A Sorted Tale of Globalization: White Collar Jobs and the Rise of Service Offshoring

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Abstract: We study how the rise of trade in services with China and India has impacted U.S. labour markets. The topic has two understudied aspects: it deals with service trade (most studies deal with manufacturing trade) and it examines the historical first of U.S. workers competing with educated but low-wage foreign workers. Our empirical agenda is made complicated by the endogeneity of service imports and the endogenous sorting of workers across occupations. To develop an estimation framework that deals with these, we imbed a partial equilibrium model of 'trade in tasks' within a general equilibrium model of occupational choice. The model highlights the need to estimate labour market outcomes using *changes* in the outcomes of individual workers and, in particular, to distinguish workers who switch 'up' from those who switch 'down'. (Switching 'down' means switching to an occupation that pays less on average than the current occupation). We apply these insights to matched CPS data for 1996-2007. The cumulative 10-year impact of rising service imports from China and India has been as follows. (1) Downward occupational switching increased by 16%. (2) Transitions to unemployment increased by almost a full percentage point, potentially raising the white-collar unemployment rate from 3.0% to 3.9%. (3) The earnings of occupational 'stayers' fell by a tiny 2.3% as did earnings average across all workers. However, for the sub-population of workers who switched down or became unemployed, earnings fell by 15% and 43%, respectively. (4) In contrast, service exports had statistically insignificant effects on average earnings, switching and unemployment.

JEL classification: F16. *Keywords:* Service offshoring; China; India; U.S. labour market.

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1. Introduction

As measured by the value added in U.S. trade flows, service imports are now almost as large as merchandise imports and service exports are now much larger than merchandise exports.[1] Yet the impact of trade on U.S. labour market outcomes remains dominated by analysis of merchandise trade e.g., Autor, Dorn and Hanson (2013). There are several reasons to consider service trade independently of merchandise trade. First, the total impact of trade on U.S. workers is the sum of the impacts of merchandise and service trade. The effects documented in this paper are thus *in addition to* the effects documented elsewhere. Second, the service tradability 'revolution' and the accompanying rise of service offshoring to China and India has a major new implication for American workers: for the first time ever educated U.S. workers are competing with educated but low-paid foreign workers. It is thus far from clear that current estimates of the elasticities of labour-market outcomes with respect to merchandise imports are relevant for service imports. Third, service imports penetrate more pervasively into the economy than do traditional merchandise imports: By most estimates the number of U.S. jobs now exposed to service imports is at least double the size of total manufacturing employment (van Welsum and Reif 2006, Blinder 2009, and Jensen and Kletzer 2010). Yet the impact of service trade on labour-market outcomes in the U.S. and elsewhere remains scant.[2]

We use an under-exploited and obvious source of data to study the impacts of service offshoring. In constructing the official statistics on service trade, the U.S. Bureau of Economic Analysis (BEA) surveys private-sector firms across all sectors of the economy and asks questions about the type of services each firm exports and sources from abroad. Since these service types map relatively neatly into occupations, we aggregate service trade to the occupation level and use it to study labour-market impacts at the individual-occupation level. For example, we study impacts on worker-level occupational switching. This occupational orientation is particularly valuable in light of research by Ebenstein, Harrison, McMillan and Phillips (2014) who show that merchandise trade impacts are larger at the occupational level than at the industry level.

The first contribution of this paper is its focus on service trade. The second contribution is its focus on occupational switching and unemployment. The largest costs of import competition are

[1] Based on 2016 U.S. trade data adjusted for the difference between value added in manufacturing and service trade as reported in Johnson and Noguera (forthcoming, figure 3).

[2] See Liu and Trefler (2008), Crino (2010b), Criscuolo and Garicano (2010), Blinder and Krueger (2013), Böckerman and Maliranta (2013), and Geishecker and Görg (2013). These papers are reviewed below.

likely borne by those who must change their labour market status. For example, occupational switches, industry switches, and unemployment transitions have profound implications for workers' lifetime welfare.[3]

Despite these well-known costs of occupational switching and unemployment, there has been no analysis of how trade in services creates or mitigates such costs. To fill the gap, we examine the impact of service trade from China and India – i.e., of competition from low-wage educated labour – on occupational switching, the incidence of unemployment, and earnings. Our results complement studies based on merchandise trade shocks by Kletzer (1998, 2001), Crino (2010a), Baumgarten, Geishecker and Gorg (2013), Ebenstein et al. (2014), Hummels, Jorgensen, Munch and Xiang (2014) and Autor, Dorn, Hanson and Song (2014). These are reviewed below.

The third and final focus of this paper is motivated by welfare analysis and policy responses to rising imports. As noted by Gibbons and Katz (1992) and many others, these responses depend critically on the role played by working sorting. If sorting is unimportant then high-paying occupations likely reflect 'good jobs' (e.g., unionized jobs or jobs associated with efficiency wages) and there are large welfare losses when these good jobs move to China and India. On the other hand, if worker sorting is important then the welfare losses are more moderate. In terms of policy, in a good-jobs world, strategic trade policy is warranted (Krugman, 1986) whereas in a sorting world the right policies are ones that improve the match between workers and firms.[4]

In order to address these issues we imbed a partial equilibrium variant of the Grossman and Rossi-Hansberg (2008) model of trade in tasks into the Ohnsorge and Trefler (2007) general equilibrium model of occupational choice. The latter is a Ricardian-Roy model in which workers with unobserved heterogeneous attributes sort across occupations that have heterogeneous returns to these attributes. The trade-in-tasks aspect of the model plays the limited role of motivating the need for and choice of instruments to deal with the endogeneity of imports and exports. Empirically, we find that this endogeneity is not important. The sorting aspect of the model helps in two ways. First, it clarifies the type of assumption needed to identify the impact of trade on the

[3]Jacobson, LaLonde and Sullivan (1993) find that displaced workers suffer long-term losses of as high as 25%. Neal (1995) shows that human capital is industry-specific and thus workers who switch industries experience greater wage losses following displacement. Parent (2000) confirms that industry-specific human capital matters a lot for workers' wage profiles. Kambourov and Manovskii (2009) find that human capital is also occupation specific: five years of occupational tenure is associated with a 12-20% increase in wages. Topel (1991) shows that 10 years of job seniority raises wages by over 25%.

[4]Gibbons, Katz, Lemieux and Parent (2005) find that manufacturing is more closely characterized by good jobs and services more closely characterized by sorting. This is another reason why it is important to distinguish between merchandise and service trade.

earnings of occupational switchers. A strong identification assumption is that workers sort only on observable characteristics and have no unobserved heterogeneity. This assumption is essentially made by Artuç, Chaudhuri and McLaren (2010). Under this assumption, we can use propensity-score matching to estimate an average treatment effect (ATE). A weaker identification assumption is that workers sort only on observables, but have unobserved heterogeneity. This assumption is made by Dix-Carneiro (2014) and Caliendo, Dvorkin and Parro (2015). The weak identification assumption leads to a very different estimation strategy and generates three conclusions. (1) The estimated earnings effects are similar to the ATEs based on propensity scoring. (2) The parameter estimates imply that workers are sorting based on unobserved characteristics. (3) The parameter estimates support the sorting mechanism described by our model. As noted, our finding of a prominent role for sorting is important for policy.[5]

Turning to our empirical work, we combine CPS data for 1996–2007 with detailed BEA data on bilateral service transactions between the United States and 31 trade partners. To examine the impact of service trade on occupational switching, transitions to unemployment, and earnings we use March-to-March matched CPS data.[6] An unexpected prediction of the model is that there will be differences between workers who switch up to higher-paying occupations versus those who switch down to lower-paying occupations. A high-paying occupation is one that pays well even after controlling for observed worker characteristics. That is, it is the occupational fixed effect in a Mincer wage regression and is often called the 'inter-occupational wage differential.' We find that rising service imports from China and India have had the following cumulative 10-year impacts. (1) Downward occupational switching increased by 16%. (2) Transitions to unemployment increased by almost a full percentage point, potentially raising the unemployment rate of white collar workers from 3.0% to 3.9%. (3) The earnings of occupational 'stayers' fell by a tiny 2.3%. In contrast, for the sub-population of workers who switched down or became unemployed, earnings fell by 15% and 43% respectively. Averaging across all workers, earnings fell by 2.3%. (4) Service

[5]There is a large literature on worker sorting and international trade. See Davidson, Martin and Matusz (1999), Grossman and Maggi (2000), Grossman (2004), Ohnsorge and Trefler (2007), Costinot (2009), Costinot and Vogel (2010), Davidson and Matusz (2010), Helpman and Itskhoki (2010), Davis and Harrigan (2011), Helpman, Itskhoki and Redding (2010) and Bombardini, Gallipoli and Pupato (2012). Our work is most closely related to Artuç et al. (2010) and Dix-Carneiro (2014). They develop and estimate a structural model of workers' dynamic choices of industry and how these choices responds to trade shocks. We are also interested in how trade affects sorting behaviour (occupational choice in our setting), but take a reduced-form approach that focuses on identification issues associated with the endogeneity of imports and the unobserved heterogeneity of workers.

[6]In an international trade context these data have been exploited by Goldberg, Tracy and Aaronson (1999) and Goldberg and Tracy (2003) in their study of the impacts of exchange rates, by Liu and Trefler (2008) in a paper superseded by the current manuscript, and by Ebenstein et al. (2014, table 9) in their study of earnings.

exports had insignificant effects on average earnings, switching and unemployment.

The tiny 2.3% effect will, at first glance, seem quite different from previous studies, but this is not the case. For example, Autor et al. (2013, table 7 and p. 2125) find a zero effect of Chinese manufacturing imports on the earnings of manufacturing workers and a -0.8% effect for earnings of non-manufacturing workers. Ebenstein et al. (2014, table 4) find a -1.07% effect for all workers and a -1.98% effect for workers in the most routine occupations. Some of the largest estimates in the literature are by Baumgarten et al. (2013, table 7), who find that imports of intermediate inputs reduced average earnings by approximately 6%. The way in which studies obtain larger 'headline' impacts is by looking at subsets of the population who are most impacted. For example, the 12–17% negative earnings impacts that Ebenstein et al. (2014) headline in their abstract are for the subset of the population that experiences an occupational switch. An exception is Autor et al. (2014) who are able to track workers in a long panel using Social Security data. Their numbers are more in line with the earlier research initiated by Jacobson et al. (1993) and discussed above.

The paper is organized as follows. Section 2 provides a brief literature review. Section 3 lays out the theory. Section 4 describes the BEA service trade data and the matched CPS data. Section 5 reports the results for occupational switching and transitions to unemployment. Section 6 reports the IV results. Section 7 reports the results for earnings changes. Section 8 summarizes the impact of service trade with China and India on earnings, switching, and unemployment. Section 9 provides a large number of specification searches that establish the robustness of our results. Section 10 concludes.

2. Literature Review

A number of papers have examined the impact of *merchandise imports* and multinationals' foreign affiliates on labour market outcomes. Using firm-level data on Japanese multinationals over 1979–1990, Head and Ries (2002) find that foreign affiliate production in low-income countries raises the skill intensity of domestic (Japanese) production. Using firm-level data on U.S. multinationals over 1982–1999, Harrison and McMillan (2011) find that foreign-affiliate employment in low-income countries decreases domestic (U.S.) employment. Using firm-level German data for 1998-2001 combined with worker information, Becker, Ekholm and Muendler (2013) find that foreign-affiliate activities increase the wage-bill shares of highly educated workers. Using firm-level French data for 1986–1992, Biscourp and Kramarz (2007) find that increased imports of goods, especially from low-income countries, displaces domestic (French) production jobs. Using U.S. data for 2000–2007 and examining the combined impact of immigration and foreign-affiliate employment, Ottaviano, Peri and Wright (2013) find that manufacturing industries with large increases in global exposure fare better in terms of native employment growth.

Only a few papers have examined the impacts of *service trade*. Using British worker-level data, Criscuolo and Garicano (2010) find that increased imports of services raises both wages and employment in occupations subject to licensing requirements. Using British household data, Geishecker and Görg (2013) find that offshoring raises the wages of skilled labour and lowers the wages of unskilled labour. Using matched CPS data, Liu and Trefler (2008) find very small impacts of service imports from China and India on U.S. industry switching, occupational switching and earnings changes. These conclusions are superseded by the current manuscript. Crino (2010b) shows that service imports drive up the *relative* demand for skilled versus unskilled labour in tradable sectors. Blinder and Krueger (2013) administered a worker-level survey on earnings and job offshorability and found no correlation between the two. Using linked employer-employee data, Böckerman and Maliranta (2013) find that offshore outsourcing to low-wage countries involves job destruction. See Amiti and Wei (2005), Trefler (2006), Crino (2009) and Feenstra (2010) for surveys.

We have already discussed the main results in Ebenstein et al. (2014) so here we focus on several dimensions in which their work differs from ours. First, the nature of the shock is different. They look at foreign-affiliate employment, distinguishing between affiliates in low- and high-wage countries. They also look at manufacturing imports of goods from all sources. In contrast, we examine imports of services. A complete picture of offshoring must *sum together* the effects we find here with those found by Ebenstein et al.. Second, our research is primarily about the impact of service offshoring on worker-level occupational switching and transitions to unemployment. We only secondarily examine wage impacts. In contrast, Ebenstein et al. primarily look at wages (including wage effects that stem from trade-induced reallocation of workers). Third, both studies find much bigger wage effects for *subsets* of the population. They look at occupational switchers and for this sub-population find no wage effects using OLS but big wage effects using IV (12–17%). In contrast, we look at subsets of the population that switched down, switched up, or transited into unemployment. For those that switched down or into unemployment, the OLS and IV wage impacts are identical and large, 15% and 43%, respectively. Fourth, we carefully examine the role of worker sorting, which is important for discussions of welfare and policy.

Finally, there are a number of studies of the impact of merchandise trade on worker displacement. Using U.S. data, Kletzer (1998, 2001) estimates small wage effects. Using U.S. data, Crino (2010a) finds that offshoring significantly lowers post-displacement wages. Using German data, Baumgarten et al. (2013) find negative wage effects of offshoring that are associated with inter-industry labor reallocation. Further, the size of the negative wage impact depends importantly on the task content of the jobs. Using detailed Danish employer-employee data, Hummels et al. (2014) find that offshoring depresses low-skilled wages and increases high-skilled wages. Using U.S. Social Security records to track workers for decades, Autor et al. (2014) find that commuting zones that are exposed to Chinese imports experience lower cumulative earnings, lower cumulative employment and lower earnings per year worked.

3. Theory

We are interested in the reduced-form relationship between individual outcomes (e.g., switching occupations or becoming unemployed) and trade in services. Let y denote the outcome, let $d \ln M$ and $d \ln X$ denote the log changes in imports and exports of services, and let C denote an additional set of controls. The reduced-form relationship of interest is

$$y = \alpha + \gamma_M d \ln M + \gamma_X d \ln X + \gamma_C C + \varepsilon \tag{1}$$

where for expositional simplicity we use a linear probability specification. In this section we lay out a simple theory that motivates the interpretation of (γ_M, γ_X), the choice of C, the potential for endogeneity, the sign of endogeneity bias, and the appropriate instruments. We first lay out a partial equilibrium model of trade in tasks adapted from Grossman and Rossi-Hansberg (2008) and then embed it into a general equilibrium model of occupational choice from Ohnsorge and Trefler (2007).

A. *A Partial Equilibrium Model of Offshoring*

There is a single industry Q and a continuum of tasks $i \in [0,1]$. Production of one unit of Q requires a fixed amount of each and every task.[7] Tasks are normalized so that a measure one of tasks is needed to produce one unit of Q. Let L measure units of labour. A task requires a units of labour

[7] Adding substitution possibilities across tasks provides no additional empirical insights.

if produced at home and a^* units if produced abroad. Tasks are identical except in one dimension: some are more easily offshored than others. In particular, a task that requires a units of labour when produced at home requires $a^*\beta t(i)$ units of labour when produced abroad. β is a measure of the efficiency of the technology for offshoring. Tasks are ordered so that $t(i)$ is increasing in i. We assume that t is differentiable, strictly increasing and strictly positive.

Domestic and foreign wages are denoted by w and w^*, respectively. Task i is done more cheaply abroad than at home when $w^*a^*\beta t(i) < wa$. We assume that some but not all tasks are offshored.[8] This 'interior' assumption and the fact that t is strictly increasing implies that there is a unique $I \in (0,1)$ given by

$$w^*a^*\beta t(I) = wa \tag{2}$$

such that all tasks $i < I$ are offshored and all tasks $i > I$ are produced at home. Imports are the measure of tasks imported:[9]

$$M \equiv IQ$$

We assume that there is an upward-sloping supply of domestic labour to the industry, denoted $L^S(w)$. We endogenize this supply function when we turn to the general equilibrium in subsection C below. Since one unit of output requires one unit of each task, the demand for domestic labour is $L^D = a\,(1 - I)\,Q$. Substituting $I = M/Q$ into this yields

$$L^D = a\,(Q - M) \tag{3}$$

Foreign labour supply is assumed infinitely elastic at wage w^*.

The unit cost of task i is wa for $i \in (I,1]$ and $w^*a^*\beta t(i)$ for $i \in [0,I)$. With constant returns to scale and free entry, price equals average cost. Hence

$$p = wa(1 - I) + w^*a^*\beta \int_0^I t(i)di. \tag{4}$$

Let $D(p,\delta_D)$ and $X(p,\delta_X)$ be domestic demand and foreign demand (exports), respectively. These are assumed to be downward sloping in price p. δ_D and δ_X are domestic and foreign demand shifters, respectively. We close the partial equilibrium model with two equilibrium conditions. The product market clearing condition is $D + X = Q$. The labour market clearing condition is

[8] In the context of trade with China or India, it is natural to assume that the productivity-adjusted foreign wage bill w^*a^* is lower than productivity-adjusted domestic wage bill wa and that $\beta t(\cdot)$ is such that in equilibrium $w^*a^*\beta t(0) < wa < w^*a^*\beta t(1)$. This condition can be guaranteed by appropriate choice of the exogenous parameters a and a^*.

[9] We could equally work with (1) the measure of tasks imported *inclusive* of offshoring costs, $\int_0^I \beta t(i)diQ$ or (2) the labour content of the measure of tasks imported, a^*IQ. Our key points hold for these definitions as well.

$L^D = L^S = L$. Our product and labour market equilibrium conditions together with $M \equiv IQ$ and equations (2)–(4) are six equations which determine the six endogeneous variables Q, L, I, M, w, and p. The exogenous variables are w^*, a^*, a, β, δ_D, and δ_X.

B. ***Biases in Estimating Labour Demand when Imports are Endogenous***

As a preliminary to estimating equation (1), consider estimating the impact of changes in imports on changes in labour demand. Plugging $Q = D + X$ into equation (3) and totally differentiating yields

$$d \ln L^D = -\theta_M d \ln M + \theta_X d \ln X + \theta_D d \ln D + d \ln a \tag{5}$$

where θ_M, θ_X, and θ_D are all positive.[10] In estimating equation (5), several possible sources of endogeneity bias arise and the model provides a way of coherently classifying them. This is the most important contribution of the partial equilibrium theory. The sign of the endogeneity bias depends on the nature of the shock generating the change in imports. To establish this we consider three shocks, a domestic demand shock (δ_D), a foreign cost shock (w^*a^*), and an offshoring cost shock (β).

Domestic demand shock (δ_D): Consider figure 1. The right panel plots demand and supply in the domestic labour market. The left panel plots the demand for imports.[11] Consider a positive shock to domestic product demand (δ_D). The resulting increase in Q shifts out both the M and L^D schedules in figure 1. There are then second-order effects as w, p, and I all rise. However, the total effect is that both M and L^D rise.[12] It follows that *a demand shock induces a non-causal positive correlation between import changes* $d \ln M$ *and labour demand changes* $d \ln L^D$. **If one naively regressed** $d \ln L^D$ **on** $d \ln M$ **without any controls for demand shocks the OLS estimate would be less negative than the 'true' coefficient i.e., the negative impact of imports would be underestimated.**

Effective foreign wage shock (w^*a^*): A decline in effective foreign wages w^*a^* is shown in the left panel of figure 2 as a downward shift of the foreign labour supply schedule. Holding w and p constant, the fall in w^* makes offshoring more attractive (I falls) so that imports increase while

[10] The coefficients are shares: $\theta_M = M/(D + X - M)$, $\theta_X = X/(D + X - M)$, and $\theta_D = D/(D + X - M)$.

[11] Appendix 1 formally proves the obvious point that labour demand L^D and import demand M both slope downwards.

[12] See Appendix 2 and especially equations (A.5) and (A.8).

Figure 1: Domestic Demand Shock (δ_D)

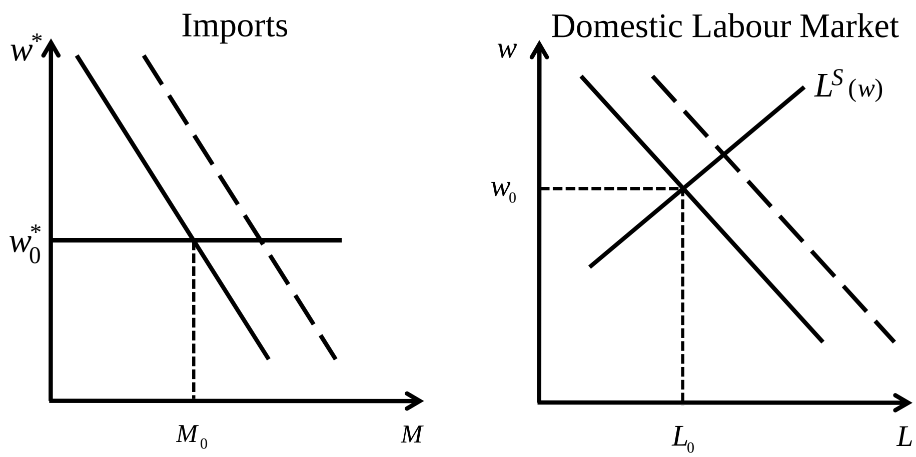
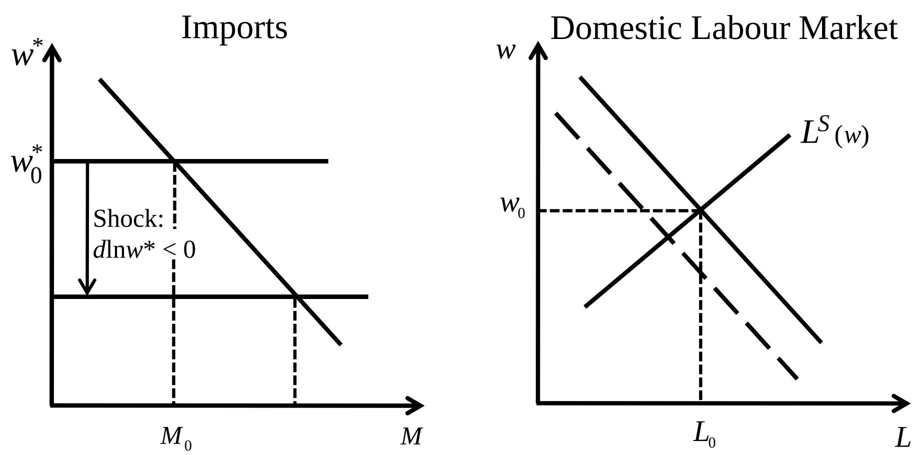


Figure 2: Effective Foreign Wage Shock (w^*a^*)



domestic labour demand L^D decreases.[13] Now however, *the change in L^D is causally related to the change in M*. This is because changes in w^*a^* have no direct impacts on domestic labour demand: changes in w^*a^* affect L^D only via changes in imports. This can be seen from the fact that w^* and a^* only appear in equation (2). **Thus, when effective foreign wages are the source of import shocks, OLS produces an unbiased estimate of the impact of imports on switching.** Another way of saying the same thing is that $d\ln w^*a^*$ is a valid instrument for $d\ln M$ in a regression of $d\ln L^D$ on $d\ln M$.

Offshoring cost shock (β): Since β and w^*a^* always appear together ($w^*a^*\beta$ in equation 2), the

[13]There will be second-order effects as w and p adjust. Appendix equation (A.6) shows that M must rise. Appendix equation (A.9) shows that L^D can rise or fall.

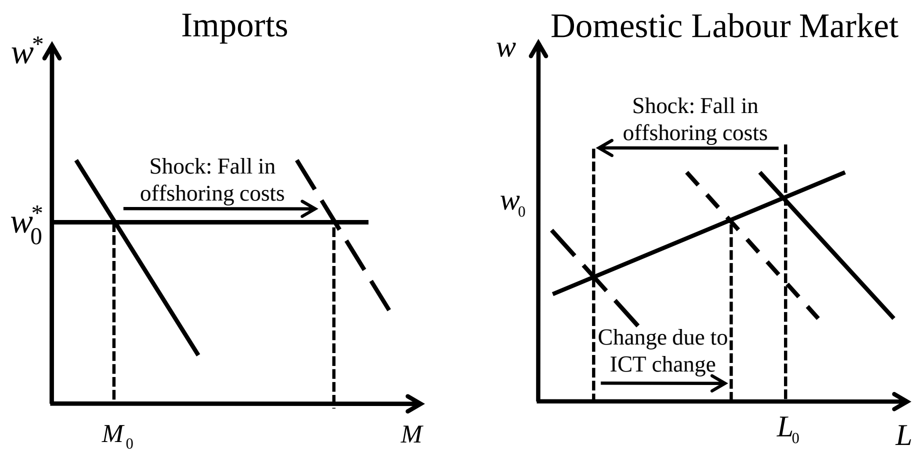
analysis of changes in w^*a^* would appear to carry over to changes in β. This is not the case. In particular, $d\ln\beta$ is not a valid instrument. When β falls, offshoring becomes more attractive and tasks are moved from the domestic economy to the foreign economy. This is shown in figure 3. The rise in β raises I directly (equation 2) which in turn raises $M \equiv IQ$ and, via M, indirectly raises L^D (equation 3). The problem with this analysis is that the reductions in offshoring costs β were driven by innovations in information and communications technologies (ICTs), innovations that are associated with skill-biased technical change and that have famously had independent impacts on U.S. labour markets e.g., Katz and Murphy (1992). The most natural way to model these independent impacts is by treating ICT innovations as labour demand shifters i.e., ICT improvements directly raise the demand for skilled labour.[14] Mathematically, we would introduce β and $d\ln\beta$ directly into equations (3) and (5), respectively. But this is exactly how a and $d\ln a$ already appear in equations (3) and (5). Thus, ICT innovations are easily introduced into the model by reinterpreting a as depending on ICTs.

Adopting this approach, the direct impact of ICT innovations is illustrated in the right panel of figure 3, which is here taken to represent the market for skilled labour. The innovations raise the demand for skilled domestic labour. Since the change in L^D is now smaller, *an OLS regression of $d\ln L^D$ on $d\ln M$ will not produce a causal estimate*. **When ICT innovations are the source of import shocks, OLS will under-estimate the negative impact of imports on skilled labour.** The solution to this problem is easy. ICT-based measures of $d\ln\beta$ should *not* be used as instruments; rather, such measures should be the empirical counterpart to $d\ln a$ and thus included directly in the second-stage equation (5).

To summarize, a regression of $d\ln L^D$ on $d\ln M$ without controls for demand and ICT shocks produces OLS estimates that are biased towards zero. One solution implied by the theory is to instrument $d\ln M$ by changes in effective foreign wages $d\ln w^*a^*$. Another solution is to include demand and ICT shocks ($d\ln D$ and $d\ln a$) directly into the second-stage equation (5). We will find empirically that when demand and ICT shocks are included and foreign wages are used as instruments, the IV estimates are larger (in absolute value) than the OLS estimates as predicted.

[14] We focus on skilled labour because, as shown in appendix table A.4, offshorable jobs are highly skill-intensive.

Figure 3: Offshoring Cost Shock (β)



C. *The Offshoring of Tasks in General Equilibrium: Worker Sorting*

We turn now to the occupational choices of workers. Let $k = 1, \ldots K$ index occupations. We assume that there are K products or industries and each is produced using a unique occupation. This eliminates a layer of complexity that has been shown to be important empirically e.g., Gathmann and Schönberg (2010) and Baumgarten et al. (2013); however, our data are not well-suited to handle tasks.[15] All the industry-level partial equilibrium variables now require k subscripts e.g., wages per unit of labour w_k and the supply of units of labour $L_k^S(w_k)$.

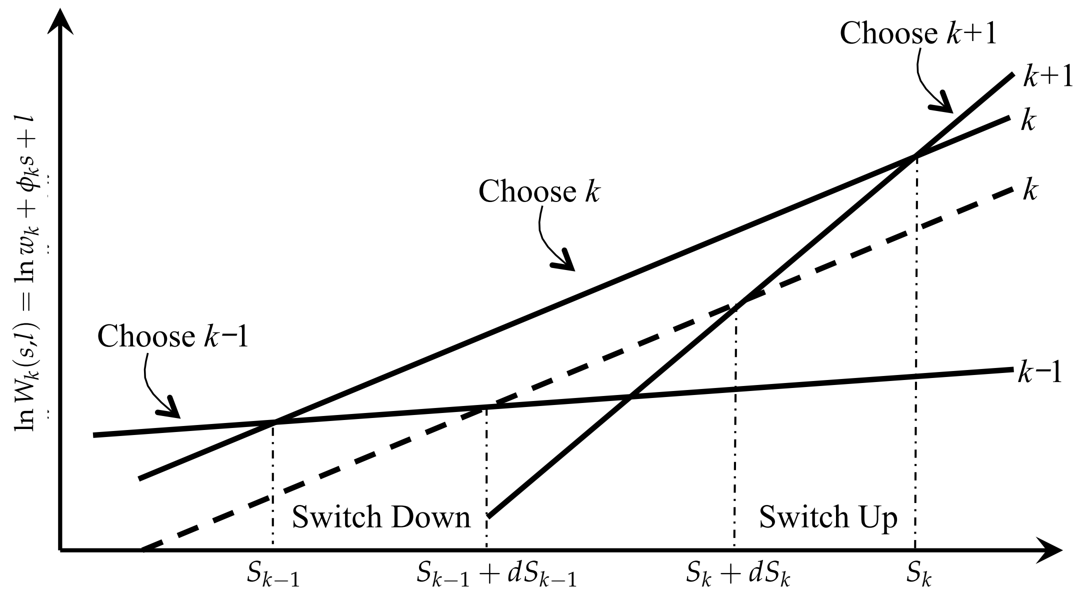
Workers in occupation k can produce any of the continuum of tasks $i \in [0,1]$ required to produce good k. Since workers are perfectly substitutable in the production of tasks, in order to know the supply of tasks it is enough to know the supply of units of labour i.e., one does not need to know how these units are distributed across worker types. We therefore turn to the supply of units of labour $L_k^S(w_k)$.

Workers are heterogeneous. Following Ohnsorge and Trefler (2007), each worker is endowed with a pair of attributes $(s,l) \in \mathbb{R}^2$ which allows the worker to supply $e^{\phi_k s + l}$ units of labour when employed in occupation k. From the previous section, the worker is paid w_k per unit of labour supplied and so earns $W_k(s,l) = w_k e^{\phi_k s + l}$. Log earnings are thus

$$\ln W_k(s,l) = \ln w_k + \phi_k s + l \ . \tag{6}$$

[15]Some work has been done on routine-ness using CPS data combined with O*Net information. See Ebenstein et al. (2014) and table 10 of our 2011 NBER working paper.

Figure 4: Worker Sorting



Equation (6) establishes that the entire occupation-k earnings schedule $W_k(\cdot,\cdot)$ is pinned down by the w_k from the partial equilibrium trade-in-tasks model.

Each worker chooses the occupation that maximizes earnings. We label occupations so that ϕ_k is increasing in k i.e., $\phi_k > \phi_{k-1}$ for all k. Then log earnings are supermodular in (k,s) and it follows that high-s workers sort into high-k occupations. Note that s controls comparative advantage sorting whereas l controls absolute advantage.

Sorting is illustrated in figure 4 where $\ln W_k(s,l)$ against s. There are three solid lines, which correspond to occupations $k-1$, k, and $k+1$. The slopes are given by the ϕ_k and are thus increasing in k. The sorting rule is characterized by the values of s at which the lines cross. Using equation (6), these crossing points are:

$$S_{k-1} \equiv \frac{\ln(w_{k-1}/w_k)}{\phi_k - \phi_{k-1}} \quad \text{and} \quad S_k \equiv \frac{\ln(w_k/w_{k+1})}{\phi_{k+1} - \phi_k}. \tag{7}$$

A type-(s,l) worker chooses occupation k if and only if $S_{k-1} < s < S_k$. Without loss of generality we assume that there is positive employment in all occupations. Then it is easy to show that $S_{k-1} < S_k$ for all $k > 1$.

We assume that there is a unit mass of workers in the economy and that the distribution of worker types is described by some bivariate distribution with density $g(s,l)$. It follows that the mass or units of labour supplied to occupation k is

$$L_k^S(w_k) = \int_{-\infty}^{\infty} \int_{S_{k-1}}^{S_k} e^{\phi_k s+l}\, g(s,l)\, ds\, dl. \tag{8}$$

A fall in w_k is shown in figure 4 as the dashed line. It shifts the boundaries S_{k-1} and S_k inwards, that is, it reduces the number of workers who choose occupation k. More formally, by inspection of equations (7)–(8), L_k^S is increasing in w_k. Thus, we have endogenously derived the upward-sloping supply function $L_k^S(w_k)$ used in the partial equilibrium analysis.

The sorting of workers across occupations/industries is the key general equilibrium result that we will exploit in our empirical work. Since we will not be exploiting empirically any other feature of general equilibrium — notably the determination of foreign wages w_k^* or income effects operating through the trade balance — we relegate a complete specification of the model and the definition of general equilibrium to Appendix 3.

D. ***Implications for the Estimation of Occupational Switching***

In this section we derive the probability of switching up and down in response to shocks. These probabilities are our estimating equations for switching. As shown empirically in table 3 there is sorting based on observables. Hence an important econometric issue is the possibility of sorting based on unobservables. We thus assume that $s = s^o + s^u$ where s^o is *o*bservable and s^u is *u*nobservable. From the econometricians's perspective, s^u is a random variable that is correlated with s^o and l.[16] Let $G(s^u \mid s^o,l)$ be the cumulative distribution function for s^u conditional on (s^o,l).

We wish to know the probability that a worker switches out of occupation k conditional on observables s^o. We derive this for the case where $d\ln w_k < 0$ so that $dS_{k-1} > 0 > dS_k$. The derivation for the case where $d\ln w_k > 0$ follows immediately and leads to the same estimating equation. A worker switches up if $S_k + dS_k < s < S_k$ or, using $s = s^o + s^u$, a worker switches up if $S_k - s^o + dS_k < s^u < S_k - s^o$ where, from equation (7), $dS_k = (\phi_{k+1} - \phi_k)^{-1} d\ln w_k$. Letting $G(s^u \mid s^o,l)$ be the cumulative distribution function for s^u conditional on (s^o,l), the probability of a worker switching up conditional on (s^o,l) is just

$$P_k^+ \equiv G(S_k - s^o \mid s^o,l) - G\left(S_k - s^o + (\phi_{k+1} - \phi_k)^{-1} d\ln w_k \mid s^o,l\right) \tag{9}$$

[16]If l also has an unobserved component ($l = l^o + l^u$) then l^u becomes the residual in our regressions and we require the standard orthogonality condition $\mathbb{E}[l^u | s^o,l^o] = 0$.

Throughout, '+' and' $-$' superscripts refer to switching up and down, respectively. Linearizing this equation yields

$$P_k^+ = \theta_k^+ + \gamma_s^+ s^o + \gamma_l^+ l - \theta_w^+ d\ln w_k \tag{10}$$

where by inspection of equation (9), $\theta_w^- > 0$. [17]

To develop an expression for $d\ln w_k$, define the elasticity of labour supply $\eta^S \equiv d\ln L_k^S(w_k)/d\ln w_k$ so that $d\ln w_k = d\ln L_k^S/\eta^S = d\ln L_k^D/\eta^S$. Plugging in equation (5) yields

$$d\ln w_k = \left[-\theta_M d\ln M + \theta_X d\ln X + \theta_D d\ln D + d\ln a\right]/\eta^S\,. \tag{11}$$

Plugging this into equation (10) yields our switching-up estimating equation:

$$P_k^+ = \theta_k^+ + \gamma_s^+ s^o + \gamma_l^+ l + \theta_M^+ d\ln M - \theta_X^+ d\ln X - \theta_D^+ d\ln D - \theta_a^+ d\ln a \tag{12}$$

where θ_M^+, θ_X^+, θ_D^+, and θ_a^+ are all positive.[18]

By a symmetric argument, our switching-down estimating equation is:

$$P_k^- = \theta_k^- + \gamma_s^- s^o + \gamma_l^- l + \theta_M^- d\ln M - \theta_X^- d\ln X - \theta_D^- d\ln D - \theta_a^- d\ln a \tag{13}$$

where θ_M^-, θ_X^-, θ_D^-, and θ_a are all positive.[19]

We have not yet discussed the signs of γ_s^+ and γ_s^-. Suppose the correlation between s^o and $s = s^o + s^u$ is positive. (A sufficient condition for this is the empirically likely possibility that obervables (s^o) are positively correlated with unobservables (s^u).) Consider two workers who initially choose k. The worker with the higher s^o has a higher s probabilistically. Hence, the high-s^o worker is less likely to be in the switching-down interval $(S_{k-1}, S_{k-1} + dS_{k-1})$ and more likely to be in the switching-up interval $(S_k + dS_k, S_k)$. That is, $\gamma_s^- < 0 < \gamma_s^+$ or at least $\gamma_s^- < \gamma_s^+$.[20] We find this to be true empirically, which provides one of several confirmations of the sorting mechanism underlying our model.

Finally, the implications of the model for earnings will be developed below, in section 7.

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[17]We are interested in the effects of a shock that originates in occupation k. Its own-industry effects are felt in occupation k and we only report its other-industry ($k-1$ and $k+1$ in figure 4) for non-traded services. Empirically, we have not found other-industry effects within traded services. In the same vein, we can also consider adding an occupation-$(k-1)$ fixed effect θ_{k-1}^-. All of our results are robust to adding this second fixed effect.

[18]$\theta_M^+ \equiv \theta_w^+ \theta_M/\eta^S > 0$, $\theta_X^+ \equiv \theta_w^+ \theta_X/\eta^S > 0$, $\theta_D^+ \equiv \theta_w^+ \theta_D/\eta^S > 0$, and $\theta_a^+ \equiv \theta_w^+/\eta^S > 0$.

[19] Proof: Consider the figure 4 case where $dS_{k+1} > 0$. A worker switches down if $S_{k-1} < s^o + s^u < S_{k-1} + dS_{k-1}$ or $S_{k-1} - s^o < s^u < S_{k-1} - s^o - (\phi_k - \phi_{k-1})^{-1} d\ln w_k$ where, from equation (7), we have used $dS_{k-1} = -(\phi_k - \phi_{k-1})^{-1} d\ln w_k$. Hence $P_k^- \equiv G\left(S_{k-1} - s^o - (\phi_k - \phi_{k-1})^{-1} d\ln w_k \mid s^o, l\right) - G(S_{k-1} - s^o \mid s^o, l)$. This leads to the linearization $P_k^- = \theta_k^- + \gamma_s^- s^o + \gamma_l^- l - \theta_w^- d\ln w_k$ where by inspection, $\theta_w^- \equiv -\partial P_k^-/\partial d\ln w_k > 0$. Plugging in equation (11) yields the estimating equation.

[20]Stepping outside of the model, education may lead to an occupational license (e.g., a law degree) and hence to less switching. Criscuolo and Garicano (2010) show this to be empirically important in an offshoring context. This consideration implies that both γ_h^- and γ_h^+ will be negative. However, it will remain true that $\gamma_h^- < \gamma_h^+$.

4. Data

A. *U.S. International Trade in White Collar Services*

We use the official U.S. balance of payments data, which documents cross-border service transactions. See Borga and Mann (2004) for data details. In these data, imports are international transactions involving the sale of a foreign-produced service to a U.S. party. Conversely, exports are international transactions involving the sale of a U.S.-produced service to a foreign party. As is standard in the offshoring literature, we only consider services within the BEA category "other private services". *We henceforth refer to these as tradable white collar services.*

Trade in white collar services is large, but not nearly as large as trade in manufactures. However, this is partly an artifact of measurement: merchandise trade data measure sales whereas service data primarily measure value added. Using U.S. input-output tables, we calculate that in 2002 the value added embodied in service trade was already 21% of that in manufacturing trade. Also, the growth of tradable services far outstripped that of manufacturing. Between 1995 and 2005, white collar service trade grew almost exactly log linearly at 0.15 log points a year for exports and 0.14 log points for imports. See appendix figure A.1. Thus, tradable white collar services is a significant new development.

The balance of payments data report bilateral trade flows by service category only for the larger U.S. trading partners. Among these countries, G8 countries (except Russia) count for about 36% of U.S. imports of white collar services. Six developing countries (including China, India, Indonesia, Malaysia, Philippines, and Thailand) account for about 6% of U.S. imports of white collar services by 2005. Most importantly, among developing countries, India and China are by far the largest (accounting for about 60% of U.S. white collar services imports from developing countries) and also the most interesting given their exponential growth during the most recent years. [21]

Table 1 provides further statistics on white collar service trade. Columns 1–2 report the average annual log change in U.S. imports over the 1995–2005 period for China plus India and for G8 countries . Columns 3–4 report the corresponding growth rates of U.S. exports. Two features of the table stand out. First, U.S. imports from China and India have been growing spectacularly in some sectors e.g., averaging 0.36 log points per year over 10 years in computer and information services. Second, columns 1 and 2 are correlated, but the correlation is far from perfect. (Likewise

[21] Following the suggestion in Feenstra, Lipsey, Deng, Ma and Mo (2005), we include Hong Kong in the Chinese data.

for columns 3 and 4.) This means that the factors driving rich-country service trade growth are not the same as those driving Sino-Indian service trade growth.

We use trade data for the period 1995-2005. 1995 is a good starting date both because it comes during the early years of the Chinese and Indian liberalizations and because U.S. service trade with these two countries was at low levels then.[22] We stop in 2005 because of a structural break in the balance of payments data.

B. ***Matched CPS Data***

We match individuals across consecutive March CPS surveys from 1996 to 2007 in order to extract longitudinal information about work histories. We start the matching procedure by extracting the subsample of all civilian adults who were surveyed in March of year t. We then apply Madrian and Lefgren's (2000) two-stage matching algorithm to find a match in the March survey of year $t+1$. In the first or 'naive' stage, individuals are matched based on three variables: a household identifier, a household number, and an individual line number within a household. If all three variables are the same in two consecutive March surveys then a naive match is made. In the second stage, a naive match is discarded if it fails the 'S|R|A' merge criterion i.e., if in the two consecutive March surveys the individual's sex changes, the individual's race changes, or the individual's age changes inappropriately.[23] The naive and final match rates for each year appear in appendix table A.1. Averaging across all years, the naive match rate is 66%, the S|R|A discard rate is 5%, and the final match rate is 63% ($0.66\times(1-0.05) = 0.63$). Note that for 2001–2007 we also discard oversamples in the State Children Health Insurance Program (SCHIP) extended sample files. Our final match rate is similar to the rates of 62% in Goldberg and Tracy (2003) and 67% in Madrian and Lefgren (2000).

Since the actual match rate is lower than the match rate of 100% that would obtain in the absence of mortality, migration, non-response and recording errors, there is obviously a selection issue associated with using matched CPS data. Neumark and Kawaguchi (2004) partly dispel this selection concern by comparing the estimation results based on matched CPS data to results based on the Survey of Income and Program Participation (SIPP) which follows individuals who move.

[22]Offshoring of services to India came to prominence during the Y2K scare of the late 1990s. China became a major player in service trade only more recently. By 2005, these two countries play a more equal role in U.S. service offshoring, e.g., India accounts for about 55% of total U.S. service offshoring to China and India.

[23]Following Madrian and Lefgren (2000) , an inappropriate age change is less than -1 or more than 3. See Madrian and Lefgren (2000) for more detailed information about the matching algorithm.

Nevertheless, in section 9 below we explicitly model selection out of our matched sample. This has no effect on our conclusions.

C. *Linking CPS Data to Service Trade Data*

Constraint by the consistent data availability, we focus on the 10 types of tradeable white collar services in Table 1. The Bureau of Economic Analysis (BEA), as the primary collector of data on US international transactions in private services, uses mandatory surveys to collect data from virtually all US firms on the amount of specific services US firms purchase from unaffiliated foreign firms. In order to ensure confidentiality, the firm-level data are then aggregated for each type of service on the survey across each foreign country (U.S. Department of Commerce (1998)). The data are therefore aggregated across service type rather than industry, for example the data capture financial services offshored by all firms in the economy and not only those offshored by the financial services industry. In Appendix 4, we detailed the methodology, classification and coverage of BEA services surveys.

Our focus in this paper is white collar workers. Therefore, using CPS data on workers' occupations, each worker in the private white collar service occupations (Census major occupation codes 1, 2, 4, and 5) first will be categorized into tradable and non-tradable white collar service occupations based on Blinder's (2009) Offshorability Index. Then, the tradable white collar service occupations are linked to one of the 10 BEA white collar service trade of table 1. Specifically, first, we apply Blinder's (2009) Offshorability Index to classify each white collar service occupations into tradable and non-tradable occupations. Blinder's index is constructed as follows. For each occupation, Blinder examines the answers to two O*NET questions: "Must the job be physically close to a specific U.S. work location?" and (*ii*) "Must the job unit be at a U.S. location?" Based on the answers, Blinder subjectively assigns the occupation a number between 0 and 100. We assume that an occupation is tradable if its Blinder Offshorability Index exceeds 50 in our baseline. For example, insurance sales must be done in a U.S. location so that the Blinder index is 0 and 'Insurance sales agent' is deemed not an offshorable occupation. In contrast, the occupation 'Financial analysts' is defined as offshorable based on that its Blinder Offshorability Index is 77. We also experiment with different cutoffs of the Blinder index to classify tradable and non-tradable white collar occupations. We obtain similar results when different criterion is used. See row 6 of table 11 below.

In the second step, we manually map tradable occupation codes into BEA tradable white collar service codes. By way of examples, the occupation 'Computer scientists and systems analysts' is mapped into the service 'Computer and information services' and the occupation 'Financial analysts' is mapped into the service 'Finance.' To make sure the maximum accuracy, we rely on (*i*) the detailed descriptions of each CPS occupation that appear in the 2000 SOC manual and (*ii*) the detailed information about the coverage of each type of BEA service trade from Borga and Mann (2004) and U.S. Department of Commerce (1998). To assign each tradable white collar service occupation to a BEA service code, we ask the question, "does this occupation provide the services that have been covered in the BEA service surveys?" The mapping is presented in appendix table A.2. Many cases are quite straightforward to map as described in the above example. However, there are cases that needed judgement from the authors to be assigned to the BEA services codes. To ensure that our empirical results are not affected by this specific crosswalk, we have tested the sensitivities of our results by using different possible crosswalks. The sensitivity results are presented in row 7 and 8 of table 11 below.

We have 172,994 workers in our matched CPS sample. 105,751 of these are in private white collar service occupations (Census major occupation codes 1, 2, 4, and 5). 38,719 of these 105,751 workers are in tradable white collar services. That is, in our sample, 22% of all workers are in tradable white collar service occupations (0.22 = 38,719/172,994). This is reassuringly comparable to what has been found elsewhere.[24] Also note that 49.4% of workers in the tradable-occupations sample completed a college degree, so this is a very educated group. See appendix table A.4. The remaining 67,032 workers (= 105,751 − 38,719) are in non-tradable white collar services.

Table 2 may help the reader to better understand the mapping between BEA trade flows and CPS data. For each industry, the table reports the share of workers who are engaged in a tradable white collar service occupation. For example, 24% of workers in manufacturing are in tradable white collar service occupations. It may surprise the reader that manufacturing jobs are in our sample. However, many workers in manufacturing are service providers e.g., computer programmers and accountants. Thus, while we are only considering CPS workers in tradable white collar service occupations, these workers appear throughout all industries in the economy.

[24]Blinder (2009) estimates that 22% of U.S. employment is potentially offshorable. van Welsum and Vickery (2005) estimate that 20% of U.S. jobs are exposed to service offshoring. Jensen and Kletzer (2006) argue that a service-based occupation is offshorable if within the United States it is highly concentrated geographically. They find that about 28% of U.S. employment is offshorable. These estimates are very similar to our own estimate of 22%.

D. *Variable Definitions*

The theory requires us to distinguish between switching up and switching down. As discussed in the introduction, we therefore need to calculate inter-occupational wage differentials (IOWDs). We do this as follows. Using the 1996-2007 unmatched CPS data (N = 295,082), we regress a worker's earnings on her observed worker characteristics (education, experience, experience squared, marital status, sex, race, and state of residence), year fixed effects, and 4-digit COC occupation fixed effects. The latter are the inter-occupational wage differentials.

We will need to define occupational switching. Consider a worker who is matched across two consecutive March CPS surveys. In both March surveys the worker is asked about her occupation in the longest job held *in the last calendar year*. For example, a worker surveyed in March of 2001 is describing her occupation in the longest job held in 2000. Since we will have to match the CPS data with calendar-year data from the BEA, we refer to data reported in the March 2001 survey as 2000 data. More generally, data relating to the longest job held last year that comes from the March CPS of year t will be referred to as data from year $t-1$. Applying this to the 1996–2007 March surveys, we have workers who switched between 1995–1996, between 1996–1997, etc. until 2005–2006. That is, we have 11 years of switching.

A worker is a 4-digit occupational switcher if in the two March surveys her occupation in the longest job held last year changes.[25] This raw switching rate is known to be noisy. We thus filter it as suggested by Moscarini and Thomsson (2008). To be a valid switch, the worker must also have changed her CPS class or looked for a job last year. See Appendix 5 for details. Our occupational switching rates at the 1- and 2-digit levels are 0.17 and 0.20, respectively. These are similar to the corresponding 0.16 and 0.18 rates reported in Kambourov and Manovskii (2008) who use 1996 PSID data.[26] [27] In our baseline results, we focus on 4-digit occupational switching because it gives us the most refined definition of an occupation (especially in services jobs). We also report 2-digit switching results in row 17 of table 11 below.

Another important labor market outcome deals with transitions from employment to unemployment. As in Murphy and Topel (1987), we operationalize this as follows. A worker is

[25]Note that a worker can only be a switcher if she worked in both years. We will come to unemployment later.

[26]Note that while switching rates calculated from the CPS are upward biased, it is essential to remember that we are not interested in switching rates, but in how switching rates change in response to trade shocks. We do not expect *changes* in occupation miscoding to vary systematically with changes in trade shocks.

[27]We are indebted to Gueorgui Kambourov for help with defining occupational switching.

employed in the first of her two CPS years if she was a full-year worker (i.e., worked at least 50 weeks last year) or she was a part-year worker (i.e., worked between 1 and 49 weeks) who neither looked for a job last year nor was laid off. A worker is unemployed in the second of her two CPS years if the worker never had a job in the past year or was a part-year worker who either looked for a job or was laid off. Below we also discuss alternative definitions of both unemployment. These all yield very similar conclusions.

Lastly, we study earnings change. Annual earnings are defined as CPI-deflated annual income from wages and salaries. We also provide robustness checks using weekly wage and hourly wage to measure earnings changes.

E. *Occupational Wage Differentials for Stayers and Switchers*

We conclude this data section with some raw numbers that provide a context for our interest in the costs of occupational switching and the role of sorting. We emphasize that what follows are facts whose interpretation is far from clear: no causal inferences are intended or drawn.

We begin by calculating inter-occupational wage differentials (IOWDs). To this end, we regress a worker's log of CPI-deflated annual earnings on her observed worker characteristics (education, experience, experience squared, marital status, sex, race, and state of residence), year dummies, and dummies for 4-digit Census occupation codes of the worker's initial occupation. The estimated occupation dummies are the IOWDs. We estimate IOWDs using the full CPS data for 1996–2007. We then track the occupational switching behaviour of the 38,719 workers in the CPS sample who can be tracked for one year (March-to-March matching) and who are in occupations that provide tradable services. Finally, we group these workers into three categories, those that do not switch occupations ('stayers'), those that 'switch down' to an occupation with a lower IOWD and those that 'switch up' to an occupation with a higher IOWD.

The first row of table 3 shows that workers who switch down have IOWDs in their new occupation that are 0.249 log points lower than in their old occupation. However, row 2 of table 3 shows that the actual wage change of downward switchers is much smaller (0.141 log points). A common explanation for why it is smaller appeals to worker sorting e.g., Gibbons and Katz (1992). Row 3 shows that workers who switch down are less educated than stayers, who in turn are less educated than workers who switch up. It is thus plausible that switchers are also different from stayers in terms of unobservables such as ability.[28] We therefore need to model sorting behaviour in a setting where worker characteristics are not fully observable.

5. An Econometric Analysis of Occupational Switching

In this section we estimate our theory-based switching-down and switching-up equations (equations 13 and 12). In our regression setting, each observation will correspond to a unique individual i. For an individual whose first of two March CPS surveys is in year t+1, let k be her occupation in the longest job held *last* year (year t) and let y^-_{ikt} equal 1 if the worker switched down between t and $t+1$ and 0 if the worker did not switch. Correspondingly, let y^+_{ikt} equal 1 if the worker switched up and 0 if the worker did not switch. These are our dependent variables.

Our section 4.C 'crosswalk' allows us to link each occupation k with a BEA service code. Equations (13) and (12) require four variables at the service level: U.S. imports from China and India (M_{kt}), U.S. exports to China and India (X_{kt}), domestic demand or sales (D_{kt}), and technology (ICT_{kt}). D_{kt} is defined as total sales less exports. ICT_{kt} is defined as the share of investment in ICT equipment and software divided by total equipment and software investment. This measure is used by Bartel, Lach and Sicherman (2005). Data sources are described in Appendix 5. Since many individuals share the same occupation, the M_{kt}, X_{kt}, D_{kt} and ICT_{kt} are repeated across individuals. We therefore cluster standard errors by occupation.

Column 1–3 of table 4 reports OLS estimates of our switching-down equation (equation 13). The sample is the set of workers in white collar service occupations that either switched down or were occupational stayers. The dependent variable is y^-_{ikt}. The regression includes the listed individual characteristics such as education, as well as state and year fixed effects. The service offshoring variable we focus on is the annual log changes in M_{kt}. Other regressors include the annual log changes in X_{kt}, D_{kt}, and ICT_{kt}. It may be that worker switching decisions and/or firm firing decisions are determined by longer-run changes in these variables. In columns 1–3 of table 4, we report results with M_{kt}, X_{kt}, D_{kt} and ICT_{kt} appearing as 3-, 5-, and 7-year average annual log changes. For any lag length l, we define $(\ln M_{kt} - \ln M_{k,t-l})/l$ as the l-year average annual log change. The coefficient on imports is statistically significant and have the expected signs. The impact of imports increases with the lag length.

[28] We also calculate the correlates of switching for the whole sample of workers and find similar patterns as presented in table 3.

The theory is not silent on the lag length. The longer the lag, the more likely that the change in imports is a sector characteristic and hence the more likely it is that imports are correlated with unobserved worker characteristics. In column 4 of table 4 we deal with this by introducing the M_{kt}, X_{kt}, D_{kt} and ICT_{kt} in log levels and adding BEA-level sector fixed effects. The interpretation is that we are now looking at long-run deviations of $\ln M_{kt}$, $\ln X_{kt}$, $\ln D_{kt}$ and $\ln ICT_{kt}$ from their sector means. We refer to this as the 'level fixed effects' specification.

Coefficient magnitudes for service offshoring variables are not comparable across the log change and level fixed effect specifications. For comparability one must multiply the latter coefficients by 10 e.g., the column 3 import coefficient of 0.208 should be compared to the column 4 import coefficient times 10 so that 0.208 is compared to 0.190. Comparing the 7-year change results to the level fixed effect results (columns 3 and 4), one very general conclusion emerges: import coefficients are very similar across the two specifications.

In table 4, the second row of numbers appears in italics. This row translates the coefficients on imports into economically meaningful magnitudes. Recall from table 1 that the most dynamic — and threatening — sector for service offshoring to China and India is in business, professional and technical services where for the last decade imports have been growing annually by 0.18 log points. We therefore multiply the import coefficients in columns 1–3 by 0.18 to obtain 0.016, 0.027, and 0.037. Using average annual changes during the past 3-, 5-, and 7- years, we estimate that rising Sino-Indian imports increased the incidence of switching down by 1.6, 2.7, and 3.7 percentage points, respectively. This means that the longer-run impacts (3.9) are more than double the shorter-run impacts (1.6). Over the past decade, U.S. service imports from China and India have increased the incidence of downward switching by 3.7 percentage points, from 21% to 24.7%.

Turning to the economic size of the level fixed effect specification (column 4), the magnitudes in italics are the import coefficient times 0.18×10 (10 being the number of years). The most important conclusion from table 4 is the economic impact of imports. From the level fixed effect specification, 10 years of service offshoring to China and India has increased downward occupational switching by 3.4 percentage points, from 21% to 24.4%. *This is a 16% increase and represents a large effect.*

There is one last feature of the specification that we have not discussed. By using trade data we are only exploiting switching behaviour within the tradable sector. However, one would also like to know if switching in the tradable sector has been rising relative to switching in the non-tradable sector. We find no evidence of this, but to understand our evidence we need to say more about our empirical specification. Our specification incorporates a difference-in-differences estimator. The first difference is between tradable and non-tradable services and the second difference is between early years (when there was no service offshoring) and later years (when service offshoring was large). To model this, we include in our sample not only workers who are in tradable white collar service occupations, but also workers who are in non-tradable white collar service occupations. Let I^{NT} be a dummy variable which indicates whether or not the worker is in non-tradables. We interact I^{NT} with year fixed effects and ask whether there is any trend in the interaction terms i.e., whether switching is trending up in tradables relative to non-tradables. We do not find any evidence of this. The interaction coefficients are reported in appendix table A.5. By implication, rising service trade has not led to an increase in occupational switching in tradables relative to non-tradables.[29]

Table 4 has imbedded in it a large number of specification choices. Section 9 below reports on an extensive set of alternative specifications that imply very similar conclusions to those in table 4. To give the reader a quick preview of section 9, the statistically significant downward switching effects of rising imports from China and India appear even when the following specification changes are made. (1) Restrict the sample to consist only of those workers in tradable occupations. (2) Control for CPS sample selection. (3) Include the service trade with G8 countries. (4) Include U.S. imports from other poor countries. (5) Use a probit or logit specification. (6) Estimate a multinomial logit with four choices: stay, switch up, switch down, or transition into unemployment, and with six choices: stay, switch far up, switch little up, switch far down, switch little down, or transition into unemployment.

A. *Switching Up*

We next turn to estimates of the switching-up equation (12). Table 5 repeats the exercise of table 4, but for the sample of workers that either switched up or stayed. The dependent variable equals 1 if the worker switched up and 0 if the worker stayed. The results are now much less significant. In our level fixed effect specification (column 4), the decadal impact of service imports from China and India is 0.7 percentage points. It is very close to the estimate based on 7-year average

[29] The reader may wonder how the estimates in table 4 change when estimated using just the subsample of workers in tradable white collar service occupations. The answer is that they barely change. This will be shown below (row 1 of table 11) when we report on sensitivity analysis.

annual changes of service offshoring (0.6 percentage points). However, both of the estimates are economically small and statistically insignificant.

As noted above, an interesting prediction of the theory is that the coefficient on schooling is more negative for those who switch down than for those who switch up. Comparing column 1 in tables 4 and 5, the schooling coefficient is –0.013 for downward switchers and –0.007 for upward switchers. The difference of –0.006 is economically large and statistically significant (χ^2_1 = 15.11, p <.0001). The corresponding numbers for the fixed effect specification (column 4) is even more dramatic, –0.014 for downward switchers and 0.000 for upward switchers. The difference of –0.014 is very significant (χ^2_1 = 93.11, p <.0001). This suggests that sorting is indeed an important feature of the data.

B. *Transitions to Unemployment*

Table 6 reports results using transitions to unemployment as a binary dependent variable. The precise definition of unemployment appears in section 4 above. The sample consists of workers who experienced no unemployment during the first of their two CPS years. The estimates are sensitive to the choice of lag length. In our level fixed effects specification (column 4), imports from China and India raised transitions to unemployment by 0.9 percentage points, from 3.0% to 3.9%. This is a large impact.

As shown in section 9, we estimate somewhat smaller unemployment impacts when measuring these as the change in weeks unemployed relative to weeks in the labour force. See row 18 of table 11 below. We also find that service imports from China and India reduced the number of weeks worked by one-third of a week. See row 19 of table 11 below. Summarizing, service imports has had consequential impacts on unemployment.

6. Instrumental Variables

Imports and exports are potentially endogenous. In presenting the partial equilibrium model we discussed how $w^*_{kt}a^*_{kt}$ is an instrument for imports. We did not, however, discuss an instrument for exports. An increase in Sino-Indian income raises Sino-Indian demand for U.S. exports X_{kt} and thus serves as an instrument. Unfortunately, the elasticity of X_{kt} with respect to Sino-Indian income varies by sector k. We could deal with this by interacting a measure of Sino-Indian GDP with a set of sectoral dummies. However, this would lead to a proliferation of instruments and the familiar weak instruments problem (e.g. Staiger and Stock, 1997). We thus estimate export elasticities by sector from an external data source. Using U.S. exports to 28 countries over the 1995–2005 period, we estimate a gravity equation separately for each of our 10 types of services.[30] Specifically, let X_{ckt} be U.S. exports to country c in sector k in year t, let Y_{ct} be GDP, and let L_{ct} be population. We regress $\ln X_{ckt}$ on $\ln Y_{ct}/L_{ct}$, $\ln L_{ct}$, and country fixed effects. The fixed effects ensure that we are estimating the effect of rising income, which is what the model requires, and not estimating the effect of cross-country differences in income. The gravity estimates by service type appear in appendix table A.6.

To understand how we translate the gravity estimates into instruments, consider the case where the coefficient on log population is set to zero. Then the estimated elasticity of exports with respect to income ($\hat{\eta}_k^X$) is just the OLS estimate of the coefficient on $\ln Y_{ct}/L_{ct}$. In the level fixed effects specification we instrument $\ln X_{kt}$ with

$$Z_{kt}^X \equiv \hat{\eta}_k^X \ln Y_t/L_t \tag{14}$$

where Y_t/L_t is the gravity-consistent aggregator of the GDP per capitas of China and India.[31] In the log changes specification (e.g., 1-year changes), we instrument $\ln X_{kt} - \ln X_{k,t-1}$ with

$$Z_{kt}^X \equiv \hat{\eta}_k^X (\ln Y_t/L_t - \ln Y_{t-1}/L_{t-1}). \tag{15}$$

The case where the coefficient on $\ln L_{ct}$ is not set to zero requires a bit more notation and appears in appendix Appendix 6.

Turning to the endogeneity of imports, we proxy $w_{kt}^* a_{kt}^*$ by GDP per capita. Thus, the procedure outlined above for exports can be repeated for imports. First, we estimate gravity equations for U.S. imports in order to obtain import elasticities $\hat{\eta}_k^M$. See appendix table A.6. Second, in equations (14)–(15) we replace the $\hat{\eta}_k^X$ with $\hat{\eta}_k^M$ in order to build an instrument Z_{kt}^M. In addition, we directly use the foreign occupational wage, w_{kt}^*, as an instrument for imports. Specifically, we extract occupational wage data in China and India from "The Occupational Wages around the World (OWW) Database" (Oostendorp 2012). We map OWW occupation codes into BEA service codes and calculate the mean occupational wage for China and India. We use this as a measure of w_{kt}^*.[32]

[30]The choice of countries is determined by the availability of disaggregated BEA data and, in order to avoid contaminating our instrument with Sino-Indian import data, we omit China and India.

[31]$Y_t/L_t \equiv (y_{China,t}^{\eta} + y_{India,t}^{\eta})^{1/\eta}$ where $y_{ct} \equiv Y_{ct}/L_{ct}$ and $\eta \equiv \hat{\eta}_k^X$.

[32]The OWW has several alternative measures of wages. In our baseline IV regressions, we use the type-3 standardized hourly wage in US dollars from OWW database as occupational wage. We also test the sensitivity of our results using the type-3 standardized monthly wage in US dollars and the type-4 standardized hourly/monthly wage from OWW database. Our IV results are robust to these alternatives.

Summarizing, we have three instruments Z^M_{kt}, Z^X_{kt} and w^*_{kt} for two endogenous variables (imports and exports). Table 7 reports the first-stage results for the specifications in columns 5–7 of table 4.[33] In the import equation, The coefficient on Sino-Indian wages (w^*_{kt}) is significant and negative as expected: the higher are Sino-Indian wages (w^*_{kt}), the lower are U.S. service imports from China and India. The gravity instrument Z^M_{kt} is negative but not statistically significant. In the export equation, Z^X_{kt} is positive. For the 3-year change specification the instruments are not jointly significant. As a result, we do not report IV results for the 3-year change specification and instead focus the discussion of the IV results for the 5-year, 7-year, and level with fixed effects specifications.

Tables 4–8 report the IV results. The IV estimates are always larger than the OLS results, as predicted by the theory. Also, we can not reject exogeneity in every case. We interpret this to mean that much of the movement in U.S. service trade with China and India has been uncorrelated with shocks that have had direct impacts on U.S. labour markets.

7. Changes in Annual Earnings

Recall from equation (6) that $\ln W_k(s,l) = \ln w_k + \phi_k(s) + l$ where $s = s^o + s^u$ has both an *o*bserved and *u*nobserved component. It follows that the change in annual earnings for a worker who switches from occupation k to k' is

$$\ln[W_{k',t+1}(s,l)/W_{kt}(s,l)] = \ln(w_{k',t+1}/w_{kt}) + (\phi_{k'} - \phi_k)s^o + \varepsilon_{k',k} \tag{16}$$

where

$$\varepsilon_{k',k} \equiv (\phi_{k'} - \phi_k)s^u$$

is a residual. In general, we expect observed and unobserved worker characteristics to be correlated so that $\mathbb{E}[\varepsilon_{k',k}|(\phi_{k'} - \phi_k)s^o] \neq 0$. Further, since s^u affects the sorting choices k and k', $\mathbb{E}[\varepsilon_{k',k}|\ln(w_{k',t+1}/w_{kt})] \neq 0$. The solutions to these problems are different for switchers and stayers. We begin with stayers.

[33]The first-stage results corresponding to the specifications in tables 5–8 are almost identical because the only first-stage difference is in the sample, i.e., in the number of workers in the regressions.

A. ***Earnings Changes of Occupational Stayers***

As noted by Gibbons and Katz (1992), for stayers $k' = k$ so that equation (16) reduces to $\ln[W_{k,t+1}(s,l)/W_{kt}(s,l)] = \ln(w_{k,t+1}/w_{kt})$. That is, there is no endogeneity problem. Substituting out $\ln(w_{k,t+1}/w_{kt})$ using equation (11) yields

$$\begin{aligned}&\ln[W_{k,t+1}(s,l)/W_{kt}(s,l)] \\ &\quad = \theta'_M \ln(M_{k,t+1}/M_{kt}) + \theta'_X \ln(X_{k,t+1}/X_{kt}) + \theta'_D \ln(D_{k,t+1}/D_{kt}) + \theta'_a \ln(a_{k,t+1}/a_{kt})\end{aligned} \tag{17}$$

where $\theta'_j = \theta_j/\eta^S$, $j = M,X,D$ and $\theta'_a = 1/\eta^S$.

Table 8 reports the results of our standard specification, but with the dependent variable now the log change in annual earnings and the sample restricted to occupational stayers. In addition, we add inital-period worker characteristics. The coefficients are statistically significant. Using 3-year changes, imports of services from China and India reduce the earnings growth of stayers by 0.72% per year (= –0.040×0.18). Over 10 years, during which service tradablility rose rapidly, this translates into a decadal effect of 7.2%. Decadal effects are reported in italics in the table. However, the decadal effect falls to 2.3% for the statistically significant level fixed effect specification. These results for annual earnings hold both for weekly wages and hourly wages. See rows 20 and 21 of sensitivity table 11. 2.3% strikes us as a modest decadal wage effect.[34]

B. ***Earnings Changes of Occupational Switchers***

For occupational switchers we must deal with $\mathbb{E}[\varepsilon_{k',k}|(\phi_{k'} - \phi_k)s^o] \neq 0$ and $\mathbb{E}[\varepsilon_{k',k}|\ln(w_{k',t+1}/w_{kt})] \neq 0$. We consider two approaches that are common in the literature. We first assume that there is only sorting based on observables, as in Ebenstein et al. (2014), Artuç et al. (2010) and Bombardini et al. (2012). We then allow for sorting on unobservables, but assume that this process is orthogonal to $(\phi_{k'} - \phi_k)s^o$ and $\ln w_{k',t+1}/w_{kt}$, as in Dix-Carneiro (2014) and

[34]In deriving equations (16), we assumed that worker characteristics are time-invariant. Including changes in all worker characteristics does not alter the coefficients on imports and exports at all. For a discussion of issues associated with time-varying unobservable worker characteristics see Gibbons et al. (2005).

Caliendo et al. (2015).[35] We start with estimates based on the (identifying) assumption that there is no sorting. We then provide evidence of sorting both on observables and unobservables.

If there is no sorting then the 'ignorability of treatment' assumption (Rosenbaum and Rubin, 1983) assumption is satisfied and we can calculate the average treatment effect (ATE) using propensity scoring that compares each switcher with a similar stayer. To implement this, we calculate the propensity score using all of the covariates that appear in our switching regressions of table 4.[36] The ATE estimates appear in table 9 in columns 1, 4, and 7. The ATE is a large for downward switchers (-14.9%), upward switchers (12.7%), and especially those who experience an unemployment spell (-43.0%). It thus appears that there are subgroups that are heavily impacted by trade-induced increases in switching.

An alternative to propensity scoring is a regression of wage changes on a switching dummy and worker covariates. The sample pools stayers with downward switchers (column 2), upward switchers (column 6), or transitioners to unemployment (column 10). As is apparent, the coefficients on the switching dummies are very similar to the corresponding ATEs.

We next provide evidence that there is sorting on both observables and unobservables. We do so by showing that the predictions of a no-sorting model are systematically violated empirically. At the heart of any occupational sorting model is the assumption that both workers and occupations are heterogeneous. In the context of our model, s varies across workers and ϕ_k varies across occupations. If there is no sorting then either all workers are the same — which contradicts the data on schooling and other worker characteristics — or ϕ_k is the same for all k. Thus, suppose $\phi_{k'} - \phi_k = 0$ so that there is no sorting. Restated, assume that workers are randomly allocated to occupations. Then averaging over all workers, an average worker who moves from occupation k to occupation k' should, after controlling for workers' observable characteristics, experience a wage change that equals the wage difference between occupations k and k'. That is, the wage change

[35] In Artuç et al. (2010), the unobserved heterogeneity $\varepsilon_k \equiv \phi_k s^u$, which is distributed iid Gumbel, is revealed *after* switching so that unobserved heterogeneity does not influence sorting. In Dix-Carneiro (2014) and Caliendo et al. (2015), ε_k is assumed to be distributed iid Gumbel with mean and variance independent of $\phi_k s^o$ and $\ln w_{kt}$. It follows that $\varepsilon_{k',k} = \varepsilon_{k'} - \varepsilon_k$ is independent $(\phi_{k'} - \phi_k)s^o$ and $\ln w_{k',t+1}/w_{kt}$. In Ebenstein et al. (2014), sorting on observables is implicit. They instrument for switching using a dummy for whether the worker is initially in a tradable occupation. This (time-invariant) tradable dummy is correlated with the characteristics of workers who sort into tradables so we can interpret their IV strategy as controlling for sorting. For the traded dummy instrument to be uncorrelated with the (second-stage) residual the sorting must be driven only by worker characteristics included in the second stage i.e., by observed worker characteristics.

[36] We use the nearest neighbour matching. Identical results obtain using up to six nearest neighbours. The balancing tests pass for every covariate (appendix table A.7).

should equal the inter-occupational wage differential $IOWD_{kt}$:[37]

$$\ln(W_{k',t+1}(s,l)/W_{kt}(s,l)) = IOWD_{k',t+1} - IOWD_{kt} \quad \forall(s,l)\,.$$

This combined with equation (16) implies

$$\ln(w_{k',t+1}/w_{kt}) = IOWD_{k',t+1} - IOWD_{kt}\,.$$

We can therefore test for sorting on observables and unobservables by estimating the regression

$$\ln[W_{k',t+1}(s,l)/W_{kt}(s,l)] = \beta(IOWD_{k',t+1} - IOWD_{kt}) + \beta'(\phi_{k'} - \phi_k)s^o + \epsilon\,. \tag{18}$$

Under the null of no sorting we expect $\widehat{\beta} = 1$ and $\widehat{\beta}' = 0$. To implement this, we measure ϕ_k as the (time-averaged) inter-occupational wage differential.

Table 9 reports the results of estimating equation (18). In columns 3, 7 and 11 we see that the coefficient on $(IOWD_{k',t+1} - IOWD_{kt})$ is less than one. This is the regression counterpart of what we already saw in table 3. $\widehat{\beta} \neq 1$ is often taken as evidence of sorting (e.g., Gibbons and Katz, 1992) because it means that the wage change of switchers is not equal to the wage change we would expect if workers were randomly chosen from k and randomly allocated to k'. In particular, our figure 4 sorting mechanism implies $\widehat{\beta} < 1$ because a worker who switches faces a smaller wage change than the average wage change of workers who are randomly chosen to switch to their next-best occupations.

In columns 4, 8 and 12 we add in the interactions of $\Delta IOWD$ with years of schooling. We find $\widehat{\beta}' \neq 0$ which is further evidence of sorting. In fact, $\widehat{\beta}'$ is positive, which is predicted by our sorting mechanism whose central mechanism rests on the log-supermodularity of wages in k and s^o i.e., on the positive effect of $(\phi_{k'} - \phi_k)s^o > 0$ on wages.

Finally, we note that the four specifications in table 9 all imply the same wage impacts of switching. For example, in column 3 if one multiplies the coefficient by either the mean or 75-25 difference in $\Delta IOWD$ the implied change in wages is 16%, which is just a little larger than what is found in columns 1 and 2. If one does the same in column 4 then the effect of $\Delta IOWD$ is 8% and

[37] Proof: The $IOWD_{kt}$ are defined as the OLS estimates of the occupation fixed effects in an earnings regression of the form $\ln W_{kt}(s,l) = \alpha_{kt} + \phi s + \gamma l + \nu$ where ϕ is the common value of the ϕ_k and ν is assumed orthogonal to the regressors. It follows that $\ln[W_{k',t+1}(s,l)/\ln W_{kt}(s,l)] = \widehat{\alpha}_{k',t+1} - \widehat{\alpha}_{kt} = IOWD_{k',t+1} - IOWD_{kt}$. If there is sorting on observables then from equation (16) with $s^u = 0$, it must be that $\nu = (\phi_k - \phi)s$ and $\ln[W_{k',t+1}(s,l)/\ln W_{kt}(s,l)] = IOWD_{k',t+1} - IOWD_{kt} + (\phi_{k',t+1} - \phi_{kt})s$.

the effect of $\Delta IOWD \times s$ is an additional 8% for a total effect of 16%. Likewise for switching up and transitioning to unemployment. [38]

8. Wage Impacts

Let j index types of worker transitions with $j = -, +, U, S$ indexing downward switches, upward switches, transitions to unemployment, and stayers, respectively. Let $\Delta \ln w^j$ be the average wage change for type-j transitions and let P^j be the incidence of type-j transitions in the population ($\sum_j P^j = 1$). Then the average wage change $\Delta \ln W$ is given by $\Delta \ln W = \sum_j P^j \Delta \ln w^j$ and its import-induced change is given by

$$\frac{\partial \Delta \ln W}{\partial \Delta \ln M} = \sum_j \left(\frac{\partial P^j}{\partial \Delta \ln M} \Delta \ln w^j \right) + \sum_j \left(P^j \frac{\partial \Delta \ln w^j}{\partial \Delta \ln M} \right) . \tag{19}$$

We have data on the P^j and estimates of $\partial P^j / \partial \Delta \ln M$ for $j = -, +, U$ from tables 4–6. Since probabilities sum to 1, $\partial P^S / \partial \Delta \ln M = -\sum_{j \neq S} \partial P^j / \partial \Delta \ln M$. We have estimates of $\Delta \ln w^j$ from table 9 and an estimate of $\partial \Delta \ln w^S / \partial \Delta \ln M$ from table 8.[39]

Table 10 reports the results of the equation (19) decomposition as well as for the corresponding one for $\partial \Delta \ln W / \partial \Delta \ln X$. The table footnotes explain the details. Here we report the headline numbers. The impact of imports and exports on average wages is -2.2% and +1.0%, respectively, for a net impact of -1.2%. Some of these impacts are calculated from statistically insignificant coefficients, especially those relating to exports. From the table the statistically significant impacts are -2.3% for imports and 0% for exports for a net 10-year impact on wages of -2.3%.

We view these average effects as relatively small. Despite small average effects, one must bear in mind that the effects are very negative for subsets of workers. Specifically, downward switchers and those who experience unemployment spells suffer wage losses of 14.9% and 43.0%, respectively. Further, trade induced very large increases in downward switching and transitions into unemployment.

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[38] We also considered alternative specifications. (1) When we add the switching dummy to columns 3, 7, or 11 nothing changes to the reported coefficients and the switch dummy is both tiny and statistically insignificant. (2) The model suggests that we can pool all three groups. The resulting coefficients are -0.115(0.006), 0.151(0.007), and -0.440 (0.012) i.e., the coefficients do not change. (3) In the Ebenstein et al. (2014) specification that generates their headline number of 12% wage cuts, they pool downward and upward switchers and include both a switching dummy and the change in the interoccupational wage differential. When we do the OLS version of this the switching dummy coefficient is 0.005 (0.005) and the $\Delta IOWD$ coefficient is 0.498 (0.011).

[39] We also have unreported estimates of $\partial \Delta \ln w^j / \partial \Delta \ln M$ for $j \neq S$ that are so small and insignificant that we set them to 0.

9. Sensitivity

Table 11 reports a large number of additional specifications. The first row repeats our baseline specification i.e., the level fixed effect OLS results from column 4 in tables 4–8. We only report the coefficient on imports and its decadal impact i.e., the number in italics in tables 4–8. Since coefficient magnitudes are not comparable across rows, the reader should focus on the 'Decadal Impacts' columns. A quick perusal of these columns shows that none of what we are about to report overly matters for our conclusions.

Excluding Non-tradable Service Occupations (Row 1): In this row we only consider workers in tradable occupations.

CPS Sample Selection (Row 2): To be in our matched sample a worker must remain in the same dwelling from March of year t to March of year $t+1$. Since service offshoring may encourage workers to move in search of jobs, our sample may not be randomly chosen and our estimates may be tainted by sample selection bias. See Neumark and Kawaguchi (2004) and Goldberg and Tracy (2003). Following Goldberg and Tracy, in this subsection we use maximum likelihood to simultaneously estimate two equations, a selection equation and an outcome equation (switching up, switching down, transitions to unemployment or earnings changes of stayers). Our specification of the selection equation borrows from the migration literature which shows that mobility is strongly tied to family characteristics that have been excluded from our outcome equations. These are family size, number of children, home ownership and whether the individual has a recent history of moving as proxied by whether the individual lived in the same house last year.[40] These instruments are drawn from responses in the first of the two March surveys. The estimates appear in table 11. Selection barely affects our estimates of service imports.

Including Rich-Country Service Trade (Row 3): Our paper focuses on the impact of trade in services with China and India. In row 3 of table 11 we include the imports and exports of services between the United States and her G8 partners. These rich countries are Canada, France, Germany, Italy, Japan and the United Kingdom. (Russia is excluded.) Inclusion of the G8 variables does not affect the coefficients on imports with China and India. For example, with the two G8 regressors added, the coefficient on Chinese and Indian imports in our baseline downward-switching speci-

[40]In the first of the two March surveys the individual is asked if he or she lived in the same house last year. The correlation of this response with whether the individual is matched across March surveys is 0.14. This is a small correlation and our results are unchanged when this variable is removed from the instrument set. Note that this is our only excluded variable not suggested by Goldberg and Tracy (2003).

fication moves slightly from 0.039 to 0.040.

Service Trade with All Low-Wage Countries (Row 4): When it comes to U.S. trade in services, China and India are by far the major low-wage trading partners. The BEA also publishes bilateral service trade data for all countries that have significant service trade with the United States. Among low-wage countries, data are available for China, India, Indonesia, Malaysia, Philippines and Thailand. We therefore include all of these in our definitions of $\ln M_{kt}$ and $\ln X_{kt}$.

Only Business, Professional and Technical (BPT) Services (Row 5): Much of the press about offshoring focuses on BPT services to the exclusion of the other service categories in table 1 such as financial and insurance services. That is, the press focuses on services for which U.S. comparative advantage is relatively weak. Table 11 presents estimates when only the eight BPT service subcategories are included in the analysis.

Use Alternative Blinder Offshorability Criterion (Row 6): Recall that in building a crosswalk in section 4.C we attached a service trade flow to a white collar worker only if the Blinder offshorability index is over 50. In row 6 we attach a service trade flow to a white collar worker if the Blinder offshorability criterion is changed to 35. That is, more white collar workers are treated as offshorable.

Use Alternative Crosswalk (Row 7): Based on the structure of the BEA service trade surveys, we have linked each offshorable white collar service occupation to each type of BEA tradable services based on the crosswalk presented in appendix table A.2. Alternatively, following the literature that dealt with manufacturing trade (e.g., Autor et al. (2014)), we could link workers in the CPS to the BEA service trade data through their affiliated industries. We have created such an alternative crosswalk in appendix table A.3. We show that our main results are not affected by using this alternative crosswalk.

Exclude Industrial Engineering and Research, Development and Testing Services (Row 8): Based on the structure of the BEA service trade surveys, we have linked each offshorable white collar service occupation to each type of BEA tradable services based on the crosswalk presented in appendix table A.2. We note that most of the cases in the crosswalk are straightforward. For example, tradable white collar service occupations that can be matched to BEA "legal services", and "finance services", etc. However, there are cases, like some offshorable occupations matched to "industrial engineering" services and "research, development and testing" services, are fuzzy. To ensure that our results are not affected by these fuzzy matches, we have run our regressions by excluding these observations that are originally matched to BEA "industrial engineering" services and "research, development and testing" services. The sensitivity results are presented in table 11. As indicated, our main findings are robust to this sensitivity analysis.

Omit the Technology Bubble Years (Row 9): NASDAQ began its precipitous decline in March 2000 and continued to decline until mid-2002. To eliminate the effects of the bubble we delete all data for the years 2000 and 2001.

Drop Domestic Demand and ICT (Row 10): Dropping D_{kt} and ICT_{kt} has very little effect on our results.

Control for Share of Immigration Workers (Row 11): One potential variable that could also affect the labor outcomes of white collar workers in the U.S. is the share of immigration workers across industries, as pointed out in Ottaviano et al. (2013). In this sensitivity check, we add the share of immigration workers into our main regressions. This variable is created based on the CPS March survey question on "Citizenship Status". Immigrants are defined as foreign born workers who are not U.S. citizens at birth. We then add up the immigration workers who are in civilian labor force for each Census2002 industries. Controlling the share of immigration workers does not change our empirical findings.

Alternative Functional Forms for Imports and Exports (Row 12): Rather than introducing imports and exports in log changes and log levels, we could have introduced them as a fraction of domestic sales: M_{kt}/D_{kt} and X_{kt}/D_{kt}. This is done in row 12.

Probit, Logit and Multinomial Logit Regression Results (Rows 13–16): We used the OLS estimator even though switching down, switching up, and transitions to unemployment are binary dependent variables. In rows 13 and 14 we report probit and logit estimates, respectively. Also, one can model the worker's decision as a four-way decision: switch down, switch up, transition to unemployment, or stay. (We have modelled it as a two-way decision: stay or switch down in table 4; stay or switch up in table 5; stay employed or transition to unemployment in table 6.) In row 15 we model the decision as a four-way decision using a multinomial logit. Further, we could model the transition status as a six-way decision: switch little down and far down, switch little up and far up, transition to unemployment, or stay. We use the sample mean of changes of IOWD for downward/upward switchers as cutoffs for "little" vs "far" downward/upward switching. The sensitivity results are presented in row 16 of table 11.

2-Digit Switching (Row 17): All of our switching results are based on 4-digit COC (occupation) switching. In row 12 we report results for 2-digit switching. Not surprisingly, in percentage point terms the decadal impacts are smaller because 2-digit switching is much less common. However, in percentage terms, 2- and 4-digit decadal impacts on downward switching are similar. The 2-digit downward switching rate is 14% so that the decadal impact in percentage terms is 15.7% (= 0.022/0.14). This is very similar to the decadal impact of 16% for 4-digit switching.

Weeks Unemployed and Employed (Rows 18–19): Rather than working with a binary transition to unemployment, in row 18 we examine changes in the proportion of labour-force hours spent unemployed. Consistent with our results for transitions into unemployment, service imports are associated with small increases in the proportion of labour-force hours spent unemployed. On the flip side, we also use the change of weeks worked as a dependent variable and find that service imports slightly decrease weeks worked.

Weekly and Hourly Earnings (Rows 20–21): Rather than using the change in real annual earnings, in rows 20–21 we use the change in real weekly wages and real hourly wages as the dependent variables. Weekly wages are defined as real annual earnings divided by weeks worked last year. Hourly wages are defined as real annual earnings divided by hours worked last year. Hours worked last year is weeks worked last year times hours worked each week. The results are vary similar to those for changes in real annual earnings.

10. Conclusions

The rise of service trade with China and India has brought with it something new – for the first time ever, educated U.S. workers are competing with educated but low-paid foreign workers. Despite the public concern about this development, there has been very little econometric work quantifying the adjustment costs for American workers. We developed a model that explicitly deals with both the endogeneity of imports and the role of worker sorting, both key features of the data. Combining matched CPS data for 1996–2007 with BEA data on U.S. service trade with China and India, we found the following cumulative 10-year impacts of this trade. (1) Downward and upward occupational switching increased by 16% and 4%, respectively. (2) Transitions to unemployment increased by a large 0.9 percentage points. (3) The earnings of occupational 'stayers' fell by a tiny 2.3% as did earnings average across all workers. However, for the sub-population of workers who switched down or became unemployed, earnings fell by 15% and 43%, respectively.

(4) Service exports had a statistically insignificant effect on average earnings (+1%), switching and unemployment.

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Table 1: U.S. Trade in White Collar Services, Average Annual Log Changes, 1995–2005

	U.S. Imports		U.S. Exports	
	China & India	G8	China & India	G8
	(1)	(2)	(3)	(4)
Business, professional, and technical services	**0.18**	0.10	**0.15**	0.11
Computer and information service	0.36	0.23	0.12	0.14
Legal services	0.10	0.08	0.11	0.09
Construction, architecture and engineering	0.03	0.04	0.07	0.07
Industrial engineering	0.23	0.00	0.00	0.10
Management consulting and public relations	0.18	0.14	0.08	0.03
Research, development and testing services	0.33	0.20	0.17	0.08
Advertising	0.05	-0.02	0.01	0.09
Other BPT services	0.10	0.07	0.28	0.14
Financial services	0.05	0.09	0.13	0.14
Insurance	-0.05	0.10	0.29	0.17
Total	0.14	0.10	0.15	0.13

Notes: These 10 white collar services are what the BEA refers to as 'Other Private Services'.

Table 2: Share of Offshorable Jobs by Industry

Industry	Share	Industry	Share
Professional	0.45	Wholesale & retail	0.15
Information	0.42	Mining	0.15
Financial	0.42	Other services	0.15
Manufacturing	0.24	Construction	0.08
Educational	0.19	Arts	0.07
Transportation & utilities	0.18	Agriculture	0.07

Table 3: The Correlates of Switching

	Stayers: Mean	'Downward' Switchers: Difference from Stayers		'Upward' Switchers: Difference from Stayers	
1. Change in the Inter-Occupational Wage Differential	0.000	-0.249***	(0.002)	0.230***	(0.002)
2. Change in the Log of Annual Earnings	0.045	-0.141***	(0.009)	0.108***	(0.010)
3. Average Years of Schooling	14.112	-0.343***	(0.024)	0.304***	(0.025)
4. Probability of an Unemployment Spell	0.000	0.081***	(0.003)	0.051***	(0.003)
5. Weeks Unemployed Conditional on an Unemployment Spell	0.000	16.5	(11.43)	15.3	(11.68)

Notes: This table reports on 4-digit occupational switching. The first column reports means for the sample of stayers. Rows 1, 2, and 4 are calculated from a regression of the indicated variable on a dummy for switching up, a dummy for switching down, and a full set of 4-digit occupational dummies for the worker's initial occupation. Row 3 and 5 are the meas for the three samples. Standard errors are in parentheses. *** indicates a difference between switchers and stayers that is statistically significant at the 1% level.

Table 4: Switching Down

	Services - OLS				Services - IV		
	Changes			Levels	Changes		Levels
	3-year	5-year	7-year	FE	5-year	7-year	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Service Characteristics							
Imports	0.087***	0.148***	0.208***	0.019***	0.140	0.203***	0.023**
	0.016	*0.027*	*0.037*	*0.034*	*0.026*	*0.039*	*0.036*
	(0.019)	(0.031)	(0.035)	(0.006)	(0.131)	(0.066)	(0.011)
Exports	-0.160***	-0.290**	-0.393***	-0.011*	-0.582***	-0.552***	-0.003
	-0.024	*-0.044*	*-0.059*	*-0.017*	*-0.087*	*-0.083*	*-0.005*
	(0.045)	(0.103)	(0.128)	(0.006)	(0.132)	(0.100)	(0.009)
Domestic Demand	-0.227**	-0.279**	-0.248**	-0.018***	-0.225***	-0.216**	-0.018***
	(0.081)	(0.097)	(0.110)	(0.005)	(0.081)	(0.084)	(0.002)
ICT	0.629**	1.163**	1.757**	0.040**	1.212***	1.767***	0.040***
	(0.273)	(0.387)	(0.678)	(0.016)	(0.322)	(0.364)	(0.009)
Individual Characteristics							
Schooling	-0.013***	-0.014***	-0.015***	-0.014***	-0.014***	-0.015***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)
Experience	-0.006***	-0.006***	-0.006***	-0.007***	-0.006***	-0.006***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Experience^2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.035***	-0.035***	-0.033***	-0.037***	-0.035***	-0.033***	-0.037***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Male	0.018	0.012	0.010	-0.004	0.007	0.006	-0.004
	(0.015)	(0.014)	(0.015)	(0.012)	(0.006)	(0.007)	(0.005)
White	-0.039***	-0.038***	-0.042***	-0.044***	-0.039***	-0.042***	-0.044***
	(0.007)	(0.008)	(0.009)	(0.008)	(0.005)	(0.006)	(0.005)
Endogeneity C Statistic					4.080	5.866	1.242
p -value					(0.130)	(0.053)	(0.537)
Overid Hansen J Statistic					0.451	0.632	0.515
p -value					(0.352)	(0.472)	(0.473)
Observations	90,615	75,425	59,876	90,615	75,425	59,876	90,615
R-squared	0.021	0.023	0.025	0.039	0.020	0.024	0.039

Notes: The dependent variable equals 1 if the worker switched down (to an occupation with a lower inter-occupational wage differential) and 0 if the worker stayed in the same occupation. The sample is the set of workers in white collar services that either switched down or stayed. All specifications include year fixed effects, state fixed effects, and interactions of year fixed effects with a non-tradable dummy. The difference between columns 1 through 3 is in the treatment of service imports and the three other service sector variables. For example, let $[\ln M_{kt} - \ln M_{k,t-l}]/l$ be the average annual change in imports over l years. The lag length appears in the column header e.g., $l = 3$ in column 1 and $l = 7$ in column 3. In column 4 the four service sector variables are entered in log levels and BEA service sector fixed effects are added. Columns 5–7 are the IV counterparts to columns 2–4. Numbers in italics are decadal impacts. Standard errors clustered at the BEA level appear in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Switching Up

	Services - OLS				Services - IV		
	Changes			Levels	Changes		Levels
	3-year	5-year	7-year	FE	5-year	7-year	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Service Characteristics							
Imports	-0.033	0.010	0.034	0.004	0.067	0.055	0.008
	-0.006	*0.002*	*0.006*	*0.007*	*-0.017*	*-0.005*	*0.016*
	(0.029)	(0.055)	(0.068)	(0.004)	(0.125)	(0.099)	(0.012)
Exports	0.105**	0.198*	0.244**	-0.003	0.425***	0.452***	-0.003
	0.016	*0.030*	*0.037*	*-0.005*	*0.064*	*0.068*	*-0.005*
	(0.035)	(0.094)	(0.093)	(0.005)	(0.114)	(0.104)	(0.009)
Domestic Demand	-0.174	-0.195	-0.183	-0.018***	-0.239***	-0.224**	-0.018***
	(0.157)	(0.166)	(0.156)	(0.005)	(0.087)	(0.102)	(0.002)
ICT	0.406**	0.478	0.748	0.022	0.458**	0.728***	0.021**
	(0.173)	(0.344)	(0.464)	(0.022)	(0.193)	(0.275)	(0.010)
Individual Characteristics							
Schooling	-0.007	-0.007	-0.008	0.000	-0.007***	-0.007***	0.000
	(0.004)	(0.005)	(0.005)	(0.004)	(0.002)	(0.002)	(0.001)
Experience	-0.008***	-0.008***	-0.007***	-0.006***	-0.008***	-0.007***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience^2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.030***	-0.029***	-0.031***	-0.024***	-0.029***	-0.031***	-0.024***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Male	0.014	0.017	0.020*	0.010	0.022***	0.024***	0.010***
	(0.011)	(0.011)	(0.010)	(0.006)	(0.005)	(0.005)	(0.003)
White	-0.041***	-0.041***	-0.040***	-0.036***	-0.041***	-0.039***	-0.036***
	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)
Endogeneity C Statistic					0.560	0.586	0.630
p -value					(0.236)	(0.150)	(0.730)
Overid Hansen J Statistic					1.023	0.341	0.039
p -value					(0.312)	(0.559)	(0.843)
Observations	87,646	72,843	57,680	87,646	72,843	57,680	87,646
R-squared	0.023	0.024	0.023	0.046	0.022	0.022	0.046

Notes: The dependent variable equals 1 if the worker switched up (to an occupation with a higher inter-occupational wage differential) and 0 if the worker stayed in the same occupation. The sample is the set of workers in white collar services that either switched up or stayed. The table is otherwise identical to table 4. See table 4 for all other details. Numbers in italics are decadal impacts. Standard errors clustered at the BEA level appear in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Transitions to Unemployment

	Services - OLS				Services - IV		
	Changes			Levels	Changes		Levels
	3-year	5-year	7-year	FE	5-year	7-year	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Service Characteristics							
Imports	0.007*	0.022**	0.022***	0.005***	0.040**	0.032	0.006**
	0.001	*0.004*	*0.004*	*0.009*	*0.007*	*0.006*	*0.011*
	(0.004)	(0.008)	(0.005)	(0.001)	(0.019)	(0.021)	(0.003)
Exports	0.003	0.000	0.006	-0.002	0.021	0.011	-0.002
	0.000	*0.000*	*0.001*	*-0.003*	*0.003*	*0.002*	*-0.003*
	(0.006)	(0.010)	(0.011)	(0.002)	(0.016)	(0.014)	(0.004)
Domestic Demand	0.011	-0.009	0.003	-0.001	-0.012	0.002	-0.001*
	(0.030)	(0.035)	(0.046)	(0.001)	(0.028)	(0.035)	(0.001)
ICT	0.142**	0.237***	0.394***	0.011**	0.232***	0.391***	0.011***
	(0.058)	(0.076)	(0.088)	(0.004)	(0.084)	(0.098)	(0.004)
Individual Characteristics							
Schooling	-0.004***	-0.004***	-0.004***	-0.003***	-0.004***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Experience	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Experience^2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.018***	-0.018***	-0.019***	-0.018***	-0.018***	-0.019***	-0.018***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Male	0.006**	0.005**	0.006**	0.005	0.005***	0.006***	0.005***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
White	-0.008***	-0.007***	-0.007***	-0.008***	-0.007***	-0.007***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Endogeneity C Statistic					3.172	1.039	0.385
p -value					(0.205)	(0.595)	(0.825)
Overid Hansen J Statistic					1.422	0.393	1.071
p -value					(0.233)	(0.531)	(0.301)
Observations	99,949	83,537	66,428	99,949	83,537	66,428	99,949
R-squared	0.009	0.009	0.009	0.010	0.008	0.009	0.010

Notes: The dependent variable equals 1 if the worker transitioned into unemployment and 0 if the worker stayed employed. The sample is the set of workers in white collar services that experienced no unemployment in the first of their two periods. The table is otherwise identical to table 4. See table 4 for all other details. Numbers in italics are decadal impacts. Standard errors clustered at the BEA level appear in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: First-Stage Regressions for Endogenous Imports and Exports

	Imports			Exports		
	Change		Level	Change		Level
VARIABLES	5-year	7-year	FE	5-year	7-year	FE
Excluded Instruments						
Chinese & Indian wages - w^*	-0.928***	-1.297***	-1.038***	0.097	-0.017	0.077
	(0.260)	(0.241)	(0.276)	(0.174)	(0.138)	(0.156)
Gravity instrument - Z^M	-0.134	0.030	0.016	0.598***	0.568***	0.919***
	(0.244)	(0.203)	(0.231)	(0.195)	(0.133)	(0.143)
Gravity instrument - Z^X	-0.032	-0.185	-0.492***	0.754***	0.866***	0.764***
	(0.184)	(0.168)	(0.165)	(0.173)	(0.148)	(0.154)
Observations	75,425	59,876	90,615	75,425	59,876	90,615
R-squared	0.673	0.781	0.990	0.825	0.878	0.998
F test	4.557	12.500	8.360	17.760	21.640	40.800
p-value	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: This table reports the first-stage results for the IV regressions in table 4. Each specification also includes all the exogenous variables in the second-stage regressions. 'F test' is the F-statistic for the joint significance of the three instruments. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Earnings for Stayers

	Services - OLS				Services - IV		
	Changes			Levels	Changes		Levels
	3-year	5-year	7-year	FE	5-year	7-year	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Service Characteristics							
Imports	-0.040*	-0.048***	-0.039*	-0.013*	-0.026	-0.072*	-0.025*
	-0.072	*-0.086*	*-0.070*	*-0.023*	*-0.047*	*-0.130*	*-0.045*
	(0.022)	(0.015)	(0.019)	(0.007)	(0.053)	(0.042)	(0.014)
Exports	0.032*	0.034	0.069*	0.007	0.077*	0.065	0.001
	0.048	*0.051*	*0.104*	*0.011*	*0.116*	*0.098*	*0.002*
	(0.016)	(0.028)	(0.039)	(0.006)	(0.046)	(0.045)	(0.012)
Domestic Demand	0.125	0.142	0.179*	-0.002	0.134*	0.178*	-0.002
	(0.071)	(0.091)	(0.086)	(0.002)	(0.076)	(0.092)	(0.002)
ICT	0.067	0.216	0.127	0.015	0.209	0.134	0.015
	(0.210)	(0.180)	(0.429)	(0.013)	(0.225)	(0.403)	(0.013)
Individual Characteristics							
Schooling	-0.004**	-0.003*	-0.002	-0.003***	-0.003**	-0.002	-0.003***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Experience	-0.008***	-0.008***	-0.009***	-0.008***	-0.008***	-0.009***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience^2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.013*	-0.015**	-0.013	-0.012	-0.015***	-0.013**	-0.012**
	(0.007)	(0.006)	(0.008)	(0.008)	(0.005)	(0.006)	(0.006)
Male	-0.010**	-0.007*	-0.012**	-0.008	-0.006	-0.011*	-0.008
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)	(0.006)
White	-0.024**	-0.023**	-0.024**	-0.023*	-0.023***	-0.024***	-0.023***
	(0.011)	(0.010)	(0.010)	(0.011)	(0.008)	(0.009)	(0.008)
Endogeneity C Statistic					1.684	0.659	0.731
p-value					(0.431)	(0.719)	(0.694)
Overid Hansen J Statistic					3.713	3.508	1.616
p-value					(0.054)	(0.061)	(0.204)
Observations	72,780	60,345	47,635	72,780	60,345	47,635	72,780
R-squared	0.007	0.007	0.006	0.008	0.007	0.006	0.008

Notes: The dependent variable is the change in the log of CPI-deflated annual earnings. The sample is the set of workers in white collar services that did not switch occupations i.e., stayers. In calculating the decadal impact of imports and exports (the numbers in italics) we multiply the coefficients, respectively, by 1.8 (= 0.18×10) and 1.5 (= 0.15×10). The table is otherwise identical to table 4. See table 4 for all other details. Standard errors clustered at the BEA level appear in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Wage Changes of Occupational Switchers and Transitioners to Unemployment

	Switching Down				Switching Up				Unemployment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Average Treatment Effect (ATE)	-0.149				0.127				-0.430			
	(0.009)				(0.009)				(0.022)			
Switching Dummy		-0.142				0.132				-0.429		
		(0.006)				(0.006)				(0.012)		
Change in IOWD			0.543	0.266			0.456	0.341			0.549	0.233
			(0.030)	(0.119)			(0.036)	(0.153)			(0.058)	(0.074)
Change in IOWD x Schooling				0.020				0.008				0.017
				(0.008)				(0.011)				(0.005)
Observations	90615	90823	17,885	17,885	87,627	87,866	14,779	14,779	99,949	100,204	3,757	3,757
R-squared		0.014	0.027	0.027		0.016	0.021	0.021		0.021	0.057	0.057

Notes: The dependent variable is wage changes $\ln[W_{k,t+1}(s,l)/W_{kt}(s,l)]$. The table is broken down into the three subgroups that appear in the column headers. Propensity score-based ATEs are reported in columns 1, 5 and 9. The propensity score uses all of the covariates that appear in the switching regressions of table 4. Balancing tests appear in table A.7. Columns 2, 6 and 10 report regressions of wage changes on a switching dummy and all of the covariates that appear in table 4 except for the four demand shocks (M,X,D,a). The remaining columns report estimates of equation (18) with $\phi_{k'} - \phi_k$ measured by the change in the interoccupational wage differential averaged across time with s^0 measured by years of schooling.

Table 10: Wage and Switching Impacts

	Transition Prob.	Wage Change	**Import**-Induced Change in: Transition Prob.	Wage Changes	Wage Impact	Switching Impact
	P^j	$\Delta \ln w^j$	$dP^j/d\Delta\ln M$	$d\Delta \ln w^j/d\Delta\ln M$		
	(1)	(2)	(3)	(4)	(5)	(6)
Downward	21.0%	-11.2% *	3.4% *	0.0%	-0.4%	16.2%
Upward	17.0%	16.4% *	0.7%	0.0%	0.1%	4.1%
Unemployment	3.0%	-39.3% *	0.9% *	0.0%	-0.4%	30.0%
Stayers	59.0%	3.7%	-5.0% *	-2.3% *	-1.5%	-8.5%
Total					-2.2%	
Total - Significant					-2.3%	

	Transition Prob.	Wage Change	**Export**-Induced Change in: Transition Prob.	Wage Changes	Wage Impact	Switching Impact
	P^j	$\Delta \ln w^j$	$dP^j/d\Delta\ln M$	$d\Delta \ln w^j/d\Delta\ln M$		
	(1)	(2)	(3)	(4)	(5)	(6)
Downward	21.0%	-11.2% *	-1.7%	0.0%	0.2%	-7.9%
Upward	17.0%	16.4% *	-0.3%	0.0%	0.0%	-1.8%
Unemployment	3.0%	-39.3% *	-0.3%	0.0%	0.1%	-10.0%
Stayers	59.0%	3.7%	2.3%	1.1%	0.7%	3.8%
Total					1.0%	
Total - Significant					0.0%	

Notes: This table reports the decomposition in equation (19). The top panel is for import-induced changes in wages and the bottom panel is for export-induced changes in wages. Column 1 reports the probability of switching down, switching up, transition to unemployments, and staying as calculated from the raw transitions. Column 2 reports wage changes. For stayers (3.7%) these are calculated from the raw data. For all other categories these are 3.7% plus the ATE in table 9. (Recall that the ATE is the change-in-wage *difference* between switchers and stayers so that the stayer change-in-wage must be added in.) A star indicates statistical significance at the 5% level. Column 3 reports estimates from column 4 of tables 4–6. The import (export) coefficients are multiplied by 1.8 (1.5), which are the 10-year changes from table 1. The stayers entry in column 3 is negative of the sum of the remaining coefficients i.e., $dP^S = -\sum_{j \neq S} dP^j$. Column 4 for stayers reports estimates from column 4 of table 8 where, again, the import (export) coefficients are multiplied by 1.8 (1.5). The other elements of column 4 are set to 0, which is our best estimate (unreported). Column 5 is (column 3) × (column 2) + (column 1) × (column 4) so that by equation (19), the column sum is the total impact of trade on wages. The 'Total – Significant' row excludes insignificant coefficients from the calculation. Column 6 is (column 3)/(column 1) and is the change-in-switching numbers that appear in the abstract and introduction.

Table 11: Sensitivity Results: The Coefficient on Imports

	Switching Down		Switching Up		Transitions to Unemployment		Log Earnings Changes of Stayers	
Sepcification description	Coeff.	Decadal Impacts	Coeff.	Decadal Impacts	Coeff.	Decadal Impacts	Coeff.	Decadal Impacts
0. Baseline	0.019 ***	*0.039*	0.004	*0.007*	0.005 ***	*0.009*	-0.013 *	*-0.023*
1. Omit Non-OPS	0.019 ***	*0.034*	0.003	*0.005*	0.006 ***	*0.011*	-0.013 *	*-0.023*
2. Correct CPS Sample Selection	0.015 ***	*0.027*	0.000	*0.000*	0.004 ***	*0.007*	-0.014 *	*-0.025*
3. Add Rich Countries	0.022 ***	*0.040*	0.004	*0.007*	0.005 ***	*0.009*	-0.013 *	*-0.023*
4. Poor Countries	0.022 ***	*0.040*	-0.002	*-0.004*	0.008 ***	*0.014*	-0.011 *	*-0.020*
5. Only BPT Services	0.014 ***	*0.025*	0.003	*0.005*	0.006 ***	*0.011*	-0.014 **	*-0.025*
6. Alternative Blinder Criterion	0.016 ***	*0.029*	0.004	*0.007*	0.004 **	*0.007*	-0.011 *	*-0.020*
7. Use Industry Crosswalk	0.011 ***	*0.020*	0.004	*0.006*	0.005 ***	*0.009*	-0.016 **	*-0.029*
8. Exclude 'IE' and 'RDT' Services	0.014 ***	*0.025*	0.003	*0.005*	0.004 ***	*0.007*	-0.011 **	*-0.020*
9. Omit Tech. Bubble	0.016 ***	*0.029*	0.001	*0.002*	0.004 ***	*0.007*	-0.010 *	*-0.018*
10. Drop Variables D & I	0.017 ***	*0.031*	0.000	*0.000*	0.005 ***	*0.009*	-0.009 **	*-0.016*
11. Control for Immigration	0.019 ***	*0.034*	0.004	*0.007*	0.005 ***	*0.009*	-0.013 *	*-0.023*
12. Use M/D and X/D	48.230 ***	*0.050*	-2.859	*-0.003*	9.880 *	*0.010*	-24.793 *	*-0.026*
13. Probit	0.014 ***	*0.025*	-0.000	*0.000*	0.006 ***	*0.011*		
14. Logit	0.014 ***	*0.025*	0.000	*0.000*	0.006 ***	*0.011*		
15. Multinomial Logit (four-way transition)	0.012 ***	*0.022*	-0.001	*-0.002*	0.005 ***	*0.009*		
16. Multinomial Logit (six-way transition): Far	0.008 ***	*0.014*	0.003	*0.006*	0.004 ***	*0.007*		
Little	0.010 ***	*0.018*	0.000	*0.000*				
17. 2-digit Switching	0.012 ***	*0.022*	-0.003	*-0.005*				
18. Δ (Weeks Unemp)/(Weeks in LF)					0.002 **	*0.004*		
19. Δ Weeks Worked					-0.200 ***	*-0.360*		
20. Log D of Weekly Wage							-0.010 **	*-0.018*
21. Log D of Hourly Wage							-0.013 **	*-0.023*

Notes: This table reports the coefficient on U.S. service imports from China and India for a large number of additional specifications. The first row repeats our baseline specification i.e., the level fixed effect OLS results from column 4 in tables 4–8. The level fixed effect specification is used throughout this table. 'Coeff.' is the coefficient on imports. 'Decadal Impacts' is the cumulative 10-year impact that appears in italics in tables 4–8. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix 1. Labour Demand Slopes Down

It is straightforward to prove that labour demand slopes down. $L^D = a(1-I)Q$ depends on w only via I. (We are holding Q fixed in this labour-demand exercise.) From equation (2), I is increasing in w. Hence $\partial L^D/\partial w = -aQ(\partial I/\partial w) < 0$. Likewise, import demand slopes down. $M = IQ$ depends on w^* via I and from equation (2), I is decreasing in w^*. Hence $\partial M/\partial w^* = (\partial I/\partial w^*)Q < 0$.

Appendix 2. Mathematical Appendix

In this appendix we fully work out the comparative statics of the model. Since we never separately examined changes in the domestic and foreign demand shifters δ_D and δ_X, we combine them here. That is, let $\delta_D = \delta_X = \delta$ and define $Q(p,\delta) = D(p,\delta) + X(p,\delta)$.

Substituting the equilibrium conditions $L^D = L^S(w)$ and $Q = Q(p,\delta)$ into equation (3) and substituting equation (2) into (4), one can re-write equations (2)–(4) as

$$\begin{aligned} wa &= w^*a^*\beta t(I) \\ L^S(w) &= a(1-I)Q(p,\delta) \\ p &= w^*a^*\beta\left[(1-I)t(I) + \int_0^I t(i)di\right]. \end{aligned}$$

Totally differenting these equations yields

$$\begin{bmatrix} 1 & -t'/t & 0 \\ \eta^S & (1-I)^{-1} & \eta^D \\ 0 & -\Delta & 1 \end{bmatrix}\begin{bmatrix} d\ln w \\ dI \\ d\ln p \end{bmatrix} = \begin{bmatrix} -1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}\begin{bmatrix} d\ln a \\ d\ln w^*a^*\beta \\ d\delta \end{bmatrix} \tag{A.1}$$

where $t' \equiv \partial t(I)/\partial I$,

$$\Delta \equiv (1-I)t'/[(1-I)t + \int_0^I t(i)di] > 0 \tag{A.2}$$

and $\eta^S \equiv \partial \ln L^S(w)/\partial w \geq 0$ and $\eta^D \equiv -\partial \ln Q^D(p,\delta)/\partial \ln p > 0$ are the elasticities of labour supply and product demand, respectively. In deriving equation (A.1) we have normalized the demand shifter δ by setting $d\ln Q(p,\delta)/d\delta$ to unity. Let

$$A \equiv (1-I)^{-1} + \eta^S t'/t + \eta^D \Delta > 0 \tag{A.3}$$

be the determinant of the 3×3 matrix on the left-hand side of equation (A.1). Then

$$\begin{bmatrix} d\ln w \\ dI \\ d\ln p \end{bmatrix} = \frac{1}{A}\begin{bmatrix} (1-I)^{-1}+\eta^D\Delta & t'/t & -\eta^D t'/t \\ -\eta^S & 1 & -\eta^D \\ -\eta^S\Delta & \Delta & (1-I)^{-1}+\eta^S t'/t \end{bmatrix}\begin{bmatrix} -1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}\begin{bmatrix} d\ln a \\ d\ln w^* a^* \beta \\ d\delta \end{bmatrix}$$
$$= \frac{1}{A}\begin{bmatrix} -(1-I)^{-1}-\eta^D\Delta+t'/t & (1-I)^{-1}-\eta^D(t'/t-\Delta) & t'/t \\ \eta^S+1 & -(\eta^S+\eta^D) & 1 \\ (\eta^S+1)\Delta & (1-I)^{-1}+\eta^S(t'/t-\Delta) & \Delta \end{bmatrix}\begin{bmatrix} d\ln a \\ d\ln w^* a^* \beta \\ d\delta \end{bmatrix}. \tag{A.4}$$

Note that $t'/t > \Delta > 0$.

We can use equation (A.4) to calculate the comparative statics behind figures 1–3. Since $M = IQ$, these coefficients are

$$\begin{aligned}\frac{d\ln M}{d\delta} &= \frac{d\ln I}{d\delta} + \frac{d\ln Q(p,\delta)}{d\ln p}\frac{d\ln p}{d\delta} + \frac{d\ln Q(p,\delta)}{d\delta} \\ &= \frac{1}{A}\frac{1}{I} - \eta^D\frac{1}{A}\Delta + 1 = \frac{1}{A}\left\{\frac{1}{I} + \frac{1}{1-I} + \eta^S\frac{t'}{t}\right\} > 0\end{aligned} \tag{A.5}$$

where we have simplified using equations (A.2)–(A.3) and $d\ln Q(p,\delta)/d\delta = 1$. Likewise,

$$\begin{aligned}\frac{d\ln M}{d\ln w^*} &= \frac{d\ln I}{dw^*} + \frac{d\ln Q(p,\delta)}{d\ln p}\frac{d\ln p}{dw^*} \\ &= -\frac{1}{I}\frac{\eta^S+\eta^D}{A} - \eta^D\frac{(1-I)^{-1}+\eta^S(t'/t-\Delta)}{A} < 0\end{aligned} \tag{A.6}$$

where the last inequality follows from the fact that $t'/t > \Delta > 0$. By inspection, $\lambda_\beta = \lambda_{w^*a^*}$. Finally,

$$\frac{d\ln M}{d\ln a} = A^{-1}(\eta^S+1)\left(I^{-1} - \eta^D\Delta\right) \tag{A.7}$$

which is positive as long as demand is not too elastic or offshoring is not too large.

In figures 1–3 we need

$$\frac{d\ln L^D}{d\delta} = A^{-1}\eta^S t'/t > 0 \tag{A.8}$$

and

$$\frac{d\ln L^D}{dw^*} = \frac{d\ln L^D}{d\beta} = A^{-1}\eta^S\left\{(1-I)^{-1} - \eta^D(t'/t-\Delta)\right\} \tag{A.9}$$

which is positive when η^D is small or I is small (so that $t'/t - \Delta$ is small).

Appendix 3. Definition of General Equilibrium

In order to define general equilibrium in our model we require three additional components. First, we need to describe the foreign labour market. This can be done as in Ohnsorge and Trefler (2007) who model the foreign and domestic labour markets in the same way, but with different distributions of worker types $g(h,u)$ and $g^*(h,u)$. Second, in the main text the demand functions $D_k(p_k,\delta_{D_k})$ and $X_k(p_k,\delta_{X_k})$ do not depend on income. We must therefore specify homothetic utility functions and derive these demands (including their dependence on income) from consumer optimization. Third, we require a balanced-trade condition. A competitive equilibrium is then a set of prices $\{p_k,w_k\}_{k=1}^{K}$ that clear the global market for each product $k = 1,\ldots,K$ and clear the national markets for workers subject to optimal occupational choice. The allocation of labour to sectors $L^S(w_k)$ is given by the sorting rule in equation (7) and the labour supply schedule in equation (8). The earnings of workers in occupation k is given by $W_k(h,u)$ in equation (6). Output Q_k and trade flows I_k (or $M_k \equiv I_k Q_k$) for each sector and each country follow from the sector/occupation supply functions described by equations (2)–(4).

Appendix 4. Appendix on BEA "Other Private Services" Data and the Crosswalk to the CPS

We have used 1995-2005 annual data on U.S. international transactions in "other private services" by service type and country provided by the BEA. Specifically, our data is extracted from "Table 5b and 5c: Other Private Services (Unaffiliated)" and "Table 7a, 7b, and 7c: Business, Professional, and Technical Services (Unaffiliated)" published on the BEA website (accessed in 2011).

All service trade data are from the "other private services" category of the BEA database. We exclude (*i*) Installation, maintenance, and repair of equipment, (*ii*) Education, (*iii*) Telecommunication, and (*iiii*) Other because these categories are difficult to concord into offshorable occupations. Constrained by the consistent data availability, we considered 10 types of services (listed in Table 1) as "tradable white collar services" and use the data on these 10 types of services in our empirical analysis.

Our measures of service imports and exports come from published BEA data on U.S. international services cross-border trade. Data for early years are sporadically missing. This could either be because values of less than 0.5 million dollars are suppressed or because of disclosure concerns.

The two likely go hand in hand: even a quick look through the data for each sector shows that when data are missing in a year there are usually neighbouring years with data and these data involve very small values of trade. We therefore used linear interpolation to fill in missing data. However, none of our results change when we restrict ourselves to non-imputed data.

The BEA service-trade surveys differ across service types in whether they report total trade or just unaffiliated trade. Total trade is available for 5 of our 10 types of services and unaffiliated trade is available for the remaining 5 service types. Given our log specification, this will matter only if the ratio of unaffiliated to total trade is trending. We have verified that this is not the case using the available data on unaffiliated and total trade in "Other Private Services". The share of unaffiliated to total trade quite stably holds at 60% between 1995 and 2005. Furthermore, in the 4 service types for which we have both modes of trade, there is no trend as well. Further, in Liu and Trefler (2008) we obtained identical results using unaffiliated trade in 9 of the 10 service types for which unaffiliated trade is available.

In the rest of this section, we document in detail the methodology, the reporting body, the classification and coverage of services in the Surveys to collect data of U.S. international transactions in private services by the BEA. The main purpose is to help readers understand how the BEA service data is categorized under different types of services that has been offshored overseas. This is the key to understand our crosswalk between CPS tradable white collar service occupations and BEA service trade data. This document is based on the official BEA document, "U.S. International Transactions in Private Services: A Guide to the Surveys Conducted by the Bureau of Economic Analysis."

The BEA data on our 10 types of "tradable white collar services" are based on two broad categories of mandatory surveys that collect data on U.S. international transactions in private services with unaffiliated foreigners: (1) the surveys of selected services, which cover mainly business, professional, and technical services (Survey Form BE-20 and BE-22); and (2) the specialized surveys of services that are complementary to the first category of surveys. They cover construction, engineering, architectural, and mining services provided by U.S. firms to unaffiliated foreign persons (Survey Form BE-47), insurance services by U.S. insurance services providers with foreign persons (Survey Form BE-48), and financial services transactions between U.S. financial services providers and unaffiliated foreign persons (Survey Form BE-80 and BE-82).

Below we briefly introduce these Surveys that are used by the BEA to collect the service trade data with a focus on the definition and coverage of the services that are surveyed.

The Surveys of Selected Services: The Surveys of Selected Services cover all U.S. persons whose total transactions in either sales or purchases in any of the covered services exceed $1 million during the relevant fiscal year in the annual surveys (or $500,000 in the benchmark surveys). The related services that covered in these surveys are:

Computer and information services combine two specific types of services: Computer and data-processing services and database and other information services. Computer and data-processing services consist data entry, batch and remote processing, and tabulation; computer systems analysis, design, and engineering; custom software and programming services; integrated hardware and software systems; and other computer services, such as timesharing, maintenance, and repair. Database and other information services consist business and economic database services, including business news, stock quotation, and financial information services; medical, legal, technical, demographic, bibliographical and similar database services; general news services, such as those purchased from a news syndicate; and other information services, including reservation systems and credit reporting systems. Transactions for the use of airline reservation systems also include the booking fees from foreign carriers for direct access, or for access through a travel agent, to a reservation system.

Research, development, and testing services: consist of laboratory and other physical research, product development services, and product testing services. These services include experiments and research and development activities aboard spacecraft, they exclude medical and dental laboratory services.

Management, consulting, and public relations services: consist of the following services: All management services except the management of health care facilities, consulting services except computer consulting services and engineering consulting services for actual or proposed construction and mining projects, and public relations services except those that are a part of an advertising campaign. Legal services consist of legal advice and other legal services, including the fees paid by insurance companies as compensation for claims adjustment services.

Industrial engineering services consist of engineering services: related to the design of movable products, including product design services. Includes services performed with the assistance of computers, such as computer-assisted design work. Excludes engineering and architectural services related to immovable products, such as those that relate to actual or proposed construction or mining services projects. Advertising services consist of preparing and placing advertising in media. Transactions in these services include both agency fees and charges for media space and time. They exclude transactions with U.S. affiliates of foreign clients or of foreign advertising agencies and transactions that are with foreign persons and that are effected by foreign affiliates of U.S. advertising agencies.

Construction, engineering, architectural, and mining services: consist only purchases of the following services: The construction of buildings and of projects, such as highways, bridges and tunnels, docks and piers, pipelines, and communication and power lines; specialized construction activities, such as the erection of structural steel for bridges and buildings and on-site plumbing, painting, electrical work, masonry, and carpentry; engineering services for construction and mining projects; architectural services; land-surveying services; and mining services, including oil and gas field services.

Other business, professional and technical services: mainly include accounting, auditing, and bookkeeping services; medical services, miscellaneous disbursements, operational leasing, sports and performing arts, training services, and other business, professional, and technical services.

Financial services: consist of purchases of credit related services and other financial services by nonfinancial U.S. firms, including credit-related services, securities transactions, and other financial services.

Insurance services: consist of the premiums paid by U.S. persons to unaffiliated foreign insurance carriers for primary insurance and the losses recovered on primary insurance purchased by U.S. persons from unaffiliated foreign insurance carriers.

The Specialized Surveys of Services: includes *The Survey of Construction, Engineering, Architectural, and Mining Services*, *The surveys of financial services*, and *The Survey of Reinsurance and Other Insurance Transactions*.

The Survey of Construction, Engineering, Architectural, and Mining Services: covers the sales of these services by U.S. firms (who have new contracts with a gross value of $1 million or more to provide the covered services or who have received gross operating revenues of $1 million or more for the covered services during the fiscal year) to unaffiliated foreign persons. The related services covered in this survey are the same as Construction, engineering, architectural, and mining services in the Surveys of Selected Services.

The Surveys of Financial Services: cover all U.S. financial services providers whose total transactions in either sales or purchases in all the financial services combined exceed $1 million during the benchmark fiscal year (or exceed $5 million in the annual surveys). The related services covered in this survey include brokerage services except foreign exchange brokerage services; private placement services; underwriting services; financial management services; credit-related services except credit care services; credit card services; financial advisory and custody services; securities lending services; foreign exchange brokerage services; and other financial services.

The Survey of Reinsurance and Other Insurance Transactions: covers reinsurance and primary insurance transactions by U.S. insurance companies with both affiliated and unaffiliated foreign persons. All U.S. persons whose total transactions in a covered service $1 million or more during the fiscal year are required to report. The related services covered in this survey include premiums earned on reinsurance assumed from insurance companies resident abroad; losses incurred on reinsurance assumed from insurance companies resident abroad; premiums incurred on reinsurance ceded to insurance companies resident abroad; losses recovered on reinsurance ceded to insurance companies resident abroad; premiums earned on primary insurance sold to foreign persons; and losses incurred on primary insurance sold to foreign persons.

Based on the design of the surveys as describe above, it is clear that the BEA service data is aggregated at the type of services that has been offshored instead of at the industry level. Therefore, in our baseline analysis, we have constructed the crosswalk between the BEA services and the CPS tradable white collar services occupations that are most likely to provide the specified offshored services.

Appendix 5. Other Data Appendix

In 2003, the CPS updated its occupation and industry classifications from 1990 Census codes to 2002 Census codes. To ensure that codes are consistent over our entire sample we converted the 1990 Census codes into 2002 Census codes.

D_{kt} is constructed as total sales Q_{kt} less exports X_{kt}. Q_{kt} is calculated from the BEA table 'GDP by Industry: 1998-2005.' We use linear interpolation to fill in missing data for 1995-1997. Data for ICT_{kt} are from the BEA table of 'Historical-Cost Investment in Private Nonresidential Fixed Assets.' Both D_{kt} and ICT_{kt} are from the BEA and are available at a finer level of aggregation than is the service trade data.

Responses to questions about occupation and industry in the longest job held last year are known to be frequently miscoded. This leads to over-estimation of switching. We therefore clean up the raw switching data using the yearly equivalent of the criteria in Moscarini and Thomsson (2008). Specifically, a switch is valid only if at least one of the following three events occurred. (1) The class of worker changed.[41] (2) There was job search during the period.[42] (3) For an occupation (industry) switch the industry (occupation) changed. Note that in most cases, criterion (3) was satisfied only when either (1) or (2) were satisfied. That is, criterion (3) has almost no bite and excluding it has no effect on our results. If in the first of the two CPS surveys a worker does not report a longest job held last year then she is deleted from the sample.

Appendix 6. Instrumental Variables

We first describe the construction of the instruments for the case where the population coefficient is not 0. Letting c index our 28 countries, we estimate $\ln X_{ckt} = \alpha^X_{ck} + \beta^X_{k,Y/L} \ln(Y_{ct}/L_{ct}) + \beta^X_{k,L} \ln(L_{ct}) + \epsilon^X_{ckt}$ separately for each sector k. Letting 'hats' denote OLS estimates, our estimate of exports in levels is $\hat{X}_{ckt} \equiv \exp\left(\hat{\beta}^X_{k,Y/L} \ln(Y_{ct}/L_{ct}) + \hat{\beta}^X_{k,L} \ln(L_{ct})\right)$. Our estimate of the log of aggregate Chinese and Indian exports is $\ln \hat{X}_{kt} \equiv \ln\left(\hat{X}_{China,kt} + \hat{X}_{India,kt}\right)$. Our level fixed effect instrument is $Z^X_{kt} \equiv \ln \hat{X}_{kt}$. Our l-year change instrument is $Z^X_{kt} \equiv (\ln \hat{X}_{kt} - \ln \hat{X}_{k,t-l})/l$. Appendix table A.6 reports the estimates of the gravity equation that were described in section 6.

[41]There are three classes of workers: (i) private, which includes working in a private for-profit company or being self-employed and incorporated; (ii) self-employed but not incorporated; and (iii) government employee.

[42]In the variable coding of LOOKED, a worker looked for a job last year if she worked last year ($WORKYN = 1$), was a part-year worker ($1 <= WKSLYR <= 51$) and looked for work last year ($LKEDPY = 0$).

Figure A.1: Growth in Other Private Services Trade

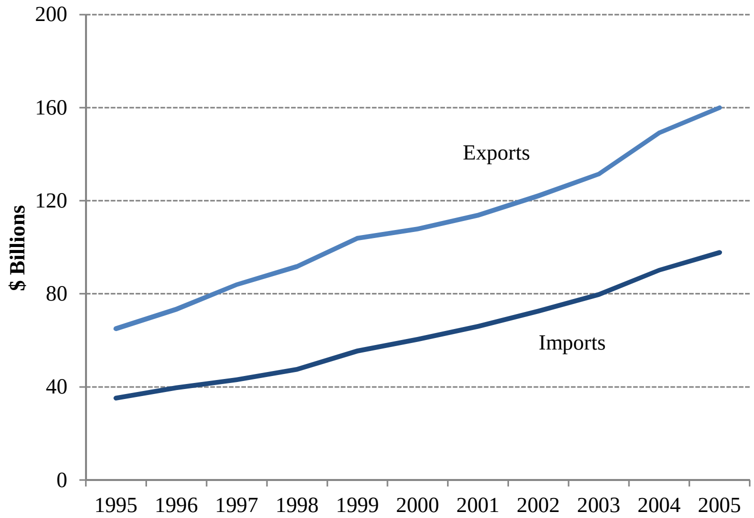

Table A.1: March-to-March CPS Matching Rates

Year	Naïve Match	Valid Match	Final Match
1996	71%	95%	67%
1997	70%	95%	67%
1998	70%	96%	67%
1999	69%	96%	66%
2000	75%	97%	73%
2001	64%	94%	60%
2002	65%	92%	60%
2003	65%	94%	61%
2004	57%	95%	54%
2005	59%	94%	55%
2006	65%	93%	60%
average	66%	95%	63%

Notes: 'Naïve Match' is the proportion of all civilian adults in March of the indicated year who can be matched to an individual in March of the subsequent year. The naïve match is based on a household identifier, a household number, and an individual line number within a household. 'Valid Match' is the percentage of naïve matches that survive the S|R|A (sex, race, age) merge criterion. 'Final Match' is the final match rate and equals (naïve match)x(valid match).

Table A.2: Concordance between Census Occupation Codes and BEA Codes

2002 Census Codes	2002 Census Categories	2002 SOC Codes	BEA 'Other Private Service' Codes	Blinder's Offshorability Index
0040	Advertising and promotions managers	11-2011	advertising	53
1310	Surveyors, cartographers, and photogrammetrists	17-1020	construction, architecture, engineering services	86
0300	Engineering managers	11-9041	construction, architecture, engineering services	54
1010	Computer programmers	15-1021	computer and information services	100
5810	Data entry keyers	43-9021	computer and information services	100
1000	Computer scientists and systems analysts	15-10XX	computer and information services	96
1210	Mathematicians	15-2021	computer and information services	96
1230	Statisticians	15-2041	computer and information services	96
1240	Miscellaneous mathematical science occupations	15-2090	computer and information services	95
5830	Desktop publishers	43-9031	computer and information services	93
1040	Computer support specialists	15-1041	computer and information services	92
1110	Network systems and data communications analysts	15-1081	computer and information services	92
5920	Statistical assistants	43-9111	computer and information services	90
1060	Database administrators	15-1061	computer and information services	75
5800	Computer operators	43-9011	computer and information services	75
1020	Computer software engineers	15-1030	computer and information services	74
1400	Computer hardware engineers	17-2061	computer and information services	73
0110	Computer and information systems managers	11-3021	computer and information services	55
1100	Network and computer systems administrators	15-1071	computer and information services	50
5230	Credit authorizers, checkers, and clerks	43-4041	finance	80
0840	Financial analysts	13-2051	finance	77
0120	Financial managers	11-3031	finance	76
5200	Brokerage clerks	43-4011	finance	67
0830	Credit analysts	13-2041	finance	64
4820	agents	41-3031	finance	51
0950	Financial specialists, all other	13-2099	finance	50
1540	Drafters	17-3010	industrial engineering	98
1550	Engineering technicians, except drafters	17-3020	industrial engineering	98
1350	Chemical engineers	17-2041	industrial engineering	72
1410	Electrical and electronic engineers	17-2070	industrial engineering	70
1430	Industrial engineers, including health and safety	17-2110	industrial engineering	70
1460	Mechanical engineers	17-2141	industrial engineering	70
1200	Actuaries	15-2011	insurance	96
5840	Insurance claims and policy processing clerks	43-9041	insurance	93
0860	Insurance underwriters	13-2053	insurance	85
2150	Miscellaneous legal support workers	23-2090	legal services	52
2140	Paralegals and legal assistants	23-2011	legal services	51
1220	Operations research analysts	15-2031	management, consulting, public relation services	82
0360	Natural sciences managers	11-9121	management, consulting, public relation services	56
0020	General and operations managers	11-1021	management, consulting, public relation services	55
0140	Industrial production managers	11-3051	management, consulting, public relation services	55
0520	Wholesale and retail buyers, except farm products	13-1022	management, consulting, public relation services	55
0530	products	13-1023	management, consulting, public relation services	55
0700	Logisticians	13-1081	management, consulting, public relation services	55
0050	Marketing and sales managers	11-2020	management, consulting, public relation services	53
0600	Cost estimators	13-1051	management, consulting, public relation services	50
2920	and editors	27-4030	other business, professional and technical services	95
4940	Telemarketers	41-9041	other business, professional and technical services	95
5020	Telephone operators	43-2021	other business, professional and technical services	95

2002 Census Codes	2002 Census Categories	2002 SOC Codes	BEA 'Other Private Service' Codes	Blinder's Offshorability Index
5910	Proofreaders and copy markers	43-9081	other business, professional and technical services	95
5240	Customer service representatives	43-4051	other business, professional and technical services	94
5410	clerks	43-4181	other business, professional and technical services	94
5820	Word processors and typists	43-9022	other business, professional and technical services	94
5860	Office clerks, general	43-9061	other business, professional and technical services	94
5930	Office and administrative support workers, all other	43-9199	other business, professional and technical services	94
2830	Editors	27-3041	other business, professional and technical services	93
2840	Technical writers	27-3042	other business, professional and technical services	93
2860	Miscellaneous media and communication workers	27-3090	other business, professional and technical services	93
5420	Information and record clerks, all other	43-4199	other business, professional and technical services	92
2850	Writers and authors	27-3043	other business, professional and technical services	90
5110	Billing and posting clerks and machine operators	43-3021	other business, professional and technical services	90
2600	Artists and related workers	27-1010	other business, professional and technical services	89
2630	Designers	27-1020	other business, professional and technical services	86
5120	Bookkeeping, accounting, and auditing clerks	43-3031	other business, professional and technical services	84
3510	Medical records and health information technicians	29-2071	other business, professional and technical services	83
5210	Correspondence clerks	43-4021	other business, professional and technical services	77
5400	Receptionists and information clerks	43-4171	other business, professional and technical services	75
0800	Accountants and auditors	13-2011	other business, professional and technical services	72
5520	Dispatchers	43-5030	other business, professional and technical services	72
5700	Secretaries and administrative assistants	43-6010	other business, professional and technical services	69
0940	Tax preparers	13-2082	other business, professional and technical services	68
5140	Payroll and timekeeping clerks	43-3051	other business, professional and technical services	67
5150	Procurement clerks	43-3061	other business, professional and technical services	67
5350	Order clerks	43-4151	other business, professional and technical services	67
5100	Bill and account collectors	43-3011	other business, professional and technical services	65
0820	Budget analysts	13-2031	other business, professional and technical services	60
3300	Clinical laboratory technologists and technicians	29-2010	other business, professional and technical services	59
5600	Production, planning, and expediting clerks	43-5061	other business, professional and technical services	54
5900	Office machine operators, except computer	43-9071	other business, professional and technical services	51
4830	Travel agents	41-3041	other business, professional and technical services	50
5010	Switchboard operators, including answering service	43-2011	other business, professional and technical services	50
5260	File Clerks	43-4071	other business, professional and technical services	50
5360	timekeeping	43-4161	other business, professional and technical services	50
1340	Biomedical engineers	17-2031	other business, professional and technical services	71
1650	Medical scientists	19-1040	other business, professional and technical services	55
1810	Market and survey researchers	19-3020	research, development and testing services	90
1800	Economists	19-3011	research, development and testing services	89
1600	Agricultural and food scientists	19-1010	research, development and testing services	85
1610	Biological scientists	19-1020	research, development and testing services	83
1710	Atmospheric and space scientists	19-2021	research, development and testing services	81
1530	Engineers, all other	17-2199	research, development and testing services	72
1450	Materials engineers	17-2131	research, development and testing services	71
1440	Marine engineers and naval architects	17-2121	research, development and testing services	69
1720	Chemists and materials scientists	19-2030	research, development and testing services	66
1760	Physical scientists, all other	19-2099	research, development and testing services	66
1900	Agricultural and food science technicians	19-4011	research, development and testing services	55
1910	Biological technicians	19-4021	research, development and testing services	55
1920	Chemical technicians	19-4031	research, development and testing services	55

Table A.3: Concordance between Census Industry Codes and BEA Codes

2002 Census Codes	2002 Census Categories	2002 NAICS Codes	BEA 'Other Private Service' Codes
7470	Advertising and related services	5418	advertising
7290	Architectural, engineering, and related services	5413	construction, architecture, engineering services
6490	Software publishing	5112	computer and information services
6675	Internet publishing and broadcasting	5161	computer and information services
6692	Internet service providers	5181	computer and information services
6695	Data processing, hosting, and related services	5182	computer and information services
6780	Other information services	5191 exc. 51912	computer and information services
7380	Computer systems design and related services	5415	computer and information services
6870	Banking and related activities	521, 52211,52219	finance
6880	Savings institutions, including credit unions	52212, 52213	finance
6890	Non-depository credit and related activities	5222, 5223	finance
6970	Securities, commodities, funds, trusts, and other financial investments	523, 525	finance
7370	Specialized design services	5414	industrial engineering
6990	Insurance carriers and related activities	524	insurance
7270	Legal services	5411	legal services
7390	Management, scientific, and technical consulting services	5416	management, consulting, public relation services
7280	Accounting, tax preparation, bookkeeping, and payroll services	5412	other business, professional and technical services
7490	Other professional, scientific, and technical services	5419 exc. 54194	other business, professional and technical services
7590	Business support services	5614	other business, professional and technical services
7780	Other administrative and other support services	5611, 5612, 5619	other business, professional and technical services
7460	Scientific research and development services	5417	research, development and testing services

Table A.4: Characteristics of Workers in Tradable and Non-Tradable Occupations

	Tradable Occupations (N=38,719)		Tradable - Non-tradable		
	Mean	Std. Dev.	Mean	t	
	(1)	(2)	(3)	(4)	
Occupation Switch					
4-digit occupation switch	0.320	0.470	0.031	10.727	*
2-digit occupation switch	0.200	0.406	-0.008	-3.303	*
1-digit occupation switch	0.170	0.380	-0.012	-5.008	*
Employment and Earnings					
incidence of unemployment	0.038	0.192	-0.003	-2.291	*
log annual earnings	10.075	0.808	0.178	31.245	*
change in annual earnings	0.033	0.612	-0.021	-5.085	*
Skills					
schooling	14.100	2.044	0.327	22.510	*
high-school dropout	0.021	0.141	-0.056	-39.090	*
high-school graduate	0.263	0.440	-0.021	-7.448	*
college dropout	0.220	0.416	0.022	8.912	*
college graduate	0.494	0.499	0.055	17.865	*
less-skilled white-collar	0.493	0.499	-0.050	-16.340	*
skilled white-collar	0.507	0.499	0.050	16.340	*
Other Demographics					
experience	19.740	11.050	-0.011	-0.163	
married	0.666	0.470	0.035	11.719	*
male	0.372	0.484	-0.080	-26.456	*
white	0.880	0.324	0.009	4.349	*

Table A.5: Coefficients on the Interaction of I^{NT} with Year Fixed Effects

	Switching Down				Switching Up				Transitions to Unemployment				Earnings for Stayers			
	Services - OLS				Services - OLS				Services - OLS				Services - OLS			
	Changes			Levels	Changes			Levels	Changes			Levels	Changes			Levels
	3-year	5-year	7-year	FE	3-year	5-year	7-year	FE	3-year	5-year	7-year	FE	3-year	5-year	7-year	FE
	(1)	(2)	(3)	(4)	(1')	(2')	(3')	(4')	(1'')	(2'')	(3'')	(4'')	(1''')	(2''')	(3''')	(4''')
Service Characteristics																
Imports	0.087***	0.148***	0.208***	0.019***	-0.033	0.010	0.034	0.004	0.007*	0.022**	0.022***	0.005***	-0.040*	-0.048***	-0.039*	-0.013*
	0.016	*0.027*	*0.037*	*0.034*	*-0.006*	*0.002*	*0.006*	*0.007*	*0.001*	*0.004*	*0.004*	*0.009*	*-0.072*	*-0.086*	*-0.070*	*-0.023*
	(0.019)	(0.031)	(0.035)	(0.006)	(0.029)	(0.055)	(0.068)	(0.004)	(0.004)	(0.008)	(0.005)	(0.001)	(0.022)	(0.015)	(0.019)	(0.007)
Exports	-0.160***	-0.290**	-0.393***	-0.011*	0.105**	0.198*	0.244**	-0.003	0.003	0.000	0.006	-0.002	*0.032**	*0.034*	*0.069**	*0.007*
	-0.024	*-0.044*	*-0.059*	*-0.017*	*0.016*	*0.030*	*0.037*	*-0.005*	*0.000*	*0.000*	*0.001*	*-0.003*	*0.048*	*0.051*	*0.104*	*0.011*
	(0.045)	(0.103)	(0.128)	(0.006)	(0.035)	(0.094)	(0.093)	(0.005)	(0.006)	(0.010)	(0.011)	(0.002)	(0.016)	(0.028)	(0.039)	(0.006)
Domestic Demand	-0.227**	-0.279**	-0.248**	-0.018***	-0.174	-0.195	-0.183	-0.018***	0.011	-0.009	0.003	-0.001	0.125	0.142	0.179*	-0.002
	(0.081)	(0.097)	(0.110)	(0.005)	(0.157)	(0.166)	(0.156)	(0.005)	(0.030)	(0.035)	(0.046)	(0.001)	(0.071)	(0.091)	(0.086)	(0.002)
ICT	0.629**	1.163**	1.757**	0.040**	0.406**	0.478	0.748	0.022	0.142**	0.237***	0.394***	0.011**	0.067	0.216	0.127	0.015
	(0.273)	(0.387)	(0.678)	(0.016)	(0.173)	(0.344)	(0.464)	(0.022)	(0.058)	(0.076)	(0.088)	(0.004)	(0.210)	(0.180)	(0.429)	(0.013)
Individual Characteristics																
Schooling	-0.013***	-0.014***	-0.015***	-0.014***	-0.007	-0.007	-0.008	0.000	-0.004***	-0.004***	-0.004***	-0.003***	-0.004**	-0.003*	-0.002	-0.003***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)	(0.005)	(0.005)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Experience	-0.006***	-0.006***	-0.006***	-0.007***	-0.008***	-0.008***	-0.007***	-0.006***	-0.001***	-0.001***	-0.001***	-0.001***	-0.008***	-0.008***	-0.009***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Experience^2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.035***	-0.035***	-0.033***	-0.037***	-0.030***	-0.029***	-0.031***	-0.024***	-0.018***	-0.018***	-0.019***	-0.018***	-0.013*	-0.015**	-0.013	-0.012
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.007)	(0.006)	(0.008)	(0.008)
Male	0.018	0.012	0.010	-0.004	0.014	0.017	0.020*	0.010	0.006**	0.005**	0.006**	0.005	-0.010**	-0.007*	-0.012**	-0.008
	(0.015)	(0.014)	(0.015)	(0.012)	(0.011)	(0.011)	(0.010)	(0.006)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
White	-0.039***	-0.038***	-0.042***	-0.044***	-0.041***	-0.041***	-0.040***	-0.036***	-0.008***	-0.007***	-0.007***	-0.008***	-0.024**	-0.023**	-0.024**	-0.023*
	(0.007)	(0.008)	(0.009)	(0.008)	(0.007)	(0.007)	(0.006)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.011)	(0.010)	(0.010)	(0.011)
Nontradeable Dummies																
I^{NT}	-0.025	-0.038	-0.042	-0.157***	-0.014	0.012	0.019		0.003	0.005	0.006	-0.021***	0.012	0.001	0.001	0.137***
	(0.040)	(0.040)	(0.042)	(0.018)	(0.042)	(0.048)	(0.045)		(0.006)	(0.007)	(0.004)	(0.006)	(0.016)	(0.016)	(0.012)	(0.018)
I^{NT} x $I_{1997\text{-}98}$	-0.020			0.002	0.005			-0.007	-0.002			-0.000	-0.005			-0.013
	(0.026)			(0.013)	(0.011)			(0.004)	(0.003)			(0.003)	(0.009)			(0.010)
I^{NT} x $I_{1999\text{-}2000}$	0.003	-0.014		0.004	-0.017	-0.003		-0.008	-0.003	-0.002		0.001	-0.016	-0.004		-0.024
	(0.020)	(0.012)		(0.013)	(0.012)	(0.009)		(0.008)	(0.005)	(0.005)		(0.004)	(0.019)	(0.019)		(0.017)
I^{NT} x I_{2001}	0.028	0.047	0.013	0.038	0.010	-0.007	0.025	0.013	-0.003	-0.004	-0.002	0.001	-0.036	-0.026	-0.017	-0.047
	(0.027)	(0.033)	(0.022)	(0.024)	(0.028)	(0.029)	(0.032)	(0.028)	(0.007)	(0.007)	(0.004)	(0.006)	(0.031)	(0.032)	(0.021)	(0.030)
I^{NT} x $I_{2002\text{-}2003}$	0.009	0.016	0.015	0.038*	-0.001	-0.013	-0.005	-0.011	-0.005	-0.006	-0.004*	-0.000	-0.004	0.008	0.013	-0.017
	(0.016)	(0.019)	(0.014)	(0.018)	(0.017)	(0.021)	(0.018)	(0.016)	(0.004)	(0.004)	(0.002)	(0.004)	(0.012)	(0.013)	(0.012)	(0.013)
I^{NT} x $I_{2004\text{-}2005}$	-0.021	-0.017	-0.014	0.026	0.006	0.002	0.000	-0.012	-0.005	-0.005	-0.005	0.001	-0.026	-0.017	-0.010	-0.043**
	(0.015)	(0.015)	(0.012)	(0.022)	(0.019)	(0.019)	(0.017)	(0.020)	(0.006)	(0.006)	(0.005)	(0.007)	(0.015)	(0.016)	(0.009)	(0.016)
Observations	90,615	75,425	59,876	90,615	87,646	72,843	57,680	87,646	99,949	83,537	66,428	99,949	72780	60345	47635	72780
Workers in Tradable Services	32,673	27,264	21,796	32,673	31,905	26,598	21,217	31,905	36,545	30,604	24,489	36,545	25865	21506	17215	25865
Workers in NonTradable Services	57,942	48,161	38,080	57,942	55,741	46,245	36,463	55,741	63,404	52,933	41,939	63,404	46,915	38,839	30,420	46,915
R-squared	0.021	0.023	0.025	0.039	0.023	0.024	0.023	0.046	0.009	0.009	0.009	0.010	0.007	0.007	0.006	0.008

Notes: This table reports coefficients that were suppressed in tables 4–8. What follows are some minor details of the specification. Recall that a worker appears in two years. For a worker who is in a non-tradable service in either one or both years, we set the log change in imports and exports to zero and set $I^{NT} = 1$. For a worker who is never in a non-tradable service we set $I^{NT} = 0$. In order to save space and increase the precision of the estimates of the interaction terms, we use dummies for pairs of years rather than for individual years.

Table A.6: Gravity Equations

	Bilateral Imports									
	Advertising	Financial	Insurance	Legal	Management Consulting	Construction, Architectural, Engineering	Computer Information	Industrial Engineering	Other BPT	R&D
$\ln(Y_{ct}/L_{ct})$	1.312**	3.259**	3.172**	1.724**	1.171**	1.803**	1.855**	2.118**	2.658**	1.310**
	(0.255)	(0.185)	(0.231)	(0.180)	(0.255)	(0.315)	(0.212)	(0.360)	(0.229)	(0.302)
$\ln(L_{ct})$	1.876**	0.202	1.581*	1.922**	0.411	-6.045**	2.191**	0.412	2.236**	0.027
	(0.728)	(0.533)	(0.790)	(0.539)	(0.956)	(0.941)	(0.677)	(1.030)	(0.545)	(1.282)
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	349	392	385	392	390	376	392	355	391	370
R-squared	0.88	0.94	0.92	0.94	0.81	0.67	0.89	0.65	0.88	0.85
F	48.67	425.92	113.07	80.13	26.35	23.45	117.94	43.61	158.79	26.75
	Bilateral Imports									
	Advertising	Financial	Insurance	Legal	Management Consulting	Construction, Architectural, Engineering	Computer Information	Industrial Engineering	Other BPT	R&D
$\ln(Y_{ct}/L_{ct})$	0.788***	3.486***	2.008***	1.519***	1.969***	-0.327	2.421***	1.292***	2.213***	2.949***
	(0.227)	(0.292)	(0.347)	(0.159)	(0.352)	(0.457)	(0.387)	(0.449)	(0.269)	(0.277)
$\ln(L_{ct})$	0.909	-0.482	0.687	1.787***	1.742*	0.674	0.266	-1.786	3.572***	2.729***
	(0.889)	(1.176)	(1.377)	(0.601)	(0.896)	(1.351)	(1.147)	(1.343)	(0.794)	(0.902)
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	380	387	311	391	385	276	303	184	391	354
R-squared	0.91	0.87	0.92	0.94	0.79	0.58	0.83	0.71	0.90	0.87
F	21.19	189.37	207.27	148.16	46.22	0.26	35.87	4.65	148.29	208.83

Notes: The dependent variables are log levels of bilateral service exports and imports between the United States and 28 countries. '*F*' is the *F*-statistic for the joint significance of $\ln(Y_{ct}/L_{ct})$ and $\ln(L_{ct})$. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.7: Balancing Test Statistics

	Switching Down			
	Standardized Differences		Variance Ratio	
	Raw	Matched	Raw	Matched
Imports	0.040	-0.007	1.010	0.993
Exports	0.020	-0.009	0.958	0.989
ICT	0.091	-0.009	1.116	0.973
Domestic Demand	-0.072	0.004	1.109	1.055
Schooling	-0.160	-0.002	0.967	1.006
Experience	-0.168	0.013	1.103	0.988
Experience^2	-0.131	0.009	0.988	0.968
Married	-0.173	-0.006	1.120	1.005
Male	0.032	0.007	1.007	1.002
White	-0.099	-0.011	1.265	1.028
Number of Obs	90615	181230		
Treated Obs	17835	90615		
Control Obs	72780	90615		

	Switching Up			
	Standardized Differences		Variance Ratio	
	Raw	Matched	Raw	Matched
Imports	0.115	0.013	1.095	1.008
Exports	0.117	0.014	1.102	1.013
ICT	0.060	0.037	0.968	0.972
Domestic Demand	-0.006	-0.006	1.139	1.042
Schooling	-0.110	0.004	0.957	0.990
Experience	-0.238	0.010	1.120	0.993
Experience^2	-0.191	0.008	0.940	0.960
Married	-0.194	0.010	1.130	0.992
Male	-0.003	0.003	0.999	1.001
White	-0.111	-0.003	1.299	1.006
Number of Obs	87646	175292		
Treated Obs	14866	87646		
Control Obs	72780	87646		

	Transition to Unemployment			
	Standardized Differences		Variance Ratio	
	Raw	Matched	Raw	Matched
Imports	0.039	0.023	1.032	1.019
Exports	0.028	0.017	1.016	1.008
ICT	0.051	0.025	1.060	1.025
Domestic Demand	0.049	-0.011	1.081	1.038
Schooling	-0.230	0.000	0.904	0.942
Experience	-0.203	-0.004	1.121	0.977
Experience^2	-0.157	-0.010	0.954	0.933
Married	-0.308	0.008	1.150	0.994
Male	0.013	-0.008	1.003	0.998
White	-0.099	0.009	1.253	0.977
Number of Obs	99949	199898		
Treated Obs	3750	99949		
Control Obs	96199	99949		