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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 and upward occupational switching increased by 17% 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%. (4) The earnings impact for occupational switchers is not identified without an assumption about worker sorting. Under the assumption of no worker sorting, downward (upward) switching was associated with an earning change of -13.9% (+12.1%). Under the assumption of worker sorting, there is no statistically significant impact on earnings.

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1. Introduction

Beginning in the mid-1990s, cumulative improvements in information and communications technologies (ICT) facilitated a dramatic expansion of international trade in services. By our calculations the value added in U.S. service trade is now one-fifth the size of the value added in U.S. goods trade, and by most estimates the number of U.S. jobs now exposed to service imports is at least double the size of total manufacturing employment (Blinder 2007, van Welsum and Reif 2006, and Jensen and Kletzer 2007). Trade in services is now large — yet its impact on U.S. labour market outcomes has received relatively little attention. An important piece of the service tradability 'revolution' is the rise of service offshoring to China and India, which 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.

This paper examines the impact of trade in services with China and India on U.S. labour market outcomes, especially occupational switching, transitions to unemployment, and earnings. The trade-and-wages debate, exemplified by the seminal papers of Feenstra and Hanson (1996, 1999), has been dominated by analysis of the impacts of merchandise trade on manufacturing workers. Remarkably, only six papers have examined the impacts of service trade: Amiti and Wei (2006), Geishecker and Görg (2008), Liu and Trefler (2008), Blinder and Krueger (2009), Crino (2009), Criscuolo and Garicano (2010), and Ebenstein, Harrison, McMillan and Phillips (2011). In short, research on the labour market impacts of service trade have been scarce.[1]

The starting point of our analysis of the impacts of service trade on the U.S. labour market is the observation that industry-level impacts on employment and wages paint an incomplete picture: If a displaced worker immediately finds work elsewhere without taking a wage cut then the implications of displacement are small. Thus, it is not enough to look at industry-level outcomes, one must also look at what happens to workers who lose their jobs. There is abundant evidence

[1] 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 (2008) 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. Using matched CPS data, Ebenstein et al. (2011) find that foreign affiliate employment has had modest effects on employment and wages. Since one-third of foreign affiliate employment is in services (Harrison, McMillan and Null, 2007, tables 1–2), Ebenstein et al. is at least partially about service trade. Using U.S. industry-level data, Amiti and Wei (2006) show that service imports only slightly lower labour demand and Crino (2009) shows that service imports drive up the *relative* demand for skilled versus unskilled labour in tradable sectors. Blinder and Krueger (2009) administered a worker-level survey on earnings and job offshorability and found no correlation between the two. See Amiti and Wei (2005) and Trefler (2005) for surveys of earlier work on service offshore outsourcing.

from the labour literature that short-run transitions of labour market status, such as occupational switches, industry switches, and unemployment transitions have profound implications for workers' lifetime welfare. For example, see Topel (1991), Jacobson, LaLonde and Sullivan (1993), Neal (1995), Parent (2000), and Kambourov and Manovskii (2009).[2] In addition, we show below in table 1 that for workers in occupations exposed to tradable services, those that switch out of their occupation have a 6.9% to 9.8% probability of becoming unemployed and these unemployed remain unemployed for between 15.3 and 16.5 weeks. These numbers paint a picture of very large costs of job loss.

In contrast, studies relating merchandise trade to worker displacement arrive at more nuanced conclusions. Kletzer (1998, 2001) estimates small effects. Crino (2010) finds larger wage effects. Hummels, Jorgensen, Munch and Xiang (2010) find very large effects (imports depress the post-displacement wages of Danish workers by between 19% and 28%). Ebenstein et al. (2011) find modest effects (wage losses of 2–4% for workers who leave manufacturing and 4–11% for workers who switch occupations.) Although Autor, Dorn and Hanson (2011) do not track workers or their displacement, they develop an innovative local labour markets approach and use regional-level U.S. data to show that U.S. merchandise imports from China have had large impacts on unemployment, labour force participation, and government transfer payments (especially disability payments).

We examine the impact of service trade from China and India — of competition from low-wage educated labour — on occupational switching, the incidence of unemployment, and earnings. Unfortunately, this is a complicated exercise because of the endogeneity of imports and the sorting behaviour of workers. Empirically, trade economists have typically dealt with import endogeneity and labour economists have typically dealt with sorting on unobservables. Unfortunately, no paper has dealt with both concerns and both are unavoidable in our setting. To address the endogeneity of imports, we use a partial equilibrium variant of the Grossman and Rossi-Hansberg (2008) model of trade in tasks. To address sorting on unobservables we imbed this partial equilibrium trade-in-tasks model within a general equilibrium model of occupational choice (Ohnsorge

[2]Jacobson et al. (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%.

and Trefler 2007). The latter is a Ricardian or Roy (1951) model in which workers with unobserved heterogeneous attributes sort across occupations that have heterogeneous returns to these attributes.[3]

As is well known from the work of Krueger and Summers (1988), Murphy and Welch (1991), and Gibbons and Katz (1992), it is essential to understand worker sorting if one is to draw conclusions about the impact of imports on welfare. If (1) workers are homogeneous *or* (2) returns are the same across occupations then inter-occupational wage differentials likely reflect good jobs (e.g., unionized jobs or jobs associated with efficiency wages) and there are large welfare losses when good jobs move to China and India. On the other hand, if worker sorting on unobservables is important, then the welfare losses are more moderate.[4]

This distinction between 'good jobs' and 'heterogeneous returns to heterogenous skills' is particularly salient in light of research by Gibbons, Katz, Lemieux and Parent (2005). They find that, relatively speaking, high-paying manufacturing occupations are associated with 'good occupations' whereas high-paying service occupations are associated with high returns to heterogenous skills. The implication is that import-induced worker displacement has more severe welfare implications in manufacturing than in services, the latter being our sector of interest.

There is now a large literature on worker sorting and international trade. See Davidson, Martin and Matusz (1999), Grossman and Maggi (2000), Grossman (2004), Davis and Harrigan (2007), Ohnsorge and Trefler (2007), Costinot (2009), Costinot and Vogel (2010), Davidson and Matusz (2010), Helpman and Itskhoki (2010), and Helpman, Itskhoki and Redding (2010). Our work is most closely related to a remarkable paper by Artuç, Chaudhuri and McLaren (2010). 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.[5]

[3]In our partial equilibrium model, an industry is associated with an occupation and there is an exogenous, upward-sloping supply of workers to an occupation. In our general equilibrium model, this supply function is generated endogenously by worker sorting across occupations.

[4]For the latter perspective, see Abowd, Kramarz and Margolis (1999) and, for a recent contribution, see Gathmann and Schönberg (2010).

[5]Two recent papers on sorting offer results that are more tangential to our work. Using matched employee-employer data for Sweden, Davidson, Matusz, Heyman, Sjöholm and Zhu (2011) show that openness leads to a greater degree of assortative matching ('good workers' matched to 'good firms') in export-oriented industries but not in import-competing industries. Bombardini, Gallipoli and Pupato (forthcoming) show that unobserved worker characteristics are a determinant of trade flows.

A major prediction of our model is that one must look at occupational switchers, and in particular, one must look separately at two groups of workers: those who 'switch down' to occupations with lower inter-occupational wage differentials and those who 'switch up' to occupations with higher inter-occupational wage differentials. For example, we show that more education lowers the probability of switching down and raises the probability of switching up. To deal with switching we use March-to-March matched CPS data. 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. (2011) in their closely related study of the wage and employment impacts of merchandise imports and foreign affiliate employment.[6]

Turning to our empirical work, we combine matched CPS data for 1996–2007 with detailed BEA data on bilateral service transactions between the United States and 31 trade partners. We find that rising service imports from China and India have had the following cumulative 10-year impacts. (1) Downward and upward occupational switching increased by 17% 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%. (4) Matched CPS data does not allow us to identify earnings impacts for occupational switchers unless an assumption is made about unobservables and worker sorting. Under the assumption of no worker sorting based on unobservables, downward switching was associated with an annual earnings hit of -13.9% and upward switching was associated with an annual earnings gain of 12.1%. Under the assumption of worker sorting, trade-induced switching had no statistically significant impact on earnings.

The paper is organized as follows. Section 2 lays out the theory. Section 3 describes the BEA service trade data and the matched CPS data. Section 4 describes the key variables and provides a simple difference-in-differences analysis. 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 presents the empirical results for sub-populations by education, by age, and especially by routinization. Following the pioneering work of Autor, Levy and Murnane (2003), we use O*NET data to explore the role of routineness of tasks. This is a minor part of our paper, but dovetails nicely with Firpo, Fortin and Lemieux (2010), Ebenstein et al. (2011), and

[6]The 2009 NBER version of their paper does not use matched CPS data; however, a new version of the paper available on their websites does use matched data.

Autor et al. (2011). Section 9 provides a large number of specification searches that establish the robustness of our results. Section 10 concludes.

Some Familiar Facts

We conclude this introduction 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 present them here because, although these numbers will be familiar to many labour economists, they will be new to most trade economists.

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) 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 (details below). 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 (in a sense defined below). 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 1 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 1 shows that the actual wage change of downward switchers is much smaller (0.148 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. We therefore need to model sorting behaviour in a setting where worker characteristics are not fully observable.

2. 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.[8] A task requires a units of labour 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. This 'interior' assumption and the fact that t is strictly increasing implies that there is a unique $I \in (0,1)$ given by

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

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

[8] As detailed below, the number of units of labour supplied by a worker varies across workers (and indeed across occupations for a given worker). Hence in the partial equilibrium we keep track of units of labour, not workers.

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[10]

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

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 $L^D = L^S = L$. 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. *Estimating Labour Demand when Imports are Endogenous*

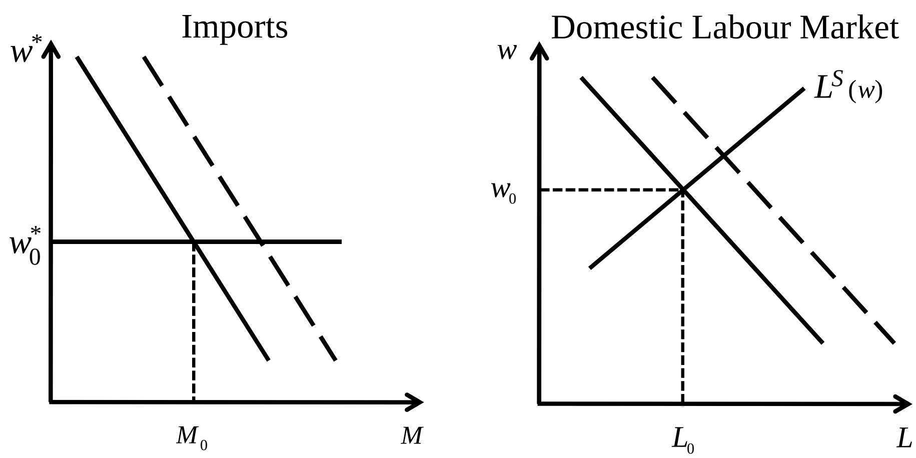
As a preliminary to estimating equation (1), consider estimating the impact of changes in imports on changes in labour demand. Plugging $Q = D + X$ into equation (3) and totally differentiating yields

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

[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.

[10]Grossman and Rossi-Hansberg (2008) use equations (2)–(4) to show that $p < wa$ i.e., offshoring reduces price below its autarchy level of wa. We will have nothing to say about this 'productivity effect'.

Figure 1. Domestic Demand Shock (δ_D)



where θ_M, θ_X, and θ_D are all positive.[11] 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. In particular, 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.[12] 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.[13] 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.**

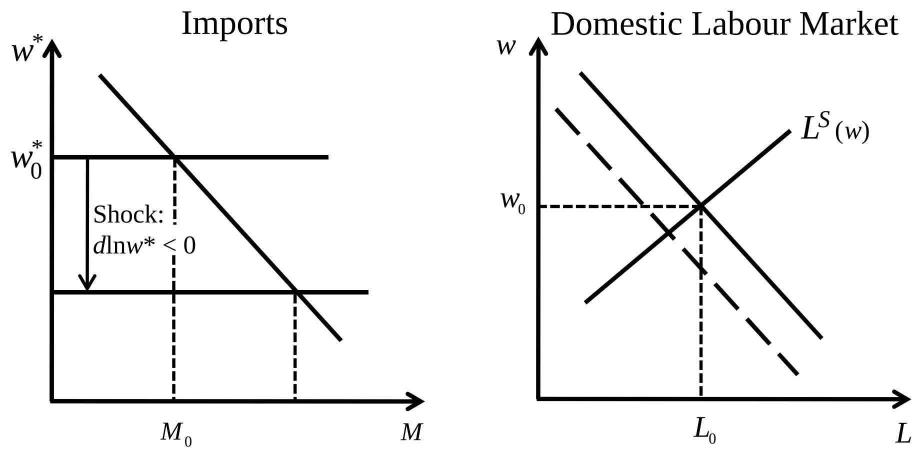
Effective foreign wage shock (w^*a^*): A decline in effective foreign wages w^*a^* is shown in the left panel of figure 2 as a downward shift of the foreign labour supply schedule. Holding w and p

[11] $\theta_M = M/(D+X-M)$, $\theta_X = X/(D+X-M)$, and $\theta_D = D/(D+X-M)$ are shares. The fact that the coefficients are shares is an artifact of the Leontief technology assumption. For more general technologies the coefficients also depend on production-function parameters.

[12] 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 $\partial M/\partial w^* = (\partial I/\partial w^*)Q < 0$

[13] See appendix 1 and especially equations (28) and (31).

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

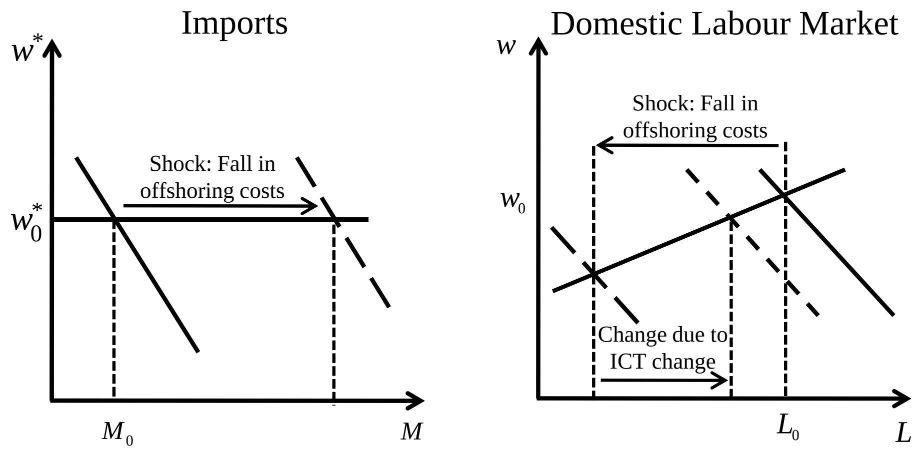


constant, the fall in w^* makes offshoring more attractive (I falls) so that imports increase while domestic labour demand L^D decreases.[14] Now however, *the change in* L^D *is causally related to the change in* M. This is because changes in $w^* a^*$ have no direct impacts on domestic labour demand: 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 analysis of changes in $w^* a^*$ should 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 recent 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

[14] There will be second-order effects as w and p adjust. Appendix equation (29) shows that M must rise. Appendix equation (32) shows that L^D can rise or fall.

Figure 3. Offshoring Cost Shock (β)



improvements directly raise the demand for skilled labour.[15] 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, the IV estimates are only modestly larger (in absolute value) than the OLS estimates and the differences are not statistically significant.

[15] We focus on skilled labour because, as shown in online appendix table B.2, offshorable jobs are highly skill-intensive.

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. As in Ventura (1997), this eliminates a useless layer of complexity. 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 are heterogeneous. Following Ohnsorge and Trefler (2007), each worker is endowed with a pair of attributes $(H,U) \in \mathbb{R}_+^2$ that is used to produce tasks according to $F_k(H,U) = H^{\phi_k} U^{1-\phi_k}$. F_k is measured in units of task. We need two attributes so that we can discuss the endogenous selection of workers across occupations based both on observables (*H*uman capital) and *U*nobservables. In this setup our key assumption is the Roy (1951) assumption that the F_k vary across occupations. The assumption of constant returns to scale simplifies the sorting rule while the Cobb-Douglas (log-linearity) assumption can be dispensed with. We label occupations so that ϕ_k is increasing in k i.e., $\phi_k > \phi_{k-1}$ for all k. This is a labelling convention, not an assumption.

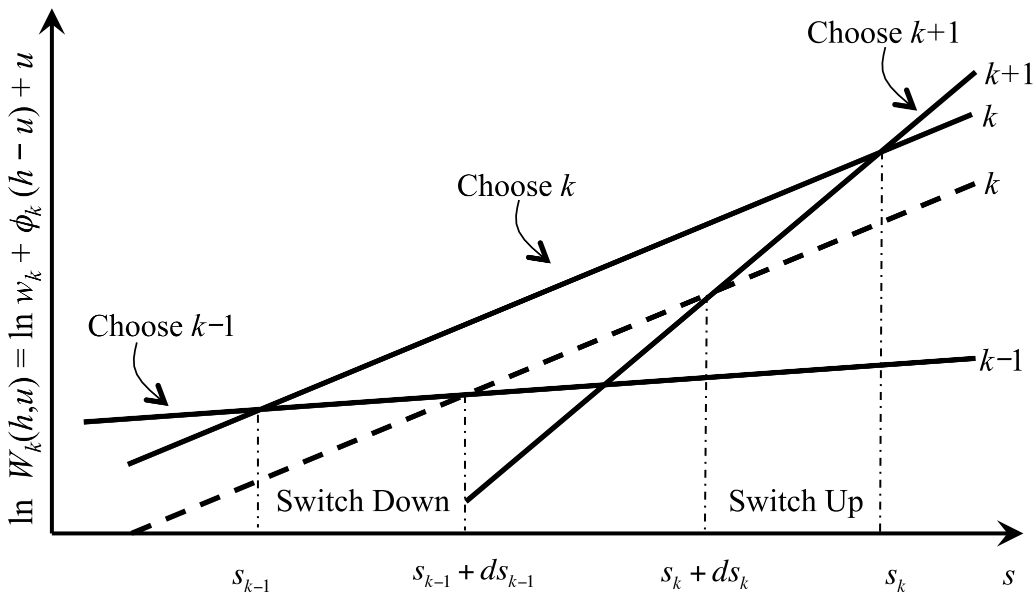
In what follows it will be easier to work with the transformed attributes $h \equiv \ln H$ and $u \equiv \ln U$. Let $f_k(h,u) \equiv F_k(H,U)$ be the output of tasks in (h,u) space. Then $f_k(0,0) = F_k(1,1) = 1$ i.e., a type-$(0,0)$ worker supplies one unit of labour. H and U will not be seen again in this paper. We assume that there is a unit mass of workers in the economy and that the distribution of worker types is described by a continuous density function $g(h,u)$.

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 $L_k^S(w_k)$.

From the partial equilibrium model, the cost and hence earnings of a unit of labour is w_k. A worker is paid the value of her marginal product (equal to her average product). Let $W_k(h,u)$ be the earnings of a type-(h,u) worker in occupation k . A type-$(0,0)$ worker supplies one unit of labour and earns $W_k(0,0) = w_k$. A type-(h,u) worker supplies $f_k(h,u)$ units of labour and earns

$$W_k(h,u) = f_k(h,u)\; w_k$$

Figure 4. Worker Sorting



or, since $\ln f_k(h,u) = \phi_k h + (1-\phi_k)u = \phi_k(h-u) + u$,

$$\ln W_k(h,u) = \ln w_k + \phi_k(h-u) + u. \tag{6}$$

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.

A type-(h,u) worker chooses the occupation k that maximizes $\ln W_k(h,u)$ of equation (6). Figure 4 characterizes the sorting rule. It plots $\ln W_k(h,u)$ against $s \equiv h-u$. 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.[16] The sorting rule is fully 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-(h,u) worker chooses occupation k if and only if $s_{k-1} < h-u < s_k$.[17]

To calculate the mass or units of labour that are supplied to occupation k, note that the workers selecting into k satisfy $s_{k-1} < h-u < s_k$ or $h - s_k < u < h - s_{k-1}$ or, from equation (7), $h -$

[16]That is, $\partial \ln W_k / \partial s$ is increasing in k. This is the familiar single-crossing or supermodularity property used for assortative matching.

[17]Without loss of generality we assume that there is positive employment in all occupations. It is then straightforward to show that in equilibrium (*a*) $s_{k-1} < s_k$ for all k and (*b*) in the interval (s_{k-1}, s_k), there is no occupation k' ($k' \neq k$) whose earnings profile lies above that of occupation k.

$\ln(w_k/w_{k+1})/(\phi_{k+1}-\phi_k) < u < h + \ln(w_k/w_{k-1})/(\phi_k - \phi_{k-1})$. Hence

$$L_k^S(w_k; w_{k-1}, w_{k+1}) = \int_{-\infty}^{\infty} \int_{h-\ln(w_k/w_{k+1})/(\phi_{k+1}-\phi_k)}^{h+\ln(w_k/w_{k-1})/(\phi_k-\phi_{k-1})} f_k(h,u)\, g(h,u)\, du\, dh. \tag{8}$$

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 equation (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. In its derivation, we have built on insights by (Mussa, 1982, section 4).

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 2.

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. Consider an occupation-k shock that lowers w_k, as in figure 4. We wish to know the probability that a worker switches out of occupation k given that u is not observed by the econometrician. Let $G_{u|h}(u \mid h)$ be the cumulative distribution function for the distribution of u conditional on h. Then the probability of switching down, conditional on observables h, is[18]

$$P_k^- \equiv G_{u|h}(h - s_{k-1} \mid h) - G_{u|h}\left(h - s_{k-1} - \frac{d\ln w_{k-1}}{\phi_k - \phi_{k-1}} + \frac{d\ln w_k}{\phi_k - \phi_{k-1}} \mid h\right) \tag{9}$$

Throughout, '$-$' and' $+$' superscripts refer to switching down and up, respectively.

We linearize this expression in order to derive our estimating equation. In the expression for P_k^-, the term $h - s_{k-1}$ appears twice and is identified only off of the curvature of $G_{u|h}$.[19] Hence, the term is too subtle for our empirical work and is ignored.[20] We are interested in the effects of a shock that originates in occupation k. Its first-order effects are felt in occupation k ($d\ln w_k \neq 0$) and

[18]To derive this equation note that workers who switch down satisfy $s_{k-1} < h - u < s_{k-1} + ds_{k-1}$ or, conditioning on h, $h - s_{k-1} - ds_{k-1} < u < h - s_{k-1}$. Using equation (7), we define $ds_{k-1} \equiv d\ln w_{k-1}/(\phi_k - \phi_{k-1}) - d\ln w_k/(\phi_k - \phi_{k-1})$, from which the equation follows.

[19]For example, if $u|h$ is uniformly distributed so that $G_{u|h}$ is linear, then the two $h - s_{k-1}$ terms cancel.

[20]This is a manifestation of a more general point by Heckman and Honoré (1990) about the sensitivity of the predictions of the Roy model to curvature.

we temporarily ignore its second-order effects on all other industries ($d \ln w_{k-1} = d \ln w_{k+1} = 0$).[21] With these assumptions, the linearization of P_k^- in equation (9) is

$$P_k^- = \theta_0^- + \gamma_h^- h - \theta_w^- d \ln w_k \tag{10}$$

where $\theta_w^- > 0$.[22]

Setting $L_k^S(w_k) = L_k^D$, defining the elasticity of labour supply $\eta_k^S \equiv \partial \ln L_k^S(w_k)/\partial \ln w_k > 0$, and using equation (5) we have

$$d \ln w_k = (\eta_k^S)^{-1} d \ln L_k^D = (\eta_k^S)^{-1} \left[-\theta_M d \ln M + \theta_X d \ln X + \theta_D d \ln D + d \ln a \right]. \tag{11}$$

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

$$P_k^- = \theta_0^- + \gamma_h^- h + \theta_M^- d \ln M - \theta_X^- d \ln X - \theta_D^- d \ln D - \theta_a^- d \ln a \tag{12}$$

where θ_M^-, θ_X^-, θ_D^-, and θ_a^- are all positive.[23]

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

$$P_k^+ = \theta_0^+ + \gamma_h^+ h + \theta_M^+ d \ln M - \theta_X^+ d \ln X - \theta_D^+ d \ln D - \theta_a^+ d \ln a \tag{13}$$

where θ_M^+, θ_X^+, θ_D^+, and θ_a^+ are all positive.[24]

We have not yet discussed the signs of γ_h^+ and γ_h^-. P_k^+ and P_k^- depend on h in two ways. The first, already mentioned, operates through the curvature of $G_{u|h}$, and cannot be signed without strong functional-form assumptions.[25] The second operates via the conditioning statement $u|h$. Its sign depends on the correlation between h and u or equivalently, on the correlation between h and $s = h - u$.[26] Suppose that h and s are positively correlated and consider two workers who initially choose k. The worker with the higher h has a higher s probabilistically. Hence, the high-h worker

[21] We have extensively explored ways of introducing $d \ln w_{k-1}$ and $d \ln w_{k+1}$ into our empirical work but have found nothing of interest. This is discussed in our section on sensitivity analysis where $d \ln w_{k-1}$ and $d \ln w_{k+1}$ are re-introduced.

[22] $\theta_w^- \equiv -\partial P_k^- / \partial \ln w_k = G'_{u|h} / (\phi_k - \phi_{k-1}) > 0$.

[23] $\theta_M^- \equiv \theta_M \theta_w^- / \eta_k^S > 0$, $\theta_X^- \equiv \theta_X \theta_w^- / \eta_k^S > 0$, $\theta_D^- \equiv \theta_D \theta_w^- / \eta_k^S > 0$, and $\theta_a^- \equiv \theta_w^- / \eta_k^S > 0$.

[24] Proof: From figure 4, the probability of switching up is the probability that u satisfies $s_k + ds_k < h - u < s_k$ or $h - s_k < u < h - s_k - ds_k$ where $ds_k \equiv d \ln w_k / (\phi_{k+1} - \phi_k) - d \ln w_{k+1} / (\phi_{k+1} - \phi_k)$. Hence,

$$P_k^+ \equiv G_{u|h} \left(h - s_k - \frac{d \ln w_k}{\phi_{k+1} - \phi_k} + \frac{d \ln w_{k+1}}{\phi_{k+1} - \phi_k} \mid h \right) - G_{u|h}(h - s_k \mid h).$$

Applying the discussion surrounding equations (10)–(12) to this equation yields equation (13).

[25] Again, this is a manifestation of the point about curvature in Heckman and Honoré (1990).

[26] The importance of the sign of this correlation has been fully discussed in the Roy literature and the case where the correlation is positive is what Heckman and Honoré (1990, page 1126) call the 'standard' case. This correlation features prominently in Ohnsorge and Trefler (2007).

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, $\gamma_h^- < 0 < \gamma_h^+$.

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 $\gamma_h^- < \gamma_h^+$. This is a feature of sorting models that has not previously been exploited to our knowledge. It will be a feature of our empirical findings.

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

3. 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." These are the 10 services listed in table 2. *We henceforth refer to these as tradable white collar services.*

The balance of payments data report bilateral trade flows by service category only for the larger U.S. trading partners. Among developing countries, India and China are by far the largest and also the most interesting. As we shall see, including the other low-wage countries for which we have bilateral trade data makes no difference to our estimates. See row 2 of table 13 below. Following the suggestion in Feenstra, Lipsey, Deng, Ma and Mo (2005), we include Hong Kong in the Chinese data.

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.[27] We stop in 2005 because of a structural break in the balance of payments data.

[27] 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.

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 online appendix figure B.2. Thus, tradable white collar services is a significant new development.

Table 2 provides some basic 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 the richest countries (the G8, excluding Russia). 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 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. While ICT improvements ($d\ln\beta$) are an important driver of rich-country trade growth, Sino-Indian trade growth is in addition driven (1) by economic reforms that have raised productivity ($d\ln(1/a^*)$) and (2) by increased openness that has improved access to their low-wage labour ($d\ln w^*$). The exogeneity of these two factors feeds into our identification strategy.

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.[28] The naive and final match rates for each year appear in online appendix table B.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. Nevertheless, in section 9.A 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*

Using CPS data on workers' occupations, each worker in the CPS sample can be linked to one of the 10 BEA white collar service sectors of table 2. We do this in two steps. First, we manually map occupation codes into BEA 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.' In contrast, 'Taxi drivers and chauffeurs' does not match into any of the 10 BEA codes and so is classified as a non-tradable occupation. Where there is any doubt about the mapping 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). The mapping appears in online appendix table B.3.

In the second stage, which turns out to be unimportant empirically, we apply Blinder's (2007) Offshorability Index to those occupations that were matched to one of the 10 BEA white collar services. For example, insurance sales agents are mapped into the insurance service, but it is unlikely that such a sales occupation will be offshored. Blinder's index is constructed as follows.

[28]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.

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. In our insurance example, sales must be done in a U.S. location so that the Blinder index is 0 and sales are deemed not offshorable. We assume that an occupation is tradable if its Blinder Offshorability Index exceeds 50.

To summarize, a white collar service occupation is deemed tradable if (1) it can be linked to one of our 10 BEA white collar services and (2) it is offshorable in Blinder's sense. It turns out that the Blinder offshorability criterion is not important for our results: we obtain similar results when the criterion is not used. See row 5 of table 13 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 i.e., in services that meet our two criteria. The remaining 67,032 workers (= 105,751 − 38,719) are in non-tradable white collar services.

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.[29] Also note that 49.4% of workers in the tradable-occupations sample completed a college degree, so this is a very educated group. See online appendix table B.2.

Table 3 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.

[29] Blinder (2007) 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 (2002) 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%.

4. Variable Definitions and a Simple Difference-in-Differences Analysis

Before presenting our regression-based estimates of the impact of white collar service trade, we present a simple difference-in-differences analysis that compares the labour market outcomes of workers in tradable versus non-tradable white collar service occupations.

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.[30] This raw switching rate is known to be noisy. We thus filter it as suggested by Moscarini and Thomsson (2006). To be a valid switch, the worker must also have changed her CPS class or looked for a job last year. See appendix 3.A 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 the more careful, PSID-based study by Kambourov and Manovskii (2008) who use 1996 PSID data.[31] [32] In our baseline results, we focus on 4-digit occupational switching because it gives us the most refined definition of an occupation (especially

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

[31]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.

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

in services jobs). We also report 2-digit switching results in row 12 of table 13 below.

The first row of table 4 deals with workers who switched down, that is, who switched to an occupation with a lower IOWD. In the first column we pool workers who switched between 1995 and 1996 and workers who switched between 1996 and 1997. We then look only at the subset of these workers who were in tradable service occupations. 19.4% of these workers switched to an occupation with a lower IOWD. The remaining columns repeat this exercise for workers in other pairs of years. Looking across columns in row 1, there is a slight upward trend in switching rates. This may mean that import competition led to more switching. However, switching rates were also rising in non-tradable services. In the 'Tradable – Non-tradable' row we report the difference in switching rates between tradables and non-tradables. In the years 1995 and 1996, switching was 2.0 percentage points higher in tradables and, a decade later in 2004–2005, this gap was virtually unchanged (2.2 percentage points). We conclude from this that the surge of imports in tradable occupations had no effect on downward switching rates. From the second set of results in table 4, the same applies to workers who switched up into occupations with higher IOWDs.

The third set of results in table 4 deals with transitions from employment to unemployment.[33] Transitions into unemployment fell over time in tradable services, but fell faster in non-tradable services so that the difference rose by 0.3 percentage points (from 0.0% to 0.3%). That is, transitions into unemployment rose in tradables relative to non-tradables. This rise in unemployment transitions is economically large; however, it is not statistically significant ($t = 1.10$).

The fourth set of results in table 4 deals with earnings. Annual earnings are defined as CPI-deflated annual income from wages and salaries. Earnings rose faster in tradables than in non-tradables. Non-tradables paid 3.2% more in the initial period, but 3.2% less in the last period, a statistically significant 6.4% improvement in tradable earnings relative to non-tradable earnings. As discussed below, the theory is clear that it is best to look at earnings changes and these results appear in the last three blocks of table 4. Relative to non-tradables, stayers in tradables did very well, an improvement in annual earnings *growth* of 3.2% [= 1.8% – (–1.5%)]. In contrast, downward switchers did worse (though not statistically so) and, somewhat puzzlingly, upward switchers did

[33] As in Murphy and Topel (1987), we operationalize this as follows. A worker is 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.

much worse.

Many studies of the impact of service trade have failed to use any trade data. Instead, they rely on a division of services into tradables and non-tradables. Using this division, we fail to find any negative impacts of rising service tradability on occupational switching or earnings. (The one exception is upward switchers.) We turn to an analysis that actually uses trade data.

5. An Econometric Analysis of Occupational Switching

In this section we estimate our theory-based switching-down and switching-up equations (equations 12 and 13). 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 3.C 'crosswalk' allows us to link each occupation k with a BEA service sector. Equations (12) and (13) require four variables at the service sector 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 and Sicherman (2005). Data sources are described in appendix 3. 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 and year.

Column 1 of table 5 reports OLS estimates of our switching-down equation (equation 12). 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 sector-level regressors are the annual log changes in M_{kt}, X_{kt}, D_{kt}, and ICT_{kt}. We lag these changes by one year e.g., $\ln M_{kt} - \ln M_{k,t-1}$. The coefficients on imports and exports are statistically significant and have the expected signs.

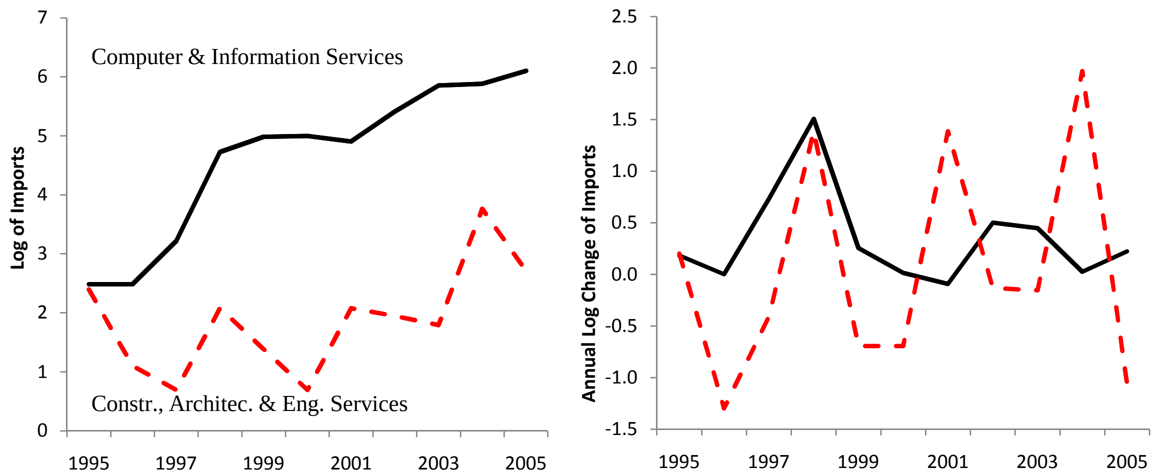
The two rows in table 5 that appear in italics translate the coefficients on imports and exports into economically meaningful magnitudes. Recall from table 2 that the most dynamic — and threatening — sector for service offshoring to China and India is in business, professional and technical services where for the last decade imports and exports have been growing annually by 0.18 and 0.15 log points, respectively. We therefore multiply the import coefficient by 0.18 to obtain 0.007 (= 0.18×0.039) and the export coefficient by 0.15 to obtain –0.013 (= 0.15×(–0.084)). This means that over the past decade U.S. service imports from China and India have increased the incidence of downward switching by 0.7 percentage points, from 20% to 20.7%, while U.S. service exports to China and India have reduced the incidence of downward switching by 1.3 percentage points. The net effect of imports and exports is thus a *reduction* in switching of 0.6 (= 1.3 – 0.7) percentage points.

The sample includes workers who are in both tradable and non-tradable white collar service occupations. For those in non-tradable occupations, the log change in imports and exports have been set to 0 and a dummy for being in a non-tradable occupation has been added (I^{NT}). The logic for including workers in the non-tradable sector is identical to that which motivated our difference-in-differences analysis of table 4. Specifically, in column 1 we interact I^{NT} with year-pair dummies.[34] As in table 4, a negative coefficient on an interaction term means that the average switching rate in non-tradables has declined relative to tradables. Given the rapid rise of service trade, we expect negative estimates of the interaction terms. In fact, they are all statistically insignificant and slightly positive. Thus, rising service trade has not led to more occupational switching in tradables relative to non-tradables. This result is rock solid and holds for the many specifications and dependent variables reviewed in this paper.

Column 1 has imbedded in it a large number of specification choices. Many of these choices do no matter; a few matter a lot. Section 9 below reports on an extensive set of alternative specifications that imply very similar conclusions to those in table 5. 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) Use contemporaneous import changes rather than lagged import changes. (2) Restrict the sample to consist only of those workers in tradable occupations. (3) Use a probit or logit specification. (4) Estimate a multinomial logit with four choices: stay, switch up, switch down, or transition into unemployment. (5) Include U.S. imports from other poor countries. (6) The most obvious alternative specification is one that includes two additional regressions, the log change in imports and the log change in exports from

[34]We use dummies for pairs of years rather than for individual years both to save space in the tables and to increase the precision of the estimates of the interaction terms.

Figure 5. Log Levels vs. Annual Log Changes



Notes: The left panel plots the time series of log imports from China and India ($\ln M_{kt}$) for two BEA service sectors, Computer and Information Services (solid line) and Construction, Architectural and Engineering Services (dashed line). The right panel plots the times series of the annual log change in imports ($d \ln M_{kt}$) for the same two service sectors.

G8 partners of the United States. As shown in table 12 below, adding these does not alter our conclusions. For example, with G8 import and export regressors added, the coefficient on imports in column 1 of table 5 becomes 0.040 (from 0.039) and the coefficient on exports becomes -0.092 (from -0.084).

In contrast to this robustness, there is one specification choice that is terribly important. In column 1, M_{kt}, X_{kt}, D_{kt} and ICT_{kt} are in annual log changes. Yet it may be that worker switching decisions and/or firm firing decisions are determined by longer-run changes in these variables. It turns out that our results are very sensitive to the choice of lag length. To see the source of the sensitivity, consider figure 5. The left panel plots $\ln M_{kt}$ for two service sectors, Computer and Information Services (solid line) and Construction, Architectural and Engineering Services (dashed line). The former has been trending up steadily while the latter has stayed at a low level for most of our period. Clearly, Computer and Information Services is the more trade-impacted of the two sectors. Yet the right panel of figure 5, which displays $\ln M_{kt}$ in annual changes, paints a very different picture: the two sectors appear as equally impacted. The very significant difference in trends up to 2003 is not apparent at all and has been swamped by high-frequency variation. This is a pervasive feature of our data. The sectors with the lowest levels of imports tend to have very large annual changes. The same is true for exports.

For any lag length l, let $(\ln M_{kt} - \ln M_{k,t-l})/l$ be the l-year average annual log change in imports. In columns 2–4 of table 5, we report results with M_{kt}, X_{kt}, D_{kt} and ICT_{kt} appearing as 3-, 5-, and 7-year average annual log changes. The impact of imports increases with the lag length: at 7 years, we estimate that rising Sino-Indian imports increased the incidence of switching down by 3.9 percentage points. A key argument for focussing on longer lags is apparent from the coefficient on ICT_{kt}. The ICT coefficient only becomes statistically significant at longer lag lengths, which means that skill-biased technical change and hence service trade take time for their effects to be felt.

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 5 of table 5 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 the four service characteristics 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 4 import coefficient of 0.215 should be compared to the column 5 import coefficient times 10 so that 0.215 is compared to 0.19. Comparing the 7-year change results to the level fixed effect results (columns 4 and 5), two very general conclusions emerge. First, import coefficients are very similar across the two specifications. Second, the export coefficient is not statistically significant in the level fixed effect specification. These two conclusions appear throughout the paper.

Turning to the economic size of the level fixed effect specification, the magnitudes in italics are the import coefficient times 0.18×10 and the export coefficient times 0.15×10. The most important conclusion from table 5 is the economic impact of imports. From the level fixed effect specification (our preferred specification), 10 years of service offshoring to China and India has increased downward occupational switching by 3.4 percentage points, from 20% to 23.4%. *This is a 17% increase and represents a large effect.*

Another way of thinking about magnitudes is to compare the results above with comparable results for manufacturing. Following Ebenstein et al. (2011), we create occupation-specific trade variables that measures the degree of occupational exposure to manufacturing trade with China and India. Details appear in appendix 3.B. We then link this occupational exposure measure to each CPS worker using the worker's occupation in the longest job held last year (as answered in the first of the worker's two March CPS responses). The results appear in columns 10 and column 11 of table 5. The specifications in columns 1 and 10 (or 5 and 11) differ only in terms of the sample of workers and the definition of imports and exports (i.e., imports and exports of services versus occupational exposure to manufacturing imports and exports). Based on column 11, the import coefficient is 0.036. Since manufacturing imports from China and India have grown by about 15% a year, this implies a 5.3% increase in switching down. We conclude from this that manufacturing has been harder hit than services by imports from China and India. We also conclude that our specification has a degree of 'external validity' in that it yields sensible results when applied to a very different data set.

A. ***Switching Up***

We next turn to estimates of the switching-up equation (13). Table 6 repeats the exercise of table 5, 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 baseline level fixed effect specification (column 5), the decadal impact of service imports from China and India is 0.7 percentage points. However, it is economically small and statistically insignificant.

A prediciton of the theory is that the coefficient on schooling is more negative for those that switch down than for those that switch up. Comparing column 1 in tables 5 and 6, the schooling coefficient is –0.13 for downward switchers and –0.008 for upward switchers. The difference of –0.005 is economically large and statistically significant (χ^2_1 = 15.11, p <.0001). The corresponding numbers for the fixed effect specification (column 5) 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 7 reports results using transitions to unemployment as a binary dependent variable. The precise definition of unemployment appears in footnote 33 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 baseline level fixed effects specification (column

5), imports from China and India raised transitions to unemployment by 0.9 percentage points, from 3.8% to 4.7%. This is a large impact. The impact of manufacturing imports from China and India is even larger: From column 11, these imports increased the probability of transitioning into unemployment by 1.6 percentage points.

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 13 of table 13 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 14 of table 13 below. Summarizing, service imports has had consequential impacts on unemployment.

6. Instrumental Variables

Imports and exports are 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 service sectors.[35] 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 sector appear in appendix table A.1.

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 ($\hat{\eta}^X_k$) is just the OLS estimate of the coefficient on $\ln Y_{ct}/L_{ct}$. In the level fixed effects

[35]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.

specification we instrument $\ln X_{kt}$ with

$$Z^X_{kt} \equiv \hat{\eta}^X_k \ln Y_t/L_t \tag{14}$$

where Y_t/L_t is the gravity-consistent aggregator of the GDP per capitas of China and India.[36] In the log changes specification (e.g., 1-year changes), we instrument $\ln X_{kt} - \ln X_{k,t-1}$ with

$$Z^X_{kt} \equiv \hat{\eta}^X_k (\ln Y_t/L_t - \ln Y_{t-1}/L_{t-1}). \tag{15}$$

The case where the coefficient on $\ln L_{ct}$ is not set to zero requires a bit more notation and appears in appendix 4.

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 $\hat{\eta}^M_k$. See appendix table A.1. Second, in equations (14)–(15) we replace the $\hat{\eta}^X_k$ with $\hat{\eta}^M_k$ in order to build an instrument Z^M_{kt}.

Note that $Z^M_{kt} \neq Z^X_{kt}$ only because $\hat{\eta}^M_k \neq \hat{\eta}^X_k$. Since the $\hat{\eta}^M_k$ and $\hat{\eta}^X_k$ are not all that much different from one another, it is advisable to find another instrument. Fortunately, this is easy. While the model allows for only one foreign country (China-India), in practice we can build an instrument by combining the gravity estimates $\hat{\eta}^X_k$ and $\hat{\eta}^M_k$ with GDP per capita from the G8 countries (less the United States and Russia). Let Y^R_t/L^R_t be the gravity-consistent aggregator of the GDP per capitas of these countries. Then in the level fixed effect specification two more instruments are

$$Z^{X,R}_{kt} \equiv \hat{\eta}^X_k \ln Y^R_t/L^R_t \;\text{ and }\; Z^{M,R}_{kt} \equiv \hat{\eta}^M_k \ln Y^R_t/L^R_t \tag{16}$$

or, in the 1-year changes specification,

$$Z^{X,R}_{kt} \equiv \hat{\eta}^X_k (\ln Y^R_t/L^R_t - \ln Y^R_{t-1}/L^R_{t-1}) \;\text{ and }\; Z^{M,R}_{kt} \equiv \hat{\eta}^M_k (\ln Y^R_t/L^R_t - \ln Y^R_{t-1}/L^R_{t-1}). \tag{17}$$

Summarizing, we have four instruments Z^M_{kt}, Z^X_{kt}, $Z^{M,R}_{kt}$ and $Z^{X,R}_{kt}$ for two endogenous variables (imports and exports). Further, Z^M_{kt} is correlated with Z^X_{kt} and $Z^{M,R}_{kt}$ is correlated $Z^{X,R}_{kt}$. Appendix table A.2 reports the first-stage results for the specifications in table 5.[37] First-stage partial regression plots appear in online appendix figure B.1. Appendix 4 offers up a detailed discussion of the first stage and we leave this to the interested reader. Only one thing stands out. Our instruments do not

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

[37] The first-stage results for the specifications in table 5–8 are almost identical because the only difference is in the sample i.e., in the number of workers per sector.

display much of the high-frequency variation displayed in figure 5. This is evident in the last row of appendix table A.2, which reports the F-test for the joint significance of the instruments. For the 1-year change specification the instruments are not jointly significant and for the 3-year change specification the instruments do not pass the Stock-Yogo criterion. As a result, we do not report IV results for the 1-year change specification and caution the reader about the validity of the results for the 3-year change specification.

Tables 5–8 report the IV results. The IV estimates are always larger than the OLS results, exactly as predicted by the theory. Also, the Hausman test rejects endogeneity in every case. Using the theory, we interpret this to mean that, after controlling for domestic demand shocks (D_{kt}) and technology shocks (ICT_{kt}), the variation in service trade with China and India has been driven (1) by economic reforms that have raised productivity ($-d\ln a^*$) and (2) by increased openness that improved access to Chinese and Indian low-wage labour ($d\ln w^*$). The exogeneity of these two factors means 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. Average Annual Earnings

A. *Theory*

From equation (6), log earnings can be expressed as (dropping t subscripts)

$$\ln W_k(h,u) = \ln w_k + \phi_k h + (1-\phi_k)u \tag{18}$$

where $(1-\phi_k)u$ is a residual and, as in the levels version of equation (11), w_k depends on imports M_k, exports X_k, domestic demand D_k, and technology ICT_k. For brevity, assume that $\ln w_k$ can be expressed as a linear function of $\ln M_k$ and ignore the X_k, D_k, and ICT_k terms. That is,

$$\ln w_k = -\psi_M \ln M_k \tag{19}$$

where $\psi_M > 0$. Then from equations (18)–(19),

$$\ln W_k(h,u) = -\psi_M \ln M_k + \phi_k h + (1-\phi_k)u. \tag{20}$$

This is a difficult equation to estimate because worker sorting induces a correlation between u and occupational characteristic M_k.

This point will be very familiar to labour economists but perhaps less familiar to trade economists. At risk of stretching the patience of labour economists, we formalize the point using our model. Let $IOWD_k$ be the inter-occupational wage differential for occupation k. The $IOWD_k$ are defined as the OLS estimates of the occupation fixed effects in an earnings regression. In our model this earnings regression has the form $\ln W_k = \alpha_k + \overline{\phi} h + \epsilon$ so that

$$IOWD_k \equiv \alpha_k = \mathbf{E}[\ln W_k(h,u) \mid s_{k-1} < h - u < s_k] - \overline{\phi}\, \mathbf{E}[h \mid s_{k-1} < h - u < s_k]$$

where the expectation is over those workers who sort into occupation k. (See equation 7.)

Using equation (20) to substitute out $\ln W_k(h,u)$,

$$IOWD_k = -\psi_M \ln M_k + (\phi_k - \overline{\phi})\mathbf{E}[h \mid s_{k-1} < h - u < s_k] + (1 - \phi_k)\mathbf{E}[u \mid s_{k-1} < h - u < s_k]\,.$$

The first term is an occupational characteristic (imports) and corresponds at least empirically to a notion of 'good' jobs. The second term is fundamental to sorting because it stems from the fact that returns to worker characteristics vary across sectors i.e., $\phi_k \neq \overline{\phi}$. For manufacturing it is commonly argued that workers in high-M_k industries have low values of observables h and sort into industries with low returns to schooling so that this second term is negatively correlated with imports. The third term depends on the average level of the unobservable characteristics of workers who sort into k. Thus, the $IOWD_k$ capture both good jobs (the first term) and the sorting of heterogeneous workers (the second and third terms). Re-stated, estimation of equation (20) yields a $\widehat{\psi}_M$ that captures the impact on wages both of imports (good jobs) and of worker sorting.

One famous solution to this identification problem is to look at earnings changes (Krueger and Summers 1988, Gibbons and Katz 1992, and Gibbons et al. 2005). Earnings changes for occupational stayers are (adding time subscripts)

$$\ln W_{k,t+1} - \ln W_{k,t} = -\psi_M(\ln M_{k,t+1} - \ln M_{kt}) \tag{21}$$

so that the problematic $(1 - \phi_k)u$ term disappears.[38]

B. ***Earnings Changes of Stayers***

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. The coefficients

[38]In order to difference out $(1 - \phi_k)u$ we have implicitly assumed that there is no time variation in worker characteristic u and or its returns $(1 - \phi_k)$.

are statistically insignificant and the economic magnitudes are small. Using 1-year changes, imports of services from China and India reduce the earnings growth of stayers by 0.02% per year (= –0.001×0.18). Over 10 years, during which service tradablility rose rapidly, this translates into a decadal effect of a mere 0.2%. Decadal effects are reported in italics in the table. The decadal effect is largest for the 5-year change specification (9.2%); however, this is not statistically significant and 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 16 and 17 of sensitivity table 13. In short, there is little evidence of a large impact of service trade on stayers.[39]

Importantly, a very different conclusion emerges for manufacturing. In the 1-year changes specification the decadal impact on earnings is a massive –20.4%.

C. *Earnings Changes of Switchers: The Homogeneous Case*

The earnings change for a worker that switches from occupation k to k' is

$$\ln W_{k',t+1} - \ln W_{k,t} = -\psi_M(\ln M_{k',t+1} - \ln M_{kt}) - (\phi_k - \phi_{k'})h + (\phi_k - \phi_{k'})u. \tag{22}$$

Thus, differencing does not eliminate the offending correlation between imports and the residual $(\phi_k - \phi_{k'})u$. We do not have an instrumental variables strategy to deal with this famous problem. However, we can look for informal bounds on the $\widehat{\psi}_M$.

The correlation between imports and the residual goes to 0 in one of two cases. (1) If workers are homogeneous so that $u = \overline{u}$ is the same for all workers then the residual can be absorbed by fixed effects for the old occupation k and the new occupation k'. This kills the correlation. (2) If the returns to unobservables are the same across occupations, $\phi_k = \phi_{k'}$, then the residual and the correlation vanish. Suppose that conditions (1) or (2) hold so that worker sorting has no impact on earnings changes. Then the impact of switching is the same for all shocks (trade shocks, domestic shocks, and technology shocks): What matters is whether workers switch, not why they switch. This motivates the type of regression examined by Ebenstein et al. (2011) for manufacturing in which earnings changes are regressed on a dummy for switching. We implement their regression as follows.

[39] In table 8, the interaction of the non-tradable occupation dummy with the year dummies is declining over time, indicating that earnings growth in non-tradable occupations has been slow relative to tradable occupations. This mirrors what we showed in the raw data (row 5 of table 4.) Thus, there is no evidence that tradable occupations have suffered relative to non-tradable occupations as a result of the rising tradability of services.

In column 1 of table 9 we consider the sample consisting of stayers and downward switchers. We regress earnings changes on a 'switching down' dummy that equals 1 for downward switchers and 0 for stayers. The regression also includes our usual worker characteristics and 4-digit occupation fixed effects.[40] All other occupation-level variables (e.g., imports) are excluded. The estimated coefficient of 0.139 indicates that, even after controlling for observable characteristics, downward switching is associated with an earnings cut of 13.9%. Column 5 reports the results for the sample consisting of stayers and upward switchers. The estimated coefficient on the 'switching up' dummy indicates that upward switching is associated with an earnings increase of 12.1%.

In columns 9 and 10 we repeat what Ebenstein et al. (2011) have already done for manufacturing and find very similar estimates. The coefficients for manufacturing are surprising in that they are very similar to those for services.

D. ***Earnings Changes of Switchers: The Heterogeneous Case***

The assumption that (1) workers have identical unobservables or (2) that returns to worker characteristics are the same across occupations are potentially very strong. How does one interpret the previous regressions when both these assumptions are violated so that sorting matters? Consider estimating inter-occupational wage differentials using data only for workers who switch down: $\ln W_{kt} = IOWD_k^- + \overline{\phi}^- h + \epsilon^-$. Differencing this yields

$$\ln W_{k',t+1} - \ln W_{kt} = IOWD_{k'}^- - IOWD_k^-. \tag{23}$$

Note that the right-hand side is 0 for stayers ($k' = k$). Thus, if one estimated this equation using a dummy for switching down, the estimated coefficient would be the average of the $IOWD_{k'}^- - IOWD_k^-$.[41] Symmetric comments hold for switching up. If this interpretation is correct, then the Ebenstein et al. switching dummies of columns 1, 5, 9, and 10 produce estimates that suffer from the same problems associated with IOWDs, namely, that they do not distinguish between the role of 'good jobs' and worker sorting.

To establish that our concern is appropriate, recall that $IOWD_k$ is the inter-occupational wage differential estimated off of the full sample. For a worker that switches from k to k' we can attach to this worker a $IOWD_{k'} - IOWD_k$. We then add this variable to the column 1 and 5 regressions.

[40]The results are very similar with or without worker characteristics and/or 4-digit fixed effects.

[41]Specifically, $\Sigma_{k,k'}(IOWD_{k'}^- - IOWD_k^-)n_{k,k'}$ where $n_{k,k'}$ is the proportion of downward switchers that switch from k to k'.

The result appear in column 2 for switching down and column 6 for switching up. With this variable included, the switching dummies are no longer economically or statistically significant. This confirms our interpretation.

The coefficients on $IOWD_{k'} - IOWD_k$ in columns 2 and 6 are very close to 0.5 for both upward and downward switchers. This mirrors the results in rows 1 and 2 of table 1 and is related to a point made by Gibbons and Katz (1992) that inter-occupational wage differentials estimated from all workers tend to be similar to those estimated from switchers. Gibbons and Katz find that in a regression of switcher IOWDs on full-sample IOWDs, the regression coefficient is not much below unity. We find that it is close to 0.5. This suggests that the role of worker sorting is more important in our sample than in theirs. Thus, individual worker characteristics matter.

If sorting matters then workers who are induced to switch because of trade shocks have very different earnings responses than those of the average switcher. We do not have anything new to add to the large literature on identifying earnings impacts when workers endogenously switch based on unobservables. However, we can directly examine within a (biased) OLS setting whether switching due to trade shocks has the same impacts as switching due to all causes. To this end, we estimate our standard regression of earnings changes on import changes separately for downward switchers and for upwards switchers. (Stayers are not included in either sample.) The results for downward switchers appear in columns 2–3 of table 9. Column 3 reports the 1-year changes specification and column 4 reports the level fixed effect specification. In both cases, the coefficient on imports is statistically insignificant and economically small (decadal impacts on earnings of at most –0.2%). Thus, either the impacts of trade-induced switching are significantly smaller than the impacts of switching from all sources or there is sorting-induced endogeneity in all of the coefficients reported in table 9.

Columns 7–8 report the results for the switching-up sample. These effects are economically large (decadal impacts on earnings of between –5.1% and –10.3%), but only marginally significant at best.[42]

Summarizing, we have seen that the effects of trade on stayers is very small. The effects on the earnings of switchers may be large, but absent an instrument for dealing with the correlation between switching and unobservables or between imports and unobservables, it is hard to know

[42] Jacobson et al. (1993) examine earnings impacts for a particularly severe trade shock – the collapse of Pennsylvania steel. They estimate earnings losses of as high as 25%, which is much larger than what we find. This is consistent with the model. As figure 4 shows, the larger the shock, the more workers there will be with large earnings cuts.

whether these large effects are due to 'good jobs' or the sorting of heterogeneous workers across occupations that have heterogeneous returns to worker skills and abilities.

8. Results by Routinization, Education, and Age

In this section we examine the impact of service offshoring for sub-populations defined by education, age, and the routineness of occupations. Following Autor et al. (2003), we use O*NET information to measure the routineness of tasks associated with each of approximately 700 Standard Occupation Classification (SOC) codes. We define 'routine cognitiveness' as the importance of 'repeating the same task' divided by the importance of 'thinking creatively'. We then classify each occupation as 'routine' or 'non-routine' depending on whether the occupation's 'routine cognitiveness' is above or below the median across all occupations covered in our sample.

In panel A of table 10, we re-estimate our core specifications separately for workers in routine and non-routine occupations. Only a few coefficients are reported.[43] As expected, the effects of service imports from China and India are most adverse for workers in routine occupations. This evidence is consistent with what has been repeatedly found in the literature e.g., Ebenstein et al. (2011) and, for service trade, Crino (2009). It is also consistent with the Firpo et al. (2010) analysis of the determinants of inequality trends. One note of caution is necessary. The row 'Chi^2 test for Imports' reports a test statistic for the difference in the estimated coefficients on imports in the routine and non-routine samples. This difference is never significant at the 1% level. In contrast, the difference in the estimated coefficients on schooling are often significantly different, with schooling being relatively more important in non-routine occupations.

In panel B of table 10 we re-estimate our core specifications separately for those with at least some high school and those with at least some college. We find little evidence of the differential effects that have been found in other studies. This may be due to our sample — half the workers in our tradable sample completed a college degree. See online appendix table B.2.

In panel C of table 10 we re-estimate our core specifications separately for workers who are under and over 40 years of age. As expected, the effects of service imports are most adverse for older workers, though the differential effect is never significant at the 1% level.

[43] The specifications in table 10 are the same as those in columns 1 and 5 of table 5 (switching down), table 6 (switching up), table 7 (transitions to unemployment), and table 8 (earnings changes of stayers). For example, the first two columns in table 10 correspond to column 1 (1-year change) of table 5 and the next two columns correspond to column 5 (level fixed effect) of table 5.

9. Sensitivity

There are a myriad of alternative, *a priori* sensible specifications that the reader will undoubtedly want to see before being persuaded of our results. We have literally tried thousands of these specifications. None of these matter beyond what we have already shown. We review these here.

A. *CPS Sample Selection*

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 a second-stage 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 second-stage 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.[44] These instruments are drawn from responses in the first of the two March surveys.

The estimates appear in table 11. Estimates of the second-stage equations appear in the top panel while estimates of the selection equation appear in the bottom panel. The Wald test for selection is reported in the row labeled 'Wald test of indep. eqns.' and indicates that in almost every case selection bias cannot be rejected.[45] Selection affects the fixed effects and the worker-characteristic coefficients, but barely affects our estimates of service imports and exports.

B. *Including Rich-Country Service Trade*

Our paper focuses on the impact of trade in services with China and India. In table 12 we include the imports and exports of services between the United States and her G8 partners. These rich

[44] 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.

[45] The Wald test is calculated by comparing the results in table 11 with the results of fitting the second-stage equation without a selection correction.

countries are Canada, France, Germany, Italy, Japan and the United Kingdom. (Russia is excluded.) The even-numbered columns repeat our baseline results from tables 5–8. The odd-numbered columns add imports and exports from the G8. The G8 variables are rarely significant and, more importantly, their inclusion does not affect the coefficients on imports and exports with China and India. For example, with the two G8 regressors added, the coefficient on Chinese and Indian imports in our baseline downward-switching specification moves slightly from 0.039 to 0.040 and the coefficient on Chinese and India exports moves slightly from -0.084 to -0.092.

C. *Other Sensitivity Analysis*

Table 13 reports a large number of additional specifications. The first row repeats our baseline specification i.e., the level fixed effect OLS results from column 5 in tables 5–8. We only report the coefficient on imports and its decadal impact i.e., the number in italics in tables 5–8. 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.

Service Trade with All Low-Wage Countries (Row 2): 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 $\ln X_{kt}$.

Excluding Non-tradable Service Occupations (Row 3): In this row we only consider workers in tradable occupations.

Only Business, Professional and Technical (BPT) Services (Row 4): Much of the press about offshoring focuses on BPT services to the exclusion of the other service categories in table 2 such as financial and insurance services. That is, the press focuses on services for which U.S. comparative advantage is relatively weak. Table 13 presents estimates when only the eight BPT service subcategories are included in the analysis.

Ignore the Blinder Offshorability Criterion (Row 5): Recall that in building a crosswalk in section 3.C we attached a service trade flow to a worker only if the Blinder offshorability criterion was met. In row 5 we attach a service trade flow to a worker even if the Blinder offshorability criterion is not met.

Omit the Technology Bubble Years (Row 6): 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 7): Dropping D_{kt} and ICT_{kt} has very little effect on our results.

Alternative Functional Forms for Imports and Exports (Row 8): 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 8.

Probit, Logit and Multinomial Logit Regression Results (Rows 9–11): We used the OLS estimator even though switching down, switching up, and transitions to unemployment are binary dependent variables. In rows 9 and 10 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 5; stay or switch up in table 6; stay employed or transition to unemployment in table 7.) In row 11 we model the decision as a four-way decision using a multinomial logit.

2-Digit Switching (Row 12): 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 17% for 4-digit switching.

Weeks Unemployed and Employed (Rows 13–14): Rather than working with a binary transition to unemployment, in row 13 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 15–16): Rather than using the change in real annual earnings, in rows 15–16 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.

In summary, our results hold for a large set of alternative specifications.

10. Conclusions

The rise of service offshoring to 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 17% 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%. (4) Matched CPS data does not allow us to identify earnings impacts for occupational switchers unless an assumption is made about how unobservable worker characteristics affect worker sorting. Under the assumption of no worker sorting, downward switching was associated with an annual earnings hit of -13.9% and upward switching was associated with an annual earnings gain of +12.1%. Under the assumption of worker sorting, trade-induced switching had no statistically significant impact on earnings. These numbers are from our baseline level fixed effect specification. In summary, service offshoring to China and India has had its adverse effects — and while these effects are smaller than one would obtain by ignoring worker sorting, they are not small enough that they can be ignored.

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Table 1. 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	0.036	-0.148*	(0.009)	0.099*	(0.010)
3. Average Years of Schooling	14.138	-0.343*	(0.024)	0.303*	(0.025)
4. Probability of an Unemployment Spell	0.000	0.098*	(0.002)	0.069*	(0.002)
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. Rows 3 and 5 are the means for the three samples. Standard errors are in parentheses. An asterisk (*) indicates a difference between switchers and stayers that is statistically significant at the 1% level.

Table 2. 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 3. 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 4. A Simple Difference-In-Differences Approach

	1995-1996	1997-1998	1999-2000	2002-2003	2004-2005
1. Switching Down					
Tradeable	0.194	0.198	0.210	0.208	0.216
Tradable - Non-tradable	0.020 *	0.025 *	0.025 *	0.010	0.022 *
s.e.	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
2. Switching Up					
Tradable	0.179	0.186	0.182	0.187	0.188
Tradable - Non-tradable	0.029 *	0.037 *	0.037 *	0.030 *	0.030 *
s.e.	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
3. Incidence of Unemployment					
Tradable	0.040	0.036	0.043	0.038	0.034
Tradable - Non-tradable	0.000	0.002	0.002	0.003	0.003
s.e.	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
4. Log(Earnings)					
Tradable	9.915	10.002	10.048	10.131	10.126
Tradable - Non-tradable	-0.032	-0.010	-0.019	0.019	0.032
s.e.	(0.015)	(0.015)	(0.014)	(0.013)	(0.014)
5. Δ ln(Earnings) – Stayers					
Tradable	0.049	0.046	0.049	0.011	0.031
Tradable - Non-tradable	-0.015	-0.005	0.007	-0.009	0.018
s.e.	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)
6. Δ ln(Earnings) – Switching Down					
Tradable	-0.060	-0.121	-0.076	-0.152	-0.121
Tradable - Non-tradable	0.000	-0.081	0.001	-0.001	-0.013
s.e.	(0.036)	(0.034)	(0.032)	(0.032)	(0.031)
7. Δ ln(Earnings) – Switching Up					
Tradable	0.207	0.196	0.213	0.117	0.165
Tradable - Non-tradable	0.018	-0.040	-0.023	-0.069	-0.090 *
s.e.	(0.038)	(0.036)	(0.034)	(0.032)	(0.032)

Notes: 'Tradable' indicates the sample means for tradable white collar service jobs. 'Tradable - Non-tradable' indicates the difference of means for the tradable white collar services sample less the non-tradable white collar services sample. Explaining the column headings by way of example, the '2004–2005' column deals with workers who switched between 2004 and 2005 plus workers who switched between 2005 and 2006. 2001 is omitted. * denotes statistical significance at the 1% level.

Table 5. Switching Down

	Services - OLS					Services - IV				Manufacturing - OLS	
	Changes in Service Characteristics				Levels	Changes in Service Characteristics			Levels	Changes	Levels
	1-year	3-year	5-year	7-year	FE	3-year	5-year	7-year	FE	1-year	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Service Characteristics											
Imports	0.039**	0.088**	0.149**	0.215**	0.019**	0.180**	0.205**	0.267**	0.023**	0.410**	0.036**
	0.007	*0.016*	*0.027*	*0.039*	*0.034*	*0.032*	*0.037*	*0.048*	*0.041*	*0.061*	*0.053*
	(0.013)	(0.026)	(0.038)	(0.035)	(0.05)	(0.068)	(0.058)	(0.044)	(0.008)	(0.043)	(0.011)
Exports	-0.084**	-0.163**	-0.296**	-0.398**	-0.011	-0.509**	-0.446**	-0.471**	-0.005	0.058	-0.022
	-0.013	*-0.024*	*-0.044*	*-0.060*	*-0.017*	*-0.076*	*-0.067*	*-0.071*	*-0.008*	*0.005*	*-0.017*
	(0.030)	(0.050)	(0.058)	(0.065)	(0.06)	(0.161)	(0.106)	(0.089)	(0.007)	(0.049)	(0.025)
Domestic Demand	-0.134*	-0.247**	-0.301**	-0.274**	-0.018**	-0.180*	-0.274**	-0.259**	-0.018**	-0.021	-0.012**
	(0.057)	(0.073)	(0.077)	(0.084)	(0.02)	(0.075)	(0.077)	(0.083)	(0.002)	(0.039)	(0.001)
ICT	0.260	0.629**	1.161**	1.758**	0.39**	0.615**	1.151**	1.748**	0.039**	0.156	0.014
	(0.151)	(0.209)	(0.320)	(0.372)	(0.09)	(0.211)	(0.320)	(0.370)	(0.009)	(0.111)	(0.008)
Individual Characteristics											
Schooling	-0.013**	-0.013**	-0.014**	-0.015**	-0.014**	-0.014**	-0.014**	-0.015**	-0.014**	-0.004**	-0.014**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Experience	-0.006**	-0.006**	-0.006**	-0.006**	-0.007**	-0.006**	-0.006**	-0.006**	-0.007**	-0.006**	-0.008**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(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)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.035**	-0.035**	-0.035**	-0.033**	-0.037**	-0.035**	-0.035**	-0.033**	-0.037**	-0.034**	-0.044**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Male	0.022**	0.018**	0.011	0.010	-0.004	0.008	0.006	0.007	-0.004	-0.010**	-0.038**
	(0.006)	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)	(0.007)	(0.005)	(0.004)	(0.003)
White	-0.040**	-0.039**	-0.038**	-0.042**	-0.044**	-0.038**	-0.038**	-0.041**	-0.044**	-0.035**	-0.052**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.004)	(0.004)
Nontradeable Dummies											
I^{NT}	-0.049	-0.025	-0.039	-0.041		-0.076	-0.054	-0.041	-0.095*		
	(0.027)	(0.033)	(0.030)	(0.027)		(0.058)	(0.041)	(0.034)	(0.044)		
I^{NT} x $I_{1995\text{-}96}$	0	0			0	0			0		
	-	-			-	-			-		
I^{NT} x $I_{1997\text{-}98}$	0.032	-0.020	0		0.002	-0.045	0		0.005		
	(0.033)	(0.033)	-		(0.011)	(0.063)	-		(0.011)		
I^{NT} x $I_{1999\text{-}2000}$	0.019	0.003	-0.014	0	0.003	0.041	-0.019	0	0.009		
	(0.035)	(0.038)	(0.030)	-	(0.012)	(0.053)	(0.034)	-	(0.013)		
I^{NT} x I_{2001}	0.058	0.028	0.048	0.013	0.038	0.048	0.058	0.008	0.045*		
	(0.059)	(0.062)	(0.056)	(0.050)	(0.022)	(0.074)	(0.058)	(0.050)	(0.023)		
I^{NT} x $I_{2002\text{-}2003}$	0.033	0.009	0.017	0.015	0.038*	0.024	0.021	0.014	0.048**		
	(0.038)	(0.041)	(0.035)	(0.032)	(0.015)	(0.055)	(0.038)	(0.033)	(0.017)		
I^{NT} x $I_{2004\text{-}2005}$	0.008	-0.021	-0.016	-0.015	0.026	-0.042	-0.023	-0.019	0.041		
	(0.037)	(0.037)	(0.032)	(0.030)	(0.017)	(0.060)	(0.035)	(0.030)	(0.022)		
Observations	90,615	90,615	75,425	59,876	90,615	90,615	75,425	59,876	90,615	138,408	138,408
R-squared	0.020	0.021	0.023	0.025	0.039					0.017	0.065

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. In columns 1–9 the sample is the set of workers in white collar services that either switched down or stayed. All specifications include year and state fixed effects. The difference between columns 1 through 5 is in the treatment of the four service characteristics. 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., $l = 1$ in column 1 and $l = 7$ in column 4. In column 5 the four service characteristics are entered in log levels and BEA service sector fixed effects are added. Columns 6–9 are the IV counterparts to columns 2–5. Numbers in italics are decadal impacts. Columns 10 and 11 are the counterparts to columns 1 and 5, but using manufacturing rather than services. Standard errors clustered at the BEA and year levels appear in parentheses. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 6. Switching Up

	Services - OLS					Services - IV				Manufacturing - OLS	
	Changes in Service Characteristics				Levels	Changes in Service Characteristics			Levels	Changes	Levels
	1-year	3-year	5-year	7-year	FE	3-year	5-year	7-year	FE	1-year	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Service Characteristics											
Imports	-0.007	-0.032	0.010	0.033	0.004	-0.051	-0.060	-0.015	0.007	0.196**	0.019
	-0.001	*-0.006*	*0.002*	*0.006*	*0.007*	*-0.009*	*-0.011*	*-0.003*	*0.013*	*0.029*	*0.028*
	(0.014)	(0.024)	(0.035)	(0.048)	(0.004)	(0.111)	(0.115)	(0.099)	(0.008)	(0.040)	(0.011)
Exports	0.032	0.107**	0.201**	0.245**	-0.002	0.355**	0.329**	0.363**	-0.003	0.024	-0.006
	0.005	*0.016*	*0.030*	*0.037*	*-0.003*	*0.053*	*0.049*	*0.054*	*-0.005*	*0.002*	*-0.005*
	(0.022)	(0.038)	(0.046)	(0.050)	(0.005)	(0.122)	(0.103)	(0.094)	(0.008)	(0.047)	(0.024)
Domestic Demand	-0.123	-0.169*	-0.194*	-0.181	-0.019**	-0.215**	-0.219*	-0.205*	-0.019**	-0.174**	-0.012**
	(0.073)	(0.074)	(0.087)	(0.102)	(0.002)	(0.075)	(0.088)	(0.102)	(0.002)	(0.038)	(0.001)
ICT	0.290	0.406*	0.479*	0.750**	0.020*	0.406*	0.488*	0.751**	0.020*	0.160	0.067**
	(0.160)	(0.185)	(0.195)	(0.277)	(0.010)	(0.184)	(0.197)	(0.277)	(0.010)	(0.127)	(0.008)
Individual Characteristics											
Schooling	-0.008**	-0.007**	-0.007**	-0.008**	0.000	-0.007**	-0.007**	-0.007**	0.000	-0.005**	0.012**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Experience	-0.008**	-0.008**	-0.008**	-0.007**	-0.006**	-0.008**	-0.008**	-0.007**	-0.006**	-0.009**	-0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(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)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.030**	-0.030**	-0.029**	-0.031**	-0.024**	-0.030**	-0.029**	-0.031**	-0.024**	-0.035**	-0.012**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)
Male	0.013**	0.014**	0.017**	0.020**	0.010**	0.020**	0.022**	0.024**	0.010**	0.002	0.032**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.003)	(0.005)	(0.005)	(0.006)	(0.003)	(0.004)	(0.003)
White	-0.041**	-0.041**	-0.041**	-0.040**	-0.036**	-0.041**	-0.042**	-0.040**	-0.036**	-0.039**	-0.016**
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Nontradeable Dummies											
I^{NT}	-0.013	-0.013	0.013	0.019		0.039	0.020	0.029	0.251**		
	(0.028)	(0.030)	(0.030)	(0.029)		(0.063)	(0.059)	(0.044)	(0.041)		
I^{NT} x $I_{1995\text{-}96}$	0	0			0	0			0		
	-	-			-	-			-		
I^{NT} x $I_{1997\text{-}98}$	-0.020	0.005	0		-0.007	0.020	0		-0.006		
	(0.038)	(0.036)	-		(0.008)	(0.050)	-		(0.010)		
I^{NT} x $I_{1999\text{-}2000}$	-0.018	-0.017	-0.002	0	-0.007	-0.053	0.005	0	-0.006		
	(0.036)	(0.037)	(0.035)	-	(0.009)	(0.053)	(0.037)	-	(0.012)		
I^{NT} x I_{2001}	0.005	0.011	-0.006	0.026	0.015	-0.013	-0.010	0.032	0.016		
	(0.053)	(0.054)	(0.053)	(0.051)	(0.025)	(0.066)	(0.061)	(0.052)	(0.026)		
I^{NT} x $I_{2002\text{-}2003}$	-0.010	-0.001	-0.013	-0.005	-0.010	-0.018	-0.012	-0.005	-0.008		
	(0.033)	(0.033)	(0.032)	(0.031)	(0.012)	(0.049)	(0.041)	(0.033)	(0.017)		
I^{NT} x $I_{2004\text{-}2005}$	-0.008	0.007	0.002	0.000	-0.011	0.013	0.012	0.004	-0.009		
	(0.032)	(0.033)	(0.032)	(0.031)	(0.014)	(0.051)	(0.039)	(0.032)	(0.023)		
Observations	87,627	87,627	72,828	57,670	87,627	87,627	72,828	57,670	87,627	139,850	139,850
R-squared	0.023	0.023	0.024	0.023	0.046					0.024	0.099

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. In columns 1–9 the sample is the set of workers in white collar services that either switched up or stayed. The table is otherwise identical to table 5. See table 5 for all other details. Numbers in italics are decadal impacts. Standard errors clustered at the BEA and year levels appear in parentheses. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 7. Transitions to Unemployment

	Services - OLS					Services - IV				Manufacturing - OLS	
	Changes in Service Characteristics				Levels	Changes in Service Characteristics			Levels	Changes	Levels
	1-year	3-year	5-year	7-year	FE	3-year	5-year	7-year	FE	1-year	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Service Characteristics											
Imports	0.002	0.007	0.022*	0.022	0.005**	0.013	0.033**	0.034*	0.006*	0.030*	0.011*
	0.000	*0.001*	*0.004*	*0.004*	*0.009*	*0.002*	*0.006*	*0.006*	*0.011*	*0.004*	*0.016*
	(0.002)	(0.004)	(0.009)	(0.012)	(0.002)	(0.011)	(0.012)	(0.017)	(0.003)	(0.014)	(0.006)
Exports	0.003	0.003	0.000	0.006	-0.002	0.019	0.019	0.011	-0.001	0.008	-0.016
	0.000	*0.000*	*0.000*	*0.001*	*-0.003*	*0.003*	*0.003*	*0.002*	*-0.002*	*0.001*	*-0.013*
	(0.004)	(0.008)	(0.010)	(0.010)	(0.002)	(0.013)	(0.013)	(0.012)	(0.003)	(0.017)	(0.013)
Domestic Demand	-0.012	0.011	-0.011	0.001	-0.001	0.008	-0.014	0.000	-0.001	-0.030*	0.000
	(0.017)	(0.023)	(0.028)	(0.036)	(0.001)	(0.023)	(0.028)	(0.036)	(0.001)	(0.015)	(0.01)
ICT	0.076	0.142*	0.237**	0.394**	0.011**	0.141*	0.233**	0.391**	0.011**	0.059	0.005
	(0.040)	(0.068)	(0.084)	(0.099)	(0.004)	(0.069)	(0.084)	(0.099)	(0.004)	(0.040)	(0.004)
Individual Characteristics											
Schooling	-0.004**	-0.004**	-0.004**	-0.004**	-0.003**	-0.004**	-0.004**	-0.004**	-0.003**	-0.005**	-0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Experience	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.002**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(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)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.018**	-0.018**	-0.018**	-0.019**	-0.018**	-0.018**	-0.018**	-0.019**	-0.018**	-0.023**	-0.020**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Male	0.006**	0.006**	0.005**	0.006**	0.005**	0.006**	0.005**	0.006**	0.005**	0.008**	0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
White	-0.008**	-0.008**	-0.007**	-0.007**	-0.008**	-0.008**	-0.007**	-0.007**	-0.008**	-0.009**	-0.007**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Nontradeable Dummies											
I^{NT}	0.003	0.003	0.005	0.006		0.010	0.013	0.010	-0.017		
	(0.005)	(0.005)	(0.007)	(0.005)		(0.006)	(0.007)	(0.006)	(0.025)		
I^{NT} x $I_{1995\text{-}96}$	0	0			0	0			0		
	-	-			-	-			-		
I^{NT} x $I_{1997\text{-}98}$	-0.003	-0.002	0		-0.000	-0.002	0		0.000		
	(0.007)	(0.006)	-		(0.005)	(0.006)	-		(0.005)		
I^{NT} x $I_{1999\text{-}2000}$	-0.003	-0.003	-0.002	0	0.001	-0.007	-0.003	0	0.002		
	(0.006)	(0.006)	(0.006)	-	(0.004)	(0.006)	(0.006)	-	(0.004)		
I^{NT} x I_{2001}	-0.003	-0.003	-0.004	-0.002	0.001	-0.007	-0.008	-0.003	0.002		
	(0.008)	(0.008)	(0.009)	(0.007)	(0.006)	(0.009)	(0.009)	(0.007)	(0.006)		
I^{NT} x $I_{2002\text{-}2003}$	-0.005	-0.005	-0.005	-0.004	-0.000	-0.008	-0.009	-0.006	0.002		
	(0.005)	(0.005)	(0.006)	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)		
I^{NT} x $I_{2004\text{-}2005}$	-0.004	-0.005	-0.005	-0.005	0.001	-0.006	-0.007	-0.006	0.004		
	(0.005)	(0.005)	(0.006)	(0.004)	(0.006)	(0.005)	(0.006)	(0.005)	(0.008)		
Observations	99,949	99,949	83,537	66,428	99,949	99,949	83,537	66,428	99,949	152,757	152,757
R-squared	0.009	0.009	0.009	0.009	0.01					0.012	0.020

Notes: The dependent variable equals 1 if the worker transitioned into unemployment and 0 if the worker stayed employed. In columns 1–9 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 5. See table 5 for all other details. Numbers in italics are decadal impacts. Standard errors clustered at the BEA and year levels appear in parentheses. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 8. Earnings for Stayers

	Services - OLS					Services - IV				Manufacturing - OLS	
	Changes in Service Characteristics				Levels	Changes in Service Characteristics			Levels	Changes	Levels
	1-year	3-year	5-year	7-year	FE	3-year	5-year	7-year	FE	1-year	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Service Characteristics											
Imports	-0.001	-0.041	-0.051	-0.041	-0.013*	-0.128*	-0.183*	-0.189*	-0.028*	-0.138**	-0.010
	-0.002	*-0.074*	*-0.092*	*-0.074*	*-0.023*	*-0.230*	*-0.329*	*-0.340*	*-0.050*	*-0.204*	*-0.015*
	(0.006)	(0.022)	(0.026)	(0.032)	(0.005)	(0.065)	(0.085)	(0.082)	(0.012)	(0.034)	(0.015)
Exports	0.005	0.032	0.035	0.071	0.007	0.017	0.041	0.023	-0.000	0.040	0.052
	0.0075	*0.048*	*0.0525*	*0.1065*	*0.0105*	*0.026*	*0.062*	*0.035*	*0.000*	*0.032*	*0.041*
	(0.010)	(0.017)	(0.025)	(0.038)	(0.008)	(0.053)	(0.058)	(0.061)	(0.011)	(0.040)	(0.037)
Domestic Demand	0.137**	0.120	0.140	0.177	-0.002	0.123*	0.138	0.183*	-0.001	0.109**	0.002
	(0.051)	(0.061)	(0.075)	(0.094)	(0.002)	(0.062)	(0.075)	(0.093)	(0.002)	(0.039)	(0.002)
ICT	0.124	0.067	0.217	0.126	0.015	0.083	0.246	0.163	0.015	-0.116	0.002
	(0.180)	(0.221)	(0.225)	(0.403)	(0.014)	(0.222)	(0.227)	(0.403)	(0.014)	(0.154)	(0.013)
Individual Characteristics											
Schooling	-0.004**	-0.004**	-0.003*	-0.002	-0.003*	-0.003**	-0.003*	-0.002	-0.003*	-0.003**	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Experience	-0.008**	-0.008**	-0.008**	-0.009**	-0.008**	-0.008**	-0.008**	-0.009**	-0.008**	-0.009**	-0.008**
	(0.001)	(0.001)	(0.001)	(0.001)	(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)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.013*	-0.013*	-0.015**	-0.013*	-0.012*	-0.013*	-0.015**	-0.013*	-0.012*	-0.010*	-0.007
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)
Male	-0.011*	-0.010	-0.007	-0.012	-0.008	-0.009	-0.004	-0.010	-0.008	-0.006	0.004
	(0.005)	(0.005)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.004)	(0.005)
White	-0.024**	-0.024**	-0.023**	-0.024*	-0.023**	-0.025**	-0.024**	-0.025**	-0.023**	-0.021**	-0.016*
	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.007)	(0.007)
Nontradeable Dummies											
I^{NT}	0.021	0.012	0.000	0.001	0.137**	-0.022	-0.036	-0.043	0.093		
	(0.014)	(0.014)	(0.015)	(0.012)	(0.038)	(0.033)	(0.035)	(0.027)	(0.051)		
I^{NT} x $I_{1995\text{-}96}$	0	0			0	0			0		
	-	-			-	-			-		
I^{NT} x $I_{1997\text{-}98}$	-0.013	-0.005	0		-0.013	0.005	0		-0.021		
	(0.018)	(0.016)	-		(0.013)	(0.018)	-		(0.015)		
I^{NT} x $I_{1999\text{-}2000}$	-0.021	-0.017	-0.004	0	-0.025	0.005	0.010	0	-0.038*		
	(0.017)	(0.017)	(0.016)	-	(0.013)	(0.028)	(0.020)	-	(0.018)		
I^{NT} x I_{2001}	-0.045	-0.036	-0.026	-0.017	-0.047	-0.014	-0.004	-0.006	-0.064*		
	(0.030)	(0.030)	(0.030)	(0.029)	(0.024)	(0.035)	(0.037)	(0.029)	(0.027)		
I^{NT} x $I_{2002\text{-}2003}$	-0.011	-0.004	0.008	0.013	-0.018	0.016	0.029	0.028	-0.039		
	(0.016)	(0.016)	(0.017)	(0.014)	(0.016)	(0.022)	(0.023)	(0.016)	(0.024)		
I^{NT} x $I_{2004\text{-}2005}$	-0.034*	-0.026	-0.016	-0.010	-0.044*	-0.009	0.003	0.006	-0.074*		
	(0.016)	(0.015)	(0.016)	(0.013)	(0.019)	(0.018)	(0.021)	(0.014)	(0.030)		
Observations	72780	72780	60345	47635	72780	72,780	60,345	47,635	72,780	113,349	113,349
R-squared	0.007	0.007	0.007	0.006	0.008					0.007	0.012

Notes: The dependent variable is the change in the log of CPI-deflated annual earnings. In columns 1–9 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 5. See table 5 for all other details. Standard errors clustered at the BEA and year levels appear in parentheses. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 9. Earnings Changes for Switchers

	Services - Switching Down Sample				Service -: Switching Up Sample				Manufacturing	
	Switch Dummy		1-year	Levels (FE)	Switch Dummy		1-year	Levels (FE)	Switch Down	Switch Up
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Service Characteristics										
Switching Down	-0.139**	0.012							-0.116**	
	(0.008)	(0.011)							(0.007)	
Switching Up					0.121**	0.022				0.131**
					(0.010)	(0.014)				(0.007)
Change in IOWD		0.522**				0.404**				
		-0.028				-0.043				
Service Characteristics										
Imports			0.010	-0.0009			-0.059*	-0.028		
			0.018	*-0.002*			*-0.106*	*-0.051*		
			(0.026)	(0.018)			(0.027)	(0.019)		
Exports			0.026	-0.0163			0.045	-0.016		
			0.039	*-0.024*			*0.067*	*-0.024*		
			(0.037)	(0.023)			(0.034)	(0.019)		
Domestic Demand			0.186	-0.006			0.175	0.006		
			(0.137)	(0.006)			(0.156)	(0.006)		
ICT			-0.118	-0.070*			0.982	-0.098*		
			-0.589	(0.035)			(0.540)	(0.038)		
Individual Characteristics										
Schooling	-0.002	-0.004**	-0.005	0.000	-0.001	-0.002	-0.005	0.000	-0.001	0.001
	(0.001)	(0.001)	(0.003)	(0.0029)	(0.002)	(0.002)	(0.004)	(0.004)	(0.001)	(0.001)
Experience	-0.007**	-0.007**	-0.008**	-0.007**	-0.009**	-0.009**	-0.018**	-0.017**	-0.007**	-0.009**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Experience^2	0.0001**	0.0001**	0.0001	0.0000	0.0001**	0.0001**	0.0003**	0.0003**	0.0001**	0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.011	-0.012*	-0.018	-0.015	-0.008	-0.008	-0.002	-0.001	-0.006	-0.006
	(0.006)	(0.006)	(0.015)	(0.015)	(0.006)	(0.006)	(0.015)	(0.015)	(0.004)	(0.004)
Male	-0.007	-0.012	-0.038**	-0.038**	-0.002	-0.003	-0.052**	-0.042**	-0.003	0.002
	(0.006)	(0.006)	(0.014)	(0.014)	(0.005)	(0.005)	(0.015)	(0.016)	(0.005)	(0.005)
White	0.004	0.002	0.080**	0.082**	-0.024**	-0.024**	-0.042	-0.041	0.001	-0.022**
	(0.009)	(0.009)	(0.021)	(0.021)	(0.008)	(0.008)	(0.022)	(0.022)	(0.007)	(0.006)
Non-Tradeable Dummies (I^{NT})										
I^{NT} x $I_{2004\text{-}2005}$			0.005	-0.024			0.111*	0.040		
			(0.054)	(0.059)			(0.043)	(0.051)		
Observations	90,823	90,823	17,835	17,835	87,847	87,716	14,847	14,847	145,337	145,337
R-squared	0.018	0.024	0.012	0.014	0.021	0.023	0.020	0.022	0.015	0.022

Notes: The dependent variable is the change in the log of CPI-deflated annual earnings. In columns 1–4 the sample is the set of workers in white collar services that either switched down or stayed. 'Switching down' equals 1 for downward switchers and 0 for stayers. 'Change in IOWD' is the difference between the IOWD in the worker's initial and final occupations. Except for the sample, the specifications in columns 3 and 4 are identical to those in columns 1 and 5, respectively, of table 8. Columns 4–8 mirror columns 1–4, but with downward switching replaced by upward switching everywhere i.e., in defining the sample and in defining the switching dummy. See table 5 for all other details. Numbers in italics are decadal impacts. Standard errors clustered at the BEA and year levels appear in parentheses. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 10. Results by Routinization, by Education, and by Age

	Switching Down				Switching Up				Transitions to Unemployment				Log Earnings Changes of Stayers			
	1-year change		level FE		1-year change		level FE		1-year change		level FE		1-year change		level FE	
A: By Rountineness	Non-Routine	Routine	Non-Routine	Routine	Non-Routine	Routine	Non-Routine	Routine	Non-Routine	Routine	Non-Routine	Routine	Non-Routine	Routine	Non-Routine	Routine
Service Characteristics																
Imports	0.014	0.041**	0.017	0.021*	0.001	0.048*	0.005	0.007	-0.000	0.008	0.007	0.005*	0.010	-0.028	-0.007	-0.008
	0.003	*0.007*	*0.031*	*0.038*	*0.000*	*0.009*	*0.009*	*0.013*	*0.000*	*0.001*	*0.013*	*0.009*	*0.018*	*-0.050*	*-0.013*	*-0.014*
	(0.015)	(0.016)	(0.010)	(0.009)	(0.018)	(0.020)	(0.006)	(0.009)	(0.002)	(0.006)	(0.004)	(0.002)	(0.007)	(0.014)	(0.007)	(0.013)
Individual Characteristics																
Schooling	-0.018**	-0.014**	-0.016**	-0.015**	0.004*	-0.015**	0.004*	-0.001	-0.003**	-0.005**	-0.003**	-0.003**	-0.000	-0.007**	-0.003	-0.004
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)
Nontradeable Dummies																
I^{NT} x $I_{2004\text{-}2005}$	-0.018	0.010	0.021	0.041	0.026	-0.048	0.008	-0.021	-0.001	-0.009	-0.007	0.009	0.006	-0.060**	-0.024	0.004
	(0.035)	(0.019)	(0.029)	(0.028)	(0.032)	(0.046)	(0.016)	(0.022)	(0.005)	(0.008)	(0.012)	(0.006)	(0.017)	(0.023)	(0.026)	(0.037)
Observations	50,252	40,363	50,252	40,363	44,344	43,283	44,344	43,283	53,697	46,252	53,697	46,252	38,466	34,314	38,466	34,314
Chi^2 test for Imports	1.48		0.06		3.24		0.06		1.40		0.30		5.48*		0.00	
Chi^2 test for Schooling	2.51		0.02		98.29**		6.43*		10.47**		0.70		6.70**		0.20	
B: By Education	High School	College	High School	College	High School	College	High School	College	High School	College	High School	College	High School	College	High School	College
Service Characteristics																
Imports	0.040*	0.038**	0.011	0.022**	0.005	-0.009	0.000	0.006	0.006	0.001	0.009*	0.004*	-0.017	0.003	0.010	-0.015*
	0.007	*0.007*	*0.020*	*0.040*	*0.001*	*-0.002*	*0.000*	*0.011*	*0.001*	*0.000*	*0.016*	*0.007*	*-0.031*	*0.005*	*0.018*	*-0.027*
	(0.016)	(0.015)	(0.010)	(0.006)	(0.018)	(0.016)	(0.010)	(0.005)	(0.006)	(0.002)	(0.004)	(0.002)	(0.021)	(0.008)	(0.017)	(0.007)
Individual Characteristics																
Schooling	-0.012**	-0.013**	-0.015**	-0.013**	-0.005	-0.009**	-0.003	-0.001	-0.003*	-0.004**	-0.003*	-0.003**	-0.010	-0.003	-0.010	-0.003
	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.002)	(0.003)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.006)	(0.002)	(0.006)	(0.002)
Nontradeable Dummies																
I^{NT} x $I_{2004\text{-}2005}$	0.012	0.008	0.004	0.031	0.007	-0.014	-0.015	-0.011	0.001	-0.006	-0.004	0.002	-0.075*	-0.018	-0.095	-0.030
	(0.034)	(0.042)	(0.035)	(0.019)	(0.035)	(0.034)	(0.024)	(0.016)	(0.009)	(0.005)	(0.012)	(0.007)	(0.029)	(0.019)	(0.065)	(0.029)
Observations	25,661	64,954	25,661	64,954	24,420	63,207	24,420	63,207	28,208	71,741	28,208	71,741	20,016	52,764	20,016	52,764
Chi^2 test for Imports	0.01		0.95		0.44		0.23		0.48		0.83		0.57		1.56	
Chi^2 test for Schooling	0.13		0.36		1.23		0.42		0.39		0.06		1.23		1.28	
C: By Age	Under 40	Above 40	Under 40	Above 40	Under 40	Above 40	Under 40	Above 40	Under 40	Above 40	Under 40	Above 40	Under 40	Above 40	Under 40	Above 40
Service Characteristics																
Imports	0.033*	0.046**	0.010	0.028**	-0.015	0.003	0.003	0.004	0.001	0.004	0.004	0.006*	0.018*	-0.021	-0.003	-0.021*
	0.006	*0.008*	*0.018*	*0.050*	*-0.003*	*0.001*	*0.005*	*0.007*	*0.000*	*0.001*	*0.007*	*0.011*	*0.032*	*-0.038*	*-0.005*	*-0.038*
	(0.015)	(0.016)	(0.007)	(0.006)	(0.014)	(0.015)	(0.005)	(0.007)	(0.003)	(0.004)	(0.002)	(0.003)	(0.008)	(0.012)	(0.008)	(0.010)
Individual Characteristics																
Schooling	-0.018**	-0.009**	-0.021**	-0.009**	-0.011**	-0.004**	-0.002	0.002	-0.005**	-0.003**	-0.004**	-0.002**	-0.002	-0.002	-0.001	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)
Nontradeable Dummies																
I^{NT} x $I_{2004\text{-}2005}$	0.008	0.005	0.003	0.048*	-0.013	-0.004	-0.015	-0.003	-0.009	0.000	-0.003	0.005	-0.028	-0.035*	-0.020	-0.059*
	(0.038)	(0.038)	(0.023)	(0.020)	(0.035)	(0.029)	(0.020)	(0.017)	(0.006)	(0.005)	(0.008)	(0.008)	(0.027)	(0.016)	(0.032)	(0.026)
Observations	42,097	48,518	42,097	48,518	40,828	46,799	40,828	46,799	46,887	53,062	46,887	53,062	32,791	39,989	32,791	39,989
Chi^2 test for Imports	0.94		4.64*		2.63		0.00		0.22		0.27		6.48*		1.33	
Chi^2 test for Schooling	31.70**		48.24**		32.21**		5.70*		22.22**		17.47**		0.06		0.01	

Notes: The specifications in this table are the same as the specifications in table 5. To save space, we only report the coefficients for imports, schooling and $I^{NT} I_{2004-2005}$. OLS coefficients are reported with standard errors, clustered at the BEA-year level, in parentheses. Numbers in italics are decadal impacts. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 11. Sensitivity Results: CPS Sample Selection

VARIABLES	Switching Down		Switching Up		Transitions to Unemployment		Log Earnings Changes of Stayers	
	1-year	levels FE	1-year	levels FE	1-year	levels FE	1-year	levels FE
Service Characteristics								
Imports	0.031*	0.015**	-0.008	0.000	0.001	0.004**	-0.008	-0.014*
	0.006	*0.027*	*-0.001*	*0.000*	*0.000*	*0.007*	*-0.014*	*-0.025*
	(0.012)	(0.004)	(0.012)	(0.004)	(0.002)	(0.001)	(0.008)	(0.005)
Exports	-0.073**	-0.011*	0.031	-0.004	0.003	-0.002	0.017	0.008
	(0.027)	(0.005)	(0.020)	(0.005)	(0.003)	(0.002)	(0.014)	(0.008)
Domestic Demand	-0.103*	-0.014**	-0.094	-0.016**	-0.012	-0.001*	0.186**	0.001
	(0.048)	(0.001)	(0.061)	(0.002)	(0.012)	(0.000)	(0.071)	(0.006)
ICT	0.174	0.027**	0.213	0.024*	0.035	0.009**	-0.181	0.010
	(0.137)	(0.007)	(0.147)	(0.010)	(0.031)	(0.003)	(0.217)	(0.017)
Individual Characteristics								
Schooling	-0.010**	-0.010**	-0.005**	0.002	-0.002**	-0.002**	0.008**	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.003)	(0.005)
Experience	-0.003**	-0.004**	-0.005**	-0.004**	-0.000*	-0.000	0.001	-0.006
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.005)
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)
Married	-0.019**	-0.020**	-0.017**	-0.013**	-0.010**	-0.010**	0.037**	0.000
	(0.003)	(0.003)	(0.004)	(0.004)	(0.001)	(0.001)	(0.010)	(0.027)
Male	0.020**	-0.003	0.010*	0.009**	0.004**	0.003*	-0.026**	-0.010
	(0.005)	(0.004)	(0.004)	(0.003)	(0.001)	(0.001)	(0.007)	(0.008)
White	-0.025**	-0.028**	-0.026**	-0.025**	-0.005**	-0.004**	0.025	-0.010
	(0.005)	(0.005)	(0.004)	(0.005)	(0.001)	(0.001)	(0.013)	(0.027)
Nontradeable Dummies								
I^{NT}	-0.042	-0.120**	-0.015	0.207**	0.001	-0.010	0.021	0.123**
	(0.027)	(0.030)	(0.027)	(0.041)	(0.003)	(0.013)	(0.014)	(0.047)
I^{NT} x $I_{1995\text{-}96}$	0	0	0	0	0	0	0	0
	-	-	-	-	-	-	-	-
I^{NT} x $I_{1997\text{-}98}$	0.032	0.003	-0.014	-0.005	-0.002	0.001	-0.010	-0.011
	(0.036)	(0.008)	(0.034)	(0.008)	(0.005)	(0.003)	(0.016)	(0.014)
I^{NT} x $I_{1999\text{-}2000}$	0.017	0.003	-0.015	-0.009	-0.001	0.002	-0.008	-0.020
	(0.036)	(0.010)	(0.034)	(0.009)	(0.004)	(0.003)	(0.020)	(0.015)
I^{NT} x I_{2001}	0.055	0.033*	0.009	0.016	-0.001	0.003	-0.051	-0.047
	(0.061)	(0.015)	(0.045)	(0.020)	(0.005)	(0.004)	(0.044)	(0.026)
I^{NT} x $I_{2002\text{-}2003}$	0.034	0.039**	-0.008	-0.014	-0.004	-0.001	-0.010	-0.017
	(0.040)	(0.013)	(0.031)	(0.011)	(0.004)	(0.003)	(0.019)	(0.015)
I^{NT} x $I_{2004\text{-}2005}$	0.007	0.024	-0.005	-0.015	-0.003	0.000	-0.026	-0.041*
	(0.036)	(0.014)	(0.031)	(0.013)	(0.003)	(0.004)	(0.019)	(0.019)
Observations	169,712	169,712	169,712	169,712	169,712	169,712	169,712	169,712
Wald test of indep. eqns.	43.16**	56.76**	26.16**	15.81**	37.57**	38.33**	38.97**	52.17**
Selection Equation								
Excluded Regressors								
Family size	-0.039**	-0.036**	-0.036**	-0.040**	-0.029**	-0.028**	-0.042**	-0.046**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Number of children	0.023**	0.019**	0.018**	0.020**	0.004	0.003	0.030**	0.032**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
House owner	0.490**	0.485**	0.475**	0.484**	0.568**	0.567**	0.378**	0.412**
	(0.013)	(0.012)	(0.010)	(0.010)	(0.011)	(0.011)	(0.013)	(0.013)
Same house last year	0.120**	0.123**	0.134**	0.131**	0.152**	0.152**	0.138**	0.141**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)

Notes: The specifications for the second-stage regressions in this table are the same as the corresponding specifications in tables 5–8. The selection equations also include all the variables in the second-stage regressions. To save space, we only report the coefficients for the excluded regressors. Numbers in italics are decadal impacts. Standard errors clustered at the BEA-year level are in parentheses. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 12. Sensitivity Results: Including Rich-Country Service Trade

	Switching Down				Switching Up				Transitions to Unemployment				Log Earnings Changes of Stayers			
	1-year change		Level FE		1-year change		Level FE		1-year change		Level FE		1-year change		Level FE	
	(1)	(2)	(9)	(10)	(11)	(12)	(19)	(20)	(21)	(22)	(29)	(30)	(31)	(32)	(39)	(40)
Service Characteristi																
Imports	0.040**	0.039**	0.022**	0.019**	-0.011	-0.007	0.005	0.004	0.002	0.002	0.002	0.005**	0.000	-0.001	-0.005	-0.013*
	0.007	*0.007*	*0.040*	*0.034*	*-0.002*	*-0.001*	*0.009*	*0.007*	*0.000*	*0.000*	*0.004*	*0.009*	*0.000*	*-0.002*	*-0.009*	*-0.023*
	(0.014)	(0.013)	(0.007)	(0.005)	(0.014)	(0.014)	(0.006)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.007)	(0.006)	(0.007)	(0.005)
Exports	-0.092**	-0.084**	-0.013*	-0.011	0.040*	0.032	-0.003	-0.002	0.003	0.003	-0.001	-0.002	0.004	0.005	0.008	0.007
	-0.014	*-0.013*	*-0.020*	*-0.017*	*0.006*	*0.005*	*-0.005*	*-0.003*	*0.000*	*0.000*	*-0.002*	*-0.003*	*0.006*	*0.008*	*0.012*	*0.011*
	(0.026)	(0.030)	(0.006)	(0.006)	(0.020)	(0.022)	(0.006)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)	(0.010)	(0.010)	(0.007)	(0.008)
G8 Imports	0.070**		-0.008		-0.051*		-0.002		0.001		0.009*		-0.002		-0.026*	
	(0.026)		(0.013)		(0.025)		(0.012)		(0.005)		(0.004)		(0.015)		(0.013)	
G8 Exports	-0.015		0.006		-0.006		0.002		0.000		-0.007		0.009		0.003	
	(0.031)		(0.010)		(0.021)		(0.011)		(0.004)		(0.005)		(0.012)		(0.011)	
Domestic Demand	-0.138*	-0.134*	-0.018**	-0.018**	-0.120	-0.123	-0.019**	-0.019**	-0.012	-0.012	-0.001	-0.001	0.137**	0.137**	-0.001	-0.002
	(0.057)	(0.057)	(0.002)	(0.002)	(0.073)	(0.073)	(0.002)	(0.002)	(0.017)	(0.017)	(0.001)	(0.001)	(0.051)	(0.051)	(0.002)	(0.002)
ICT	0.273	0.260	0.038**	0.039**	0.286	0.290	0.020*	0.020*	0.076	0.076	0.011**	0.011**	0.120	0.124	0.015	0.015
	(0.150)	(0.151)	(0.009)	(0.009)	(0.161)	(0.160)	(0.010)	(0.010)	(0.040)	(0.040)	(0.004)	(0.004)	(0.181)	(0.180)	(0.014)	(0.014)
Individual Characteristics																
Schooling	-0.013**	-0.013**	-0.014**	-0.014**	-0.007**	-0.008**	0.000	0.000	-0.004**	-0.004**	-0.003**	-0.003**	-0.004**	-0.004**	-0.003*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Experience	-0.006**	-0.006**	-0.007**	-0.007**	-0.008**	-0.008**	-0.006**	-0.006**	-0.001**	-0.001**	-0.001**	-0.001**	-0.008**	-0.008**	-0.008**	-0.008**
	(0.000)	(0.000)	(0.000)	(0.000)	(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**	-0.037**	-0.037**	-0.030**	-0.030**	-0.024**	-0.024**	-0.018**	-0.018**	-0.018**	-0.018**	-0.013*	-0.013*	-0.012*	-0.012*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.006)	(0.006)	(0.006)
Male	0.021**	0.022**	-0.004	-0.004	0.013**	0.013**	0.010**	0.010**	0.006**	0.006**	0.005**	0.005**	-0.011*	-0.011*	-0.008	-0.008
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.006)	(0.006)
White	-0.040**	-0.040**	-0.044**	-0.044**	-0.041**	-0.041**	-0.036**	-0.036**	-0.008**	-0.008**	-0.008**	-0.008**	-0.024**	-0.024**	-0.023**	-0.023**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.008)	(0.008)	(0.008)	(0.008)
Nontradeable Dummies																
I^{NT}	-0.043	-0.049			-0.019	-0.013			0.003	0.003			0.022	0.021	0.027	0.137**
	(0.029)	(0.027)			(0.028)	(0.028)			(0.005)	(0.005)			(0.014)	(0.014)	(0.081)	(0.038)
I^{NT} x $I_{1995\text{-}96}$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
I^{NT} x $I_{1997\text{-}98}$	0.037	0.032	0.003	0.002	-0.025	-0.020	-0.007	-0.007	-0.003	-0.003	-0.002	-0.000	-0.012	-0.013	-0.017	-0.013
	(0.033)	(0.033)	(0.012)	(0.011)	(0.037)	(0.038)	(0.009)	(0.008)	(0.007)	(0.007)	(0.005)	(0.005)	(0.018)	(0.018)	(0.014)	(0.013)
I^{NT} x $I_{1999\text{-}2000}$	0.017	0.019	0.004	0.003	-0.015	-0.018	-0.007	-0.007	-0.003	-0.003	-0.000	0.001	-0.021	-0.021	-0.033*	-0.025
	(0.034)	(0.035)	(0.014)	(0.012)	(0.036)	(0.036)	(0.011)	(0.009)	(0.006)	(0.006)	(0.005)	(0.004)	(0.017)	(0.017)	(0.016)	(0.013)
I^{NT} x I_{2001}	0.051	0.058	0.040	0.038	0.012	0.005	0.016	0.015	-0.003	-0.003	-0.002	0.001	-0.046	-0.045	-0.052*	-0.047
	(0.063)	(0.059)	(0.023)	(0.022)	(0.054)	(0.053)	(0.025)	(0.025)	(0.008)	(0.008)	(0.006)	(0.006)	(0.030)	(0.030)	(0.025)	(0.024)
I^{NT} x $I_{2002\text{-}2003}$	0.032	0.033	0.040*	0.038*	-0.007	-0.010	-0.009	-0.010	-0.005	-0.005	-0.002	-0.000	-0.012	-0.011	-0.023	-0.018
	(0.038)	(0.038)	(0.017)	(0.015)	(0.033)	(0.033)	(0.013)	(0.012)	(0.005)	(0.005)	(0.005)	(0.004)	(0.017)	(0.016)	(0.019)	(0.016)
I^{NT} x $I_{2004\text{-}2005}$	0.004	0.008	0.028	0.026	-0.004	-0.008	-0.010	-0.011	-0.004	-0.004	-0.002	0.001	-0.035*	-0.034*	-0.051*	-0.044*
	(0.037)	(0.037)	(0.019)	(0.017)	(0.032)	(0.032)	(0.016)	(0.014)	(0.005)	(0.005)	(0.007)	(0.006)	(0.016)	(0.016)	(0.021)	(0.019)
Observations	90,615	90,615	90,615	90,615	87,627	87,627	87,627	87,627	99,949	99,949	99,949	99,949	72,780	72,780	72,780	72,780
R-squared	0.021	0.020	0.039	0.039	0.023	0.023	0.046	0.046	0.009	0.009	0.010	0.010	0.007	0.007	0.008	0.008

Notes: The even-numbered columns repeat our baseline results that appear in columns 1 and 5 of tables 5–8. The odd-numbered specifications add to these baseline specifications two more regressors: imports and exports of services with the G8. OLS coefficients are reported. Numbers in italics are decadal impacts. Standard errors, clustered at the BEA-year level, appear in parentheses. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 13. Other 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. *M* and *X* Not Lagged	0.021 *	*0.038*	0.001	*0.002*	0.004 *	*0.007*	-0.013 *	*-0.023*
2. Poor Countries	0.022 **	*0.040*	-0.002	*-0.004*	0.008 **	*0.014*	-0.011	*-0.020*
3. Omit Non-OPS	0.019 **	*0.034*	0.003	*0.005*	0.006 **	*0.011*	-0.013 *	*-0.023*
4. Only BPT Services	0.014 **	*0.025*	0.003	*0.005*	0.006 **	*0.011*	-0.014 **	*-0.025*
5. Drop Blinder Criterion	0.016 **	*0.029*	0.004	*0.007*	0.004 *	*0.007*	-0.011 *	*-0.020*
6. Omit Tech. Bubble	0.016 **	*0.029*	0.001	*0.002*	0.004 **	*0.007*	-0.010 *	*-0.018*
7. Drop Variables D & I	0.017 **	*0.031*	0.000	*0.000*	0.005 **	*0.009*	-0.009 **	*-0.016*
8. Use M/D and X/D	48.230 **	*0.050*	-2.859	*-0.003*	9.880	*0.010*	-24.793	*-0.026*
9. Probit	0.014 **	*0.025*	-0.000	*0.000*	0.006 **	*0.011*		
10. Logit	0.014 **	*0.025*	0.000	*0.000*	0.006 **	*0.011*		
11. Multinomial Logit	0.012 **	*0.022*	-0.001	*-0.002*	0.005 **	*0.009*		
12. 2-digit Switching	0.012 **	*0.022*	-0.003	*-0.005*				
13. Δ (Weeks Unemp) / (Weeks in LF)					0.002 *	*0.004*		
14. Δ Weeks Worked					-0.200 **	*-0.360*		
15. Log Δ of Weekly Wage							-0.010 *	*-0.018*
16. Log Δ 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 5 in tables 5–8. 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 5–8. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

1. 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

$$\begin{bmatrix} 1 & -t'/t & 0 \\ \eta^S & (1-I)^{-1} & \eta^D \\ 0 & -\Delta & 1 \end{bmatrix} \begin{bmatrix} d\ln w \\ dI \\ d\ln p \end{bmatrix} = \begin{bmatrix} -1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} d\ln a \\ d\ln w^* a^* \beta \\ d\delta \end{bmatrix} \tag{24}$$

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

$$\Delta \equiv (1-I)t'/[(1-I)t + \int_0^I t(i)di] > 0 \tag{25}$$

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 (24) we have normalized the demand shifter δ by setting $d\ln Q(p,\delta)/d\delta$ to unity. Let

$$A \equiv (1-I)^{-1} + \eta^S t'/t + \eta^D \Delta > 0 \tag{26}$$

be the determinant of the 3×3 matrix on the left-hand side of equation (24). Then

$$\begin{aligned} \begin{bmatrix} d\ln w \\ dI \\ d\ln p \end{bmatrix} &= \frac{1}{A} \begin{bmatrix} (1-I)^{-1} + \eta^D \Delta & t'/t & -\eta^D t'/t \\ -\eta^S & 1 & -\eta^D \\ -\eta^S \Delta & \Delta & (1-I)^{-1} + \eta^S t'/t \end{bmatrix} \begin{bmatrix} -1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} d\ln a \\ d\ln w^* a^* \beta \\ d\delta \end{bmatrix} \\ &= \frac{1}{A} \begin{bmatrix} -(1-I)^{-1} - \eta^D \Delta + t'/t & (1-I)^{-1} - \eta^D (t'/t - \Delta) & t'/t \\ \eta^S + 1 & -(\eta^S + \eta^D) & 1 \\ (\eta^S + 1)\Delta & (1-I)^{-1} + \eta^S (t'/t - \Delta) & \Delta \end{bmatrix} \begin{bmatrix} d\ln a \\ d\ln w^* a^* \beta \\ d\delta \end{bmatrix}. \end{aligned} \tag{27}$$

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

We can use equation (27) to calculate the comparative statics behind figures 1–3. Since $M = IQ$, these coefficients are

$$\begin{aligned}\frac{d\ln M}{d\delta} &= \frac{d\ln I}{d\delta} + \frac{d\ln Q(p,\delta)}{d\ln p}\frac{d\ln p}{d\delta} + \frac{d\ln Q(p,\delta)}{d\delta} \\ &= \frac{1}{A}\frac{1}{I} - \eta^D\frac{1}{A}\Delta + 1 = \frac{1}{A}\left\{\frac{1}{I} + \frac{1}{1-I} + \eta^S\frac{t'}{t}\right\} > 0 \end{aligned} \tag{28}$$

where we have simplified using equations (25)–(26) and $d\ln Q(p,\delta)/d\delta = 1$. Likewise,

$$\begin{aligned}\frac{d\ln M}{d\ln w^*} &= \frac{d\ln I}{dw^*} + \frac{d\ln Q(p,\delta)}{d\ln p}\frac{d\ln p}{dw^*} \\ &= -\frac{1}{I}\frac{\eta^S+\eta^D}{A} - \eta^D\frac{(1-I)^{-1} + \eta^S(t'/t-\Delta)}{A} < 0 \end{aligned} \tag{29}$$

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

$$\frac{d\ln M}{d\ln a} = A^{-1}(\eta^S+1)\left(I^{-1} - \eta^D\Delta\right) \tag{30}$$

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

In figures 1–3 we need

$$\frac{d\ln L^D}{d\delta} = A^{-1}\eta^S t'/t > 0 \tag{31}$$

and

$$\frac{d\ln L^D}{dw^*} = \frac{d\ln L^D}{d\beta} = A^{-1}\eta^S\left\{(1-I)^{-1} - \eta^D(t'/t-\Delta)\right\} \tag{32}$$

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

2. 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, 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).

3. 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. We then linked 2002 Census occupation codes with the 10 BEA service trade sectors. In order to do this as accurately as possible we used (*i*) the 2002 NAICS manual for detailed industry definitions and the 2000 SOC manual for detailed occupation definitions, and (*ii*) Borga and Mann (2004) and U.S. Department of Commerce (1998) for detailed information about the coverage of each type of trade in services.

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.

Our measures of service imports and exports come from published BEA data on U.S. international services cross-border trade and sales through affiliates. 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 sectors in whether they report total trade or just unaffiliated trade. Total trade is available for 5 of our 10 sectors and unaffiliated trade is available for the remaining 5 sectors. Given our log specification, this will matter only if the ratio of unaffiliated to total trade is trending. This is not the case. In the 4 sectors for which we have both types of trade, there is no trend. Further, in Liu and Trefler (2008) we obtained identical results using unaffiliated trade in 9 of the 10 sectors for which unaffiliated trade is available.

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.

A. *Switching*

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 (2006). Specifically, a switch is valid only if at least one of the following three events occurred. (1) The class of worker changed.[1] (2) There was job search during the period.[2] (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.

B. *Occupation Exposure to Manufacturing Trade*

In order to examine the impact of service offshoring on white collar jobs, we have linked the BEA service trade data to offshorable white collar occupations and run the baseline estimations. To be comparable with our service results, we need to construct variables that measure the occupational exposure to manufacturing trade. To do so, we follow Ebenstein et al. (2011). Specifically, we have converted the industry exposure to manufacturing trade into occupation exposure to manufacturing trade as follows,

$$M_{o,t} = \sum_{j} s_{o,j} M_{j,t}. \tag{33}$$

where $s_{o,j} = E_{o,j}/E_o$ is the share of workers in occupation o and industry j over all workers across all industries in occupation o in year 1992. We calculated this ratio using 1993 March CPS data. M_{jt}

[1] 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.

[2] 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 ($LKEDPY = 0$).

is imports of manufacturing industry j in year t. The industry-level manufacturing trade data is from Peter Schott's website. Occupation-specific measures of export variables are also converted in the same fashion.

4. 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 $Z^X_{kt} \equiv (\ln \hat{X}_{kt} - \ln \hat{X}_{k,t-l})/l$. For the rich-country instrument $Z^{X,R}_{kt}$, $\hat{X}_{China,kt} + \hat{X}_{India,kt}$ above is replaced with the sum of the $\hat{X}_{ckt}$ over the six rich countries in the G8. Z^M_{kt} and $Z^{M,R}_{kt}$ are constructed analogously.

Appendix table A.1 reports the estimates of the gravity equation that were described in section 6. Appendix table A.2 reports the first-stage results for the specifications in columns 2–5 of table 5. Many of the instruments' coefficient signs are either as expected or insignificant. In the export equation, Z^X_{kt} is positive. In the import equation $Z^{X,R}_{kt}$ is negative as we would expect if U.S. exports to rich countries indicated a U.S. comparative advantage and hence low U.S. imports from China and India. Conversely, the positive coefficient on $Z^{M,R}_{kt}$ reflects a U.S. comparative disadvantage and hence more imports from China and India. To get a good sense of how the instruments are performing, online appendix figure B.1 presents the four partial regression plots for the import equation. These plots are almost identical to the plots for the 3-year, 7-year, and level-fixed-effect specifications.

Table A.1. Gravity Equations

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

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 $*$ denote statistical significance at the 1% and 5% levels, respectively.

Table A.2. First-Stage Regressions

	Imports				Exports			
	Change			Level	Change			Level
VARIABLES	3-year	5-year	7-year	FE	3-year	5-year	7-year	FE
Excluded Instruments								
Z^{M}	-1.535**	-1.614**	-1.623**	-1.701**	0.270	0.350*	0.203	0.638**
	(0.432)	(0.235)	(0.172)	(0.238)	(0.279)	(0.162)	(0.152)	(0.180)
Z^{X}	2.219**	2.202**	2.066**	1.716**	0.612	0.712**	0.854**	0.923**
	(0.519)	(0.299)	(0.227)	(0.331)	(0.339)	(0.207)	(0.176)	(0.194)
$Z^{M,R}$	4.504**	4.199**	4.404**	4.950**	0.703	0.701	0.909*	0.554
	(1.527)	(0.773)	(0.611)	(0.730)	(0.798)	(0.481)	(0.404)	(0.443)
$Z^{X,R}$	-6.942**	-6.812**	-6.696**	-6.219**	0.190	0.141	0.051	-0.515
	(1.447)	(0.757)	(0.596)	(0.867)	(0.803)	(0.527)	(0.459)	(0.460)
Observations	90,615	75,425	59,876	90,615	90,615	75,425	59,876	90,615
R-squared	0.62	0.81	0.87	0.87	0.70	0.84	0.90	0.90
F test	7.013	25.47	43.98	25.24	4.655	12.58	24.61	36.87

Notes: This table reports the first-stage results for the IV regressions in table 5. The dependent variables are service imports and exports. 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 four instruments. $**$ and $*$ denote statistical significance at the 1% and 5% levels, respectively.

Online Appendix

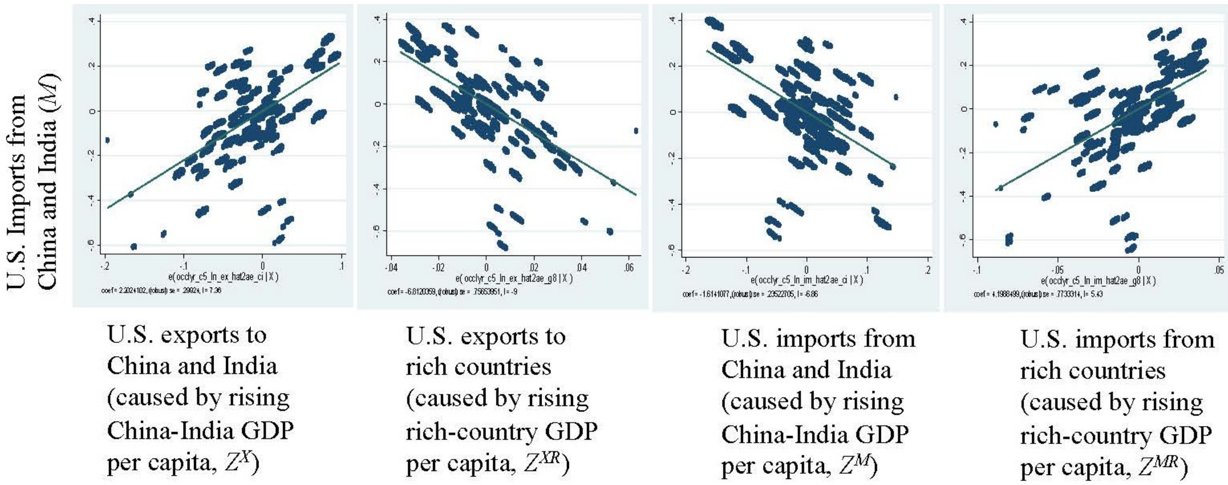
to

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

by

Runjuan Liu and Daniel Trefler

Figure B.1. Partial Regression Plots, First-Stage Import (M_{kt}) Equation



Notes: This figure presents the partial regression plots for the 5-year change specifications of the first-stage import equation reported in table A.2.

Figure B.2. Growth in Other Private Services Trade

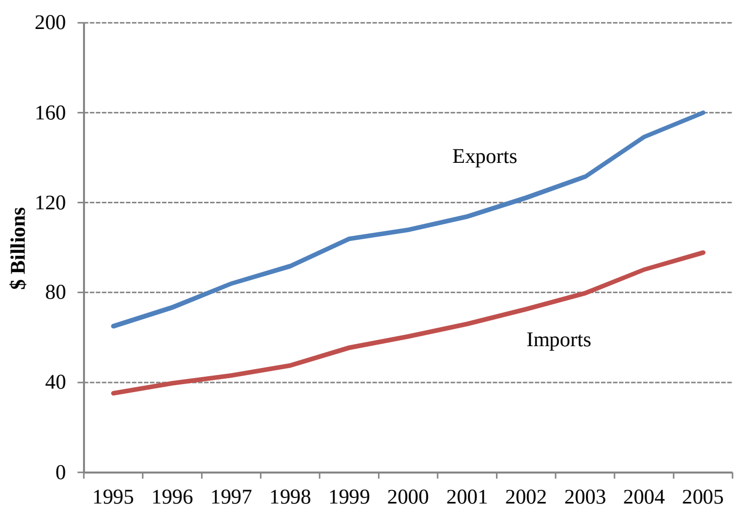


Table B.1. March-to-March CPS Matching Rates

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 B.2. 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 *
routineness	1.110	0.780	0.293	83.780 *
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 B.3. 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	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	5910	Proofreaders and copy markers	43-9081	other business, professional and technical service	95
1310	Surveyors, cartographers, and photogrammetrists	17-1020	construction, architecture, engineering servic	86	5240	Customer service representatives	43-4051	other business, professional and technical service	94
0300	Engineering managers	11-9041	construction, architecture, engineering servic	54	5410	Reservation and transportation ticket agents and travel clerks	43-4181	other business, professional and technical service	94
1010	Computer programmers	15-1021	computer and information services	100	5820	Word processors and typists	43-9022	other business, professional and technical service	94
5810	Data entry keyers	43-9021	computer and information services	100	5860	Office clerks, general	43-9061	other business, professional and technical service	94
1000	Computer scientists and systems analysts	15-10XX	computer and information services	96	5930	Office and administrative support workers, all other	43-9199	other business, professional and technical service	94
1210	Mathematicians	15-2021	computer and information services	96	2830	Editors	27-3041	other business, professional and technical service	93
1230	Statisticians	15-2041	computer and information services	96	2840	Technical writers	27-3042	other business, professional and technical service	93
1240	Miscellaneous mathematical science occupations	15-2090	computer and information services	95	2860	Miscellaneous media and communication workers	27-3090	other business, professional and technical service	93
5830	Desktop publishers	43-9031	computer and information services	93	5420	Information and record clerks, all other	43-4199	other business, professional and technical service	92
1040	Computer support specialists	15-1041	computer and information services	92	2850	Writers and authors	27-3043	other business, professional and technical service	90
1110	Network systems and data communications analysts	15-1081	computer and information services	92	5110	Billing and posting clerks and machine operators	43-3021	other business, professional and technical service	90
5920	Statistical assistants	43-9111	computer and information services	90	2600	Artists and related workers	27-1010	other business, professional and technical service	89
1060	Database administrators	15-1061	computer and information services	75	2630	Designers	27-1020	other business, professional and technical service	86
5800	Computer operators	43-9011	computer and information services	75	5120	Bookkeeping, accounting, and auditing clerks	43-3031	other business, professional and technical service	84
1020	Computer software engineers	15-1030	computer and information services	74	3510	Medical records and health information technicians	29-2071	other business, professional and technical service	83
1400	Computer hardware engineers	17-2061	computer and information services	73	5210	Correspondence clerks	43-4021	other business, professional and technical service	77
0110	Computer and information systems managers	11-3021	computer and information services	55	5400	Receptionists and information clerks	43-4171	other business, professional and technical service	75
1100	Network and computer systems administrators	15-1071	computer and information services	50	0800	Accountants and auditors	13-2011	other business, professional and technical service	72
5230	Credit authorizers, checkers, and clerks	43-4041	finance	80	5520	Dispatchers	43-5030	other business, professional and technical service	72
0840	Financial analysts	13-2051	finance	77	5700	Secretaries and administrative assistants	43-6010	other business, professional and technical service	69
0120	Financial managers	11-3031	finance	76	0940	Tax preparers	13-2082	other business, professional and technical service	68
5200	Brokerage clerks	43-4011	finance	67	5140	Payroll and timekeeping clerks	43-3051	other business, professional and technical service	67
0830	Credit analysts	13-2041	finance	64	5150	Procurement clerks	43-3061	other business, professional and technical service	67
4820	Securities, commodities, and financial services sales agents	41-3031	finance	51	5350	Order clerks	43-4151	other business, professional and technical service	67
0950	Financial specialists, all other	13-2099	finance	50	5100	Bill and account collectors	43-3011	other business, professional and technical service	65
1540	Drafters	17-3010	industrial engineering	98	0820	Budget analysts	13-2031	other business, professional and technical service	60
1550	Engineering technicians, except drafters	17-3020	industrial engineering	98	3300	Clinical laboratory technologists and technicians	29-2010	other business, professional and technical service	59
1350	Chemical engineers	17-2041	industrial engineering	72	5600	Production, planning, and expediting clerks	43-5061	other business, professional and technical service	54
1410	Electrical and electronic engineers	17-2070	industrial engineering	70	5900	Office machine operators, except computer	43-9071	other business, professional and technical service	51
1430	Industrial engineers, including health and safety	17-2110	industrial engineering	70	4830	Travel agents	41-3041	other business, professional and technical service	50
1460	Mechanical engineers	17-2141	industrial engineering	70	5010	Switchboard operators, including answering service	43-2011	other business, professional and technical service	50
1200	Actuaries	15-2011	insurance	96	5260	File Clerks	43-4071	other business, professional and technical service	50
5840	Insurance claims and policy processing clerks	43-9041	insurance	93	5360	Human resources assistants, except payroll and timekeeping	43-4161	other business, professional and technical service	50
0860	Insurance underwriters	13-2053	insurance	85	1810	Market and survey researchers	19-3020	research, development and testing services	90
2150	Miscellaneous legal support workers	23-2090	legal services	52	1800	Economists	19-3011	research, development and testing services	89
2140	Paralegals and legal assistants	23-2011	legal services	51	1600	Agricultural and food scientists	19-1010	research, development and testing services	85
1220	Operations research analysts	15-2031	management, consulting, public relation serv	82	1610	Biological scientists	19-1020	research, development and testing services	83
0360	Natural sciences managers	11-9121	management, consulting, public relation serv	56	1710	Atmospheric and space scientists	19-2021	research, development and testing services	81
0020	General and operations managers	11-1021	management, consulting, public relation serv	55	1530	Engineers, all other	17-2199	research, development and testing services	72
0140	Industrial production managers	11-3051	management, consulting, public relation serv	55	1340	Biomedical engineers	17-2031	research, development and testing services	71
0520	Wholesale and retail buyers, except farm products	13-1022	management, consulting, public relation serv	55	1450	Materials engineers	17-2131	research, development and testing services	71
0530	Purchasing agents, except wholesale, retail, and farm products	13-1023	management, consulting, public relation serv	55	1440	Marine engineers and naval architects	17-2121	research, development and testing services	69
0700	Logisticians	13-1081	management, consulting, public relation serv	55	1720	Chemists and materials scientists	19-2030	research, development and testing services	66
0050	Marketing and sales managers	11-2020	management, consulting, public relation serv	53	1760	Physical scientists, all other	19-2099	research, development and testing services	66
0600	Cost estimators	13-1051	management, consulting, public relation serv	50	1650	Medical scientists	19-1040	research, development and testing services	55
2920	editors	27-4030	other business, professional and technical ser	95	1900	Agricultural and food science technicians	19-4011	research, development and testing services	55
4940	Telemarketers	41-9041	other business, professional and technical ser	95	1910	Biological technicians	19-4021	research, development and testing services	55
5020	Telephone operators	43-2021	other business, professional and technical ser	95	1920	Chemical technicians	19-4031	research, development and testing services	55