civil engineers(172051)	13	High skilled	87.5
Agricultural engineers(172021)	13	High skilled	80.7
Medium skilled			
Medic and health serv manag(119111)	12	High skilled	59.9
Chief executives(111011)	12	High skilled	57.3
Budget analysts(132031)	12	High skilled	75.0
Purchasing managers(113061)	12	High skilled	57.9
Administr serv manag(113011)	12	Medium-low skilled	41.0
Construction managers(119021)	12	Medium-low skilled	29.6
Database administrators(151061)	12	High skilled	72.4
Computer system analysts(151051)	12	High skilled	65.8
Computer support specialists(151041)	12	Medium-low skilled	41.1
Computer programmers(151021)	12	High skilled	72.2
Human resources manag(113040)	12	Medium-low skilled	60.8
Adv, MKTG, prom, PR and sales manag(112000)	12	High skilled	70.0
Compliance officers(131041)	12	Medium-low skilled	58.4
Hum resources, training and lab rel spec(131070)	12	High skilled	57.5
Advert sales agents(413011)	12	Medium-low skilled	54.8
Financial managers(113031)	12	High skilled	59.2
Low skilled			
Cost estimators(131051)	11	High skilled	32.8
Life, phys and soc scien technicians(194000)	11	Medium-low skilled	39.7
Buyers and purch agents(131020)	11	Medium-low skilled	38.0
Exec secretaries and admin assistants(436011)	11	Medium-low skilled	17.5
Sales representatives(414010)	11	Medium-low skilled	49.6
Statistical assistants(439111)	11	Medium-low skilled	30.7
Drafters(173010)	11	Medium-low skilled	21.6
Engineering technicians(173020)	11	Medium-low skilled	17.8
First line superv of off and admin workers(431011)	11	Medium-low skilled	28.9
Indust prod manag(113051)	11	Medium-low skilled	44.9
Prop, real est, and comm assoc manag(119141)	11	High skilled	36.3
Order, receptionists and record clerks(434100)	10	Medium-low skilled	14.4
Other off and admin support workers(439000)	10	Medium-low skilled	21.6
Demonstrat and prod promoters(419011)	10	Medium-low skilled	36.1
Financial clerks(433000)	10	Medium-low skilled	15.0
Retail salespers(412031)	10	Medium-low skilled	26.1
Transp, stor, and distrib, manag(113071)	10	Medium-low skilled	23.6
Parts salespers(412022)	10	Medium-low skilled	5.4
Info and record clerks(434000)	10	Medium-low skilled	21.3
Switchboard operators(432011)	10	Medium-low skilled	9.6
Telemarketers(419041)	10	Medium-low skilled	15.9
Mat record, sched, dispatch workers(435000)	9	Medium-low skilled	13.6
Weighers, measurers, checkers(435111)	9	Medium-low skilled	12.4
Cashiers(412011)	9	Medium-low skilled	9.9

The first column reports the skill classification based on PUMS. High skilled occupations are those requiring at least a bachelor's degree (*schooling>12* medium skilled occupations those requiring an associate degree in college (*schooling=12*), low skilled occupations those requiring lower degrees of schooling (*schooling<12*). The second column reports the *skill classification based on BLS* , which defines as high skilled the occupations requiring at least a bachelor's degree, and as medium-low skilled all the others. The third column reports the *share of college graduate+* , i.e. the fraction of workers with at least a bachelor's degree in each occupation.

Table A4 - Indices of Tradability and Other Occupational Characteristics: Background Variables

Index	Background variable: *Name*	*Description*	*Source*	Tradability index
Routine cognitive 1 Routine cognitive 3	Importance of repeating the same tasks	How important is repeating the same physical activities (e.g., key entry) or mental activities (e.g., checking entries in a ledger) over and over, without stopping, to performing this job?	O*NET 12.0	yes
Routine cognitive 1 Routine cognitive 3	Visual color discrimination	The ability to match or detect differences between colors, including shades of color and brightness	O*NET 12.0	yes
Routine cognitive 2	STS	Adaptability to set limits, tolerances, and standards	DOT 1991	no
Routine cognitive 3	Documenting/recording information	Entering, transcribing, recording, storing, or maintaining information in either written form or by electronic/magnetic recording	O*NET 12.0	yes
Routine cognitive 3	Getting information	Observing, receiving, and otherwise obtaining information from all relevant sources	O*NET 12.0	yes
Routine cognitive 3	Inspecting equipment, structures, materials	Inspecting or diagnosing equipment, structures, or materials to identify the causes of errors or other problems or defects	O*NET 12.0	yes
Face-to-face 1 Face-to-face 2	Face-to-face	Frequency of face-to-face interactions with individuals and groups	O*NET 12.0	yes
Face-to-face 1 Face-to-face 2	Performing for/working with public	Performing for people or dealing directly with the public, including serving persons in restaurants and stores, and receiving clients or guests	O*NET 12.0	yes
Face-to-face 2	Deal with external customers	Deal with external customers (e.g., retail sales) or the public in general (e.g., police work)	O*NET 12.0	yes
Face-to-face 2	Establishing and maintaining relationships	Developing constructive and cooperative working relationships with others	O*NET 12.0	yes
Face-to-face 3	Blinder's offshorability index	The job does not need to be performed at a specific work location in the U.S., and either: 1) the worker does not need to be physically close to her work unit; or 2) the work unit can be moved outside the U.S.	Blinder (2007)	no
Interaction with PCs	Interacting with computers	Controlling computer functions by using programs, setting up functions, writing software, or otherwise communicating with computer systems	O*NET 12.0	yes
Non-routine cognitive	Analyzing data or information	Identifying underlying principles, reasons, or facts by breaking down information or data into separate parts	O*NET 12.0	no
Non-routine cognitive	Developing objectives and strategies	Establishing long range objectives and specifying the strategies and actions to achieve these objectives	O*NET 12.0	no
Non-routine cognitive	Mathematical reasoning	The ability to understand and organize a problem and then to select a mathematical method or formula to solve it	O*NET 12.0	no
Non-routine cognitive	Processing information	Compiling, coding, categorizing, calculating, tabulating, auditing, verifying, or processing information or data	O*NET 12.0	no
Non-routine cognitive	Thinking creatively	Originating, inventing, designing, or creating new applications, ideas, relationships, systems, or products, including artistic contributions	O*NET 12.0	no
Routine manual	Finger dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects	O*NET 12.0	no
Routine manual	Manual dexterity	The ability to quickly make coordinated movements of one hand, a hand together with its arm, or two hands to grasp, manipulate, or assemble objects	O*NET 12.0	no

Composite indices of several variables are obtained by Principal Components Analysis using only the first factor. All indices except *routine cognitive 2* have mean 0 and standard deviation 1, and are normalized so that higher values indicate higher levels of the corresponding characteristic. *Routine cognitive 2* is a dummy equal to 1 if the occupation requires to attain precise set limits, tolerances and standards. The last column of the table indicates whether or not each variable enters the *tradability index*.

Table A5 - Indices of Tradability and Other Occupational Characteristics: Values

Minor occupation(SOC code)	*Tradability index*	*Routine cognitive 1*	*Routine cognitive 2*	*Routine cognitive 3*	*Interaction with PCs*	*Face-to-face 1*	*Face-to-face 2*	*Face-to-face 3*	*Non-routine cognitive*	*Routine manual*
Database administrators(151061)	1.57	-0.02	-	-0.31	1.40	0.47	-1.82	-0.94	1.25	1.38
Drafters(173010)	1.48	-0.12	Y	-0.07	1.13	-1.38	-1.08	-1.51	0.23	1.77
Computer support specialists(151041)	1.38	-0.25	-	0.86	1.45	-1.18	-0.60	-1.45	-3.01	0.72
Materials engineers(172131)	1.35	1.26	Y	1.65	0.84	-0.88	-1.14	-0.82	0.86	0.20
Petroleum engineers(172171)	1.31	1.27	Y	1.12	-0.37	-1.20	-1.93	1.30	0.91	-0.33
Statistical assistants(439111)	1.21	-0.19	-	-0.30	1.24	-1.28	-1.03	-1.39	1.78	0.85
Life, phys and soc scien technicians(194000)	1.20	0.24	Y	1.06	0.10	-0.42	-1.19	-0.01	0.18	0.93
Computer programmers(151021)	1.19	-0.32	Y	-0.04	1.59	-1.34	-1.21	-1.69	-0.12	0.05
Mining and geolog engin(172151)	1.18	0.88	Y	1.25	0.48	-1.11	-0.73	1.30	1.01	-0.60
Agricultural engineers(172021)	1.17	1.46	-	1.16	0.61	-0.87	-1.08	1.30	0.44	1.26
Industrial engineers(172110)	1.15	-0.86	Y	-0.03	0.50	-1.44	-1.21	-0.12	0.79	-1.00
Engineering technicians(173020)	1.14	1.48	Y	1.36	0.13	-0.79	-1.06	-0.40	0.01	1.06
Marine engineers(172121)	1.04	0.90	Y	0.82	0.61	-0.87	-1.08	-0.76	0.48	0.15
Computer system analysts(151051)	1.00	0.18	Y	-0.47	1.58	-0.35	-1.19	-1.48	0.84	0.45
Physical scientists(192000)	0.88	1.04	Y	1.20	0.76	-0.53	-0.51	-0.57	1.13	-0.39
Life scientists(191000)	0.86	0.71	N	1.10	0.05	0.00	-0.49	-0.93	0.91	0.23
Mechanical engineers(172141)	0.85	1.61	Y	0.85	0.23	-0.90	-1.27	-0.79	-0.33	0.46
Budget analysts(132031)	0.73	-1.00	-	-1.51	0.55	-1.22	-1.14	-0.49	0.77	-0.73
Computer hardw engin(172061)	0.65	1.22	Y	0.83	1.56	-1.28	-0.84	-0.88	-0.31	0.19
Civil engineers(172051)	0.65	1.92	Y	1.81	0.76	0.64	-0.16	1.30	0.44	0.73
Aerospace engineers(172011)	0.55	-0.19	Y	-0.91	0.90	-0.34	-1.44	0.19	1.19	-2.06
Weighers, measurers, checkers(435111)	0.52	-0.40	Y	-0.67	0.58	0.20	-0.55	0.49	-0.65	1.51
Sales engineers(419031)	0.49	0.95	Y	1.34	1.01	-0.75	0.64	1.30	1.07	0.71
Indust prod manag(113051)	0.42	0.34	Y	0.88	-0.48	-1.09	-0.74	-0.34	-0.24	0.18
Engineering managers(119041)	0.32	0.94	Y	0.84	-0.93	-0.51	-0.61	-0.31	0.25	-0.86
Other off and admin support workers(439000)	0.15	-0.76	Y	-0.74	0.28	0.16	-0.33	-0.95	-0.75	0.85
Management analysts(131111)	0.03	-0.27	Y	0.12	0.02	-0.25	0.79	1.30	1.27	-1.53
Medic and health serv manag(119111)	-0.03	0.07	-	0.57	-0.10	-1.09	0.79	1.30	1.14	-0.21
Purchasing managers(113061)	-0.05	0.79	N	1.42	0.27	0.43	1.10	-0.16	0.35	1.51
MKT and survey researchers(193020)	-0.11	-0.54	-	-0.95	0.49	0.89	-0.15	-1.39	0.71	-0.80
Financial clerks(433000)	-0.15	-2.64	Y	-2.06	0.74	-0.01	-0.13	-0.93	-0.42	-0.84
Hum resources, training and lab rel spec(131070)	-0.25	-0.59	N	-0.39	0.44	0.66	0.61	-0.07	0.41	-0.14
Info and record clerks(434000)	-0.26	-1.06	Y	-1.18	0.51	0.00	0.86	-0.73	-0.53	0.64
Exec secretaries and admin assistants(436011)	-0.26	-2.03	Y	-1.54	0.88	0.33	0.71	1.30	-0.91	-1.47
Compliance officers(131041)	-0.30	-0.64	Y	-0.52	-0.03	0.22	0.38	1.30	0.48	-0.75
Accountants and auditors(132011)	-0.30	-0.64	Y	-0.52	-0.03	0.22	0.38	-0.85	0.48	-0.75
Human resources manag(113040)	-0.34	0.21	-	-0.30	0.17	0.39	0.77	-0.16	0.49	-0.02
Transp, stor, and distrib, manag(113071)	-0.43	0.01	Y	0.36	-0.65	-0.05	0.65	-0.16	0.18	-0.42
Financial managers(113031)	-0.43	0.01	N	0.36	-0.65	-0.05	0.65	-0.94	0.18	-0.42
Mat record, sched, dispatch workers(435000)	-0.45	-0.45	Y	-0.21	-1.32	0.37	-0.17	0.02	-0.93	0.61
Order, receptionists and record clerks(434100)	-0.55	-1.33	Y	-1.63	0.40	0.92	0.19	-0.72	-1.43	0.92
First line superv of off and admin workers(431011)	-0.58	-1.55	Y	-0.49	0.43	0.36	1.35	1.30	0.73	1.06
Telemarketers(419041)	-0.60	-1.55	-	-2.02	-0.10	0.53	-0.51	-1.54	-2.04	-0.87
Construction managers(119021)	-0.60	-0.58	-	0.64	-2.03	-0.10	0.11	1.30	-0.16	-1.40
Administr serv manag(113011)	-0.87	-0.75	N	-0.23	-0.55	0.21	1.11	-0.16	-0.26	0.46
Cost estimators(131051)	-0.94	-0.38	-	0.29	-0.64	0.57	1.21	-0.19	0.29	-0.73
Adv, MKTG, prom, PR and sales manag(112000)	-0.97	0.58	N	0.31	0.49	1.41	1.83	-0.02	0.65	-1.03
Prop, real est, and comm assoc manag(119141)	-1.01	-1.12	Y	0.26	-2.06	-0.03	1.34	1.30	-0.85	-2.20
Lawyers(230000)	-1.02	0.87	N	0.09	-1.38	0.09	0.68	-0.22	0.49	-1.26
Buyers and purch agents(131020)	-1.05	-0.96	N	-1.12	-0.50	1.37	0.43	-0.34	-0.32	-0.61
Chief executives(111011)	-1.15	-0.36	N	-0.83	-1.34	-0.11	0.83	1.30	0.43	-0.67
Demonstrat and prod promoters(419011)	-1.29	2.49	-	1.66	-2.16	3.68	0.50	1.30	-1.25	-0.08
Sales representatives(414010)	-1.45	0.38	-	-0.41	-1.20	-0.26	1.27	1.30	-0.73	-0.80
Parts salespers(412022)	-1.49	0.17	N	-0.51	-0.76	1.98	1.16	1.30	-1.39	1.25
Switchboard operators(432011)	-1.51	-0.96	Y	-1.52	-1.46	1.49	0.60	-0.19	-2.06	0.85
Advert sales agents(413011)	-1.72	0.54	-	-0.41	-0.42	0.43	2.28	0.55	0.02	-1.41
Retail salespers(412031)	-2.05	0.56	N	-0.74	-2.37	1.62	0.91	1.30	-2.06	1.24
Cashiers(412011)	-2.32	-0.61	Y	-1.57	-1.67	2.02	1.25	1.30	-2.06	2.17

See Appendix Table A4 for the detailed description of each index.

Table A6 - Descriptive Statistics on Occupations

Occupation(SOC Code)	Share of national employment	% zero observations	Mean	Std. dev.
	(1)	(2)	(3)	(4)
Minor occupations (white-collar only)			**Wage bill shares**	
High skilled				
Lawyers(230000)	74.7	69.9	0.5	5.8
Petroleum engineers(172171)	15.8	95.3	0.5	3.4
Life scientists(191000)	47.0	74.5	6.8	17.6
Physical scientists(192000)	58.3	29.9	23.4	24.3
Materials engineers(172131)	77.4	43.9	3.7	7.3
Sales engineers(419031)	78.1	44.3	6.2	10.1
Computer hardw engin(172061)	68.0	71.0	2.8	10.3
Accountants and auditors(132011)	65.2	0.6	42.3	16.7
MKT and survey researchers(193020)	68.2	32.3	36.1	40.2
Management analysts(131111)	62.4	53.4	3.9	8.3
Engineering managers(119041)	77.8	12.5	7.7	7.9
Mining and geolog engin(172151)	27.6	97.3	0.1	0.9
Industrial engineers(172110)	82.0	4.8	39.1	26.0
Aerospace engineers(172011)	85.9	88.3	1.3	7.1
Mechanical engineers(172141)	82.5	13.1	22.6	17.4
Marine engineers(172121)	48.7	97.7	0.1	2.0
Civil engineers(172051)	56.2	71.7	1.3	5.4
Agricultural engineers(172021)	50.1	93.9	0.5	2.8
Medium skilled				
Medic and health serv manag(119111)	5.3	92.7	0.1	0.9
Chief executives(111011)	53.9	0.1	47.5	13.9
Budget analysts(132031)	31.3	62.4	1.1	2.3
Purchasing managers(113061)	74.3	10.6	2.6	1.6
Administr serv manag(113011)	37.6	12.9	2.1	1.7
Construction managers(119021)	8.5	81.6	0.2	1.0
Database administrators(151061)	54.0	31.5	6.4	6.5
Computer system analysts(151051)	66.2	15.9	31.2	22.1
Computer support specialists(151041)	53.1	6.8	26.7	15.8
Computer programmers(151021)	69.3	5.8	36.7	21.8
Human resources manag(113040)	54.5	9.5	3.2	2.1
Adv, MKTG, prom, PR and sales manag(112000)	72.6	4.8	11.0	5.5
Compliance officers(131041)	23.8	59.5	1.3	3.1
Hum resources, training and lab rel spec(131070)	39.4	15.3	10.8	8.4
Advert sales agents(413011)	40.8	84.6	0.9	3.9
Financial managers(113031)	70.1	3.7	7.9	3.5
Low skilled				
Cost estimators(131051)	27.0	24.7	8.9	12.0
Life, phys and soc scien technicians(194000)	48.8	22.7	33.7	31.2
Buyers and purch agents(131020)	71.3	3.2	31.9	13.5
Exec secretaries and admin assistants(436011)	38.7	1.9	14.8	7.0
Sales representatives(414010)	88.3	0.1	84.2	18.1
Statistical assistants(439111)	27.7	82.8	0.1	0.4
Drafters(173010)	80.6	32.5	7.4	11.2
Engineering technicians(173020)	59.2	11.2	21.1	15.8
First line superv of off and admin workers(431011)	46.8	2.2	10.2	3.6
Indust prod manag(113051)	90.0	2.9	16.5	6.9
Prop, real est, and comm assoc manag(119141)	80.1	94.4	0.3	3.2
Order, receptionists and record clerks(434100)	39.4	4.3	5.9	3.0
Other off and admin support workers(439000)	39.4	1.4	13.8	6.2
Demonstrat and prod promoters(419011)	75.6	75.2	0.4	1.3
Financial clerks(433000)	47.7	0.7	18.1	5.3
Retail salespers(412031)	95.9	35.6	5.7	9.7
Transp, stor, and distrib, manag(113071)	41.7	33.3	1.3	1.8
Parts salespers(412022)	93.8	85.5	0.2	0.9
Info and record clerks(434000)	46.9	35.6	0.5	1.2
Switchboard operators(432011)	30.8	28.2	0.6	0.7
Telemarketers(419041)	28.8	75.5	1.2	6.5
Mat record, sched, dispatch workers(435000)	73.8	0.1	34.6	10.8
Weighers, measurers, checkers(435111)	56.0	22.1	1.6	2.0
Cashiers(412011)	87.2	74.7	1.7	7.6
Major groups (white- and blue-collar) & non-labor inputs			**Variable cost shares**	
Management occupations(110000)	55.7	0.7	4.4	4.8
Business and financial operations occupations(130000)	54.9	2.0	1.0	1.9
Computer and mathematical occupations(150000)	61.5	7.9	0.7	3.2
Architecture and engineering occupations(170000)	69.5	6.9	1.2	2.2
Life, physical, and social science occupations(190000)	56.3	16.8	0.3	0.7
Legal occupations(230000)	74.7	69.9	0.5	5.8
Building and grounds cleaning and maintenance occupations(370000)	12.9	3.1	0.1	0.2
Sales and related occupations(410000)	88.2	2.1	1.6	4.1
Office and administrative support occupations(430000)	47.9	0.6	3.1	4.0
Construction and extraction occupations(470000)	7.6	13.9	0.4	0.7
Installation, maintenance and repair occupations(490000)	35.9	5.5	0.5	0.5
Production occupations(510000)	78.7	0.6	9.3	6.1
Transportation and material moving occupations(530000)	45.6	1.1	1.8	1.8
Energy	-	0.0	2.3	3.2
Non-energy material	-	0.0	72.9	17.4

Column (1) reports the fraction of national employment accounted for in 2006 by the industries included in the sample. Column (2) reports the fraction of zero observations in the sample. Columns (3)-(4) report descriptive statistics on the dependent variables of the FAST model: wage bill shares are the shares of the minor occupations in the wage bill of the corresponding major groups. Variable-cost shares are the shares of the major groups and of the non-labor inputs in total variable costs.

Table A7 - Descriptive Statistics on the Shift-Factors and Quasi-Fixed Inputs

	Obs.	Mean	Std. dev.
Service offshoring	1438	2.5	10.4
Material offshoring	1433	16.6	12.6
Computer and software share of capital stock	1440	4.4	5.0
High-tech share of capital stock	1440	5.9	6.8
Industry-specific ICT prices	1440	0.0	0.1
Opennes	1380	-1.2	1.5
Import penetration	1373	-2.0	1.5
Export intensity	1373	-2.4	1.4
Log capital stock	1440	15.5	1.9
Log real output	1440	16.6	1.7

Service offshoring is the share of imported private services in total non-energy input purchases. *Material offshoring* is the share of imported intermediate inputs in total non-energy input purchases. *High-tech capital* includes computer and peripheral equipment, software, communications, photocopy and related equipment, office and accounting equipment. *Industry-specific ICT prices* are obtained by multiplying the economy-wide time series of computer prices with the average capital share of computer and software equipment in each industry between 1987 and 1996. *Openness* is log exports plus imports over total shipments. *Import penetration* is log imports over apparent consumption. *Export intensity* is log exports over total shipments. *Real output* is the real value of shipments.

Table A8 - Price Elasticities Matrix Estimated with Quasi-Maximum Likelihood

	w11	w13	w15	w17	w19	w23	w37	w41	w43	w47	w49	w51	w53	pen	pmat
w11	***-0.97***	-0.26	0.11	-0.53	0.02	0.83	-0.01	-0.09	-0.18	0.01	-0.09	0.19	0.22	-0.13	-0.07
w13	-1.13	***-0.31***	0.55	-0.84	0.18	2.29	-0.01	-0.24	-1.07	0.42	0.26	-0.16	0.62	-0.12	-1.35
w15	0.17	0.19	***-0.97***	-0.04	-0.06	0.90	0.01	0.05	0.21	0.11	-0.01	-0.80	-0.10	0.18	-0.76
w17	-1.16	-0.42	-0.06	***-1.44***	0.11	1.22	-0.03	-0.01	-0.39	-0.07	-0.03	-0.13	-0.27	0.31	1.43
w19	0.08	0.24	-0.23	0.28	***-1.28***	0.76	0.00	-0.05	0.83	-0.11	0.09	-0.30	-0.35	-0.09	-0.79
w23	0.36	0.23	0.26	0.25	0.06	***-0.48***	0.00	0.08	0.10	0.05	-0.01	-0.02	-0.07	0.05	-1.79
w37	-0.19	-0.08	0.33	-0.39	0.01	0.19	***-1.05***	0.09	-0.26	0.15	0.18	-0.29	-0.15	-0.17	0.68
w41	-0.43	-0.25	0.15	-0.02	-0.04	0.78	0.01	***-1.10***	-0.26	0.10	-0.07	0.08	-0.13	-0.17	0.43
w43	-0.72	-1.02	0.59	-0.73	0.60	0.98	-0.03	-0.23	***-1.78***	-0.77	0.02	0.16	-0.03	-0.34	0.69
w47	0.08	0.74	0.54	-0.25	-0.15	0.76	0.03	0.17	-1.44	***-1.21***	-0.02	0.22	-0.24	0.02	-0.20
w49	-1.09	0.73	-0.08	-0.18	0.20	-0.17	0.07	-0.19	0.06	-0.03	***-1.21***	0.25	0.13	0.05	0.53
w51	0.11	-0.02	-0.33	-0.03	-0.03	-0.04	-0.01	0.01	0.02	0.02	0.01	***-1.03***	0.02	-0.07	0.42
w53	0.72	0.47	-0.23	-0.40	-0.20	-0.57	-0.01	-0.10	-0.02	-0.10	0.04	0.07	***-0.82***	-0.06	0.29
pen	-0.37	-0.08	0.32	0.39	-0.04	0.27	-0.01	-0.11	-0.23	0.01	0.01	-0.35	-0.05	***-0.84***	0.15
pmat	-0.02	-0.08	-0.13	0.16	-0.03	-1.04	0.01	0.02	0.04	-0.01	0.01	0.17	0.03	0.02	***-0.10***

Legend: w11 (wage of "management occupations"); w13 (wage of "business and financial operations occupations"); w15 (wage of "computer and mathematical occupations"); w17 (wage of "architecture and engineering occupations"); w19 (wage of "life, physical and social science occupations"); w23 (wage of "legal occupations"); w37 (wage of "building and grounds cleaning and maintenance occupations"); w41 (wage of "sales and related occupations"); w43 (wage of "office and administrative support occupations"); w47 (wage of "construction and extraction occupations"); w49 (wage of "installation, maintenance and repair occupations"); w51 (wage of "production occupations"); w53 (wage of "transportation and material moving occupations"); pen (price of energy); pmat (price of non-energy materials).