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Mary Amiti
Shang-Jin Wei

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1050 Massachusetts Avenue
Cambridge, MA 02138
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ABSTRACT

The practice of sourcing service inputs from overseas suppliers has been growing in response to new technologies that have made it possible to trade in some business and computing services that were previously considered non-tradable. This paper estimates the effects of offshoring on productivity in US manufacturing industries between 1992 and 2000, using instrumental variables estimation to address the potential endogeneity and errors in measurement of offshoring. It finds that service offshoring has a significant positive effect on productivity in the US, accounting for around 11 percent of productivity growth during this period. Offshoring material inputs also has a positive effect on productivity, but the magnitude is smaller accounting for approximately 5 percent of productivity growth.

Mary Amiti
Trade and Investment Division
Research Department
International Monetary Fund
700 19th Street
Washington, DC 20431
mamiti@imf.org

Shang-Jin Wei
Trade and Investment Division
Research Department
International Monetary Fund
700 19th Street
Washington, DC 20431
and NBER
swei@imf.org

1. Introduction

New technologies are making it increasingly possible for firms to source their service inputs from suppliers abroad. Recent examples include call centers in India, as well as some more skill intensive tasks such as computer software development. The practice of global production networks has been commonplace for decades. In the OECD, the use of imported inputs in producing goods that are exported accounted for 21 percent of trade in 1990, and this grew by 30 percent between 1970 and 1990 (see Hummels, Ishii and Yi, 2001).[1] However, until recently, global production networks mostly involved the offshoring of manufactured intermediate inputs, whereas now many services that were previously seen as non-tradable have become tradeable.[2] Whilst service offshoring by manufacturing industries in the US is still at fairly low levels, the practice is growing rapidly, at an average annual rate of 6.3 percent between 1992 and 2000.[3] (See Table 1). Yet the empirical evidence on the effects of service offshoring is scant. In this paper we estimate whether there are any benefits of offshoring in the form of productivity growth.[4]

[1]The fragmentation of production stages has been widely studied within a trade theoretic framework by Dixit and Grossman (1982), Jones and Kierzkowski (1990, 1999, 2001), Deardorff (1998, 2001), Cordella and Grilo (1998), Amiti (2005) and others. This same phenomenon has also been referred in the literature as international production sharing, globalized production, de-localization, slicing up the value chain and offshoring. Some authors go on to distinguish between who owns the production stage abroad: when it is owned by the same firm it is referrred to as vertical FDI or intra-firm trade; and when it is owned by a foreign firm is it referred to as arms length trade or international outsourcing. Antras and Helpman (2004) distinguish between domestic and international outsourcing.

[2]This increasing practice of service offshoring has led to strong opposition. Support for free trade among white collar workers with incomes over $100,000 slid from 57 percent in 1999 to 28 percent in 2004, according to a study by the University of Maryland. Furthermore, on March 4, 2004, the US Senate passed restrictions on offshoring by barring companies from most federal contracts if they planned to carry out any of the work abroad. Some exceptions were to apply, for example defence, homeland security and intelligence contracts deemed necessary for national security, but this legislation was not passed in the House.

[3]See Amiti and Wei (2005a) for world trends in service offshoring.

[4]Note that we do not undertake an overall welfare analysis, and recognize that there could be negative effects such as a deterioration in the terms of trade. See Samuelson (2004).

Offshoring can increase productivity either due to compositional or structural changes. If a firm relocates its relatively inefficient parts of the production process to another country, where they can be produced more cheaply, it can expand its output in stages it has comparative advantage. In this case, the average productivity of the remaining workers increases due to the change in the composition of the workforce. Moreover, structural changes that increase the productivity of the remaining workers are also likely. These benefits can arise due to offshoring material inputs or service inputs due to the access of new input varieties. However, even larger benefits are likely to arise from offshoring service inputs, such as computing and information services, either due to workers becoming more efficient from restructuring or through firms learning to improve the way activities are performed from importing a software package, for example. We estimate the effects of both service and material offshoring on productivity.

Measuring offshoring by industry requires detailed input/output tables. These are provided on an annual basis for the period 1992 to 2000 by the Bureau of Labor Statistics (BLS) for the US economy. We combine the input/output information with trade data, to measure service and material offshoring, defined as the share of imported services and materials, respectively, analogous to the measure of material offshoring in Feenstra and Hanson (1999). Thus our measure includes imports from affiliated and unaffiliated firms. Total factor productivity (TFP) and labor productivity are also measured using data from the BLS. The data are aggregated up from 450 SIC manufacturing industries to 96 manufacturing industries in order to match the level of aggregation of the input/output (I/O) tables, which provides details of service inputs. It is important to net out service inputs when calculating productivity in order to avoid conflating measures due to missing inputs. Labor productivity in manufacturing grew at an annual average rate of 4 percent between 1992 and 2000.

A key estimation issue is the possible endogeneity of offshoring. High productivity firms may be the ones that are more likely to engage in global production strategies which could lead to reverse causality. Alternatively, it could be the low productivity firms that engage in offshoring in the expectation that this would improve productivity, hence it is unclear which way the bias would go. If the same set of firms are most likely to engage in offshoring over the sample period then industry fixed effects in a time differenced equation would suffice. However, if there are time varying factors that affect offshoring and productivity growth then it is necessary to instrument for offshoring. Service offshoring is also likely to be measured with errors leading to a downward bias. Instrumental variable estimation can potentially address this bias as well.

A good instrument is one that only affects productivity through service offshoring, and has sufficient explanatory power in predicting changes in service offshoring.[5] Changes in technology that have made transactions possible through the internet and digital telephone services are likely candidates for changes in service offshoring. Freund and Weinhold (2002) found evidence that internet penetration, measured by the number of internet hosts in a country, had a positive and significant effect on services trade between 1997 and 1999. In line with this, we use the number of internet users in the countries that the US imports most of its service inputs, to reflect the change in technology that has enabled the offshoring of services. These time varying country measures are interacted with the share of services in

[5] See Murray (2005) for a discussion of desirable features in instruments.

total output at the beginning of the period to provide time/industry varying instruments. Those with higher service intensities would be most affected by changes in technology that enable service offshoring. The instrument for material offshoring is the freight cost of inputs.

The results show that service offshoring has a significant positive effect on productivity in the manufacturing sector. It accounts for around 11 percent of labor productivity growth over the sample period. These results are robust to including additional controls such as the use of high technology capital, and the share of total imports. The instrumental variables estimates indicate a slightly larger positive productivity effect from service offshoring than those indicated by OLS. Material offshoring also has a positive effect on productivity but this was not robust across all specifications, and the magnitude of the effects is lower than service offshoring, only accounting for 5 percent of total labor productivity growth between 1992 and 2000.

This is the first comprehensive study to find a link between service offshoring and productivity.[6] There is only one other study on productivity and international offshoring of services in the US (see Mann, 2004),[7] which is a "back of the envelope" type calculation and considers only the IT industry. Mann calculates that offshoring in the IT industry led to an annual increase in productivity of 0.3 percentage points for the period 1995 to 2002,

[6] A number of other studies have focused on employment effects from offshoring. For example, Amiti and Wei (2005b) shows that offshoring has a small negative effect on employment using disaggregated manufacturing industry data (450 industries) in the US. However, this affect disappears at a more aggregated level of 96 industries indicating that there is sufficient growth in demand in other industries within these broadly defined classifications to offset any negative effects. Harrison and McMillan (2005) report correlations between US multinational employment at home and abroad. Other studies such as Ekholm and Hakkala (2005) go on to disentangle the employment effects by skill, using Swedish data.

[7] Ten Raa and Wolff (2001) find evidence of positive effects of domestic outsourcing on US manufacturing productivity – it explains 20% of productivity growth, but does not consider the effects of international outsourcing.

which translates into a cumulative effect of $230 billion in additional GDP.[8] There have been a few more studies on the productivity effects of offshoring using European data. Gorg and Hanley (2003) find that service offshoring had a positive impact on productivity in the electronics industry in Ireland between 1990 and 1995. However, this affect disappears when they extend the study to all manufacturing industries in Ireland, and over a longer period, between 1990 and 1998 (see Gorg *et al* , 2005). The only instruments provided in these studies are predetermined ones whereas our study also includes exogenous instruments. A related study by Girma and Gorg (2004) finds positive evidence of service outsourcing on labor productivity and total factor productivity in the UK between 1980 and 1992, but this study does not distinguish between domestic and foreign outsourcing, and the study only covers three manufacturing industries.[9] In contrast, we focus on international sourcing of inputs and our data covers all manufacturing industries in the US.

The rest of the paper is organized as follows. Section 2 sets out the model and estimation strategy. Section 3 describes the data. Section 4 presents the results and Section 5 concludes.

2. Model and Estimating Framework

This section describes a conceptual framework that motivates the empirical specification.

[8]This is calculated as follows: globalization led to a fall of 10 to 30 percent in prices of IT hardware; taking the mid-point of 20% times the price elasticity of investment equals the change in IT's investment to productivity growth. See footnote 5 in Mann (2004).

[9]Egger and Egger (2005) study the effects of international outsourcing of materials inputs. They find that material input outsourcing has a negative effect on productivity of low skilled workers in the short-run but a positive effect in the long-run. They found that international outsourcing contributed to 3.3% of real value added per low-skilled worker in the EU from 1993 to 1997. They attribute the negative short-run effect to imperfections in the EU labor and goods markets. However, they do not include services in their study.

2.1. Model

The production function for an industry i is given by

$$Y_i = A_i(oss_i, osm_i)F(L_i, K_i, M_i, S_i), \tag{2.1}$$

where output, Y_i, is a function of labor, L_i, capital, K_i, materials, M_i, and service inputs, S_i. The technology shifter, A_i, is a function of offshoring of services (oss_i), and offshoring of material inputs (osm_i).

There are at least four possible channels through which offshoring can affect productivity, A_i: (i) a static efficiency gain; (ii) restructuring; (iii) learning externalities; and (iv) variety effects. First, when firms decide to outsource materials or services to overseas locations they relocate the less efficient parts of their production stage, so average productivity increases due to a compositional effect. Second, the remaining workers may become more efficient if offshoring makes it possible for firms to restructure in a way that pushes out the technology frontier. This is more likely to arise from offshoring of service inputs, such as computing and information, rather than offshoring of material inputs. Third, efficiency gains might arise as firms learn to improve the way activities are performed by importing services. For example, a new software package can improve the average productivity of workers.[10] Fourth, productivity could increase due to the use of new material or service input varieties as in Ethier (1982). Since we cannot distinguish the exact channel of the productivity gain arising from offshoring, we will specify it in this more general way as entering A_i.

[10] Most people would expect that learning externalities would go from the US to other countries rather than to the US, but it is in principle a possibility and there has been some evidence showing that US productivity increased as a result of inward FDI. See Keller and Yeaple (2003).

We assume that a firm chooses the total amount of each input in the first stage, and chooses what proportion of material and service inputs will be imported in the second stage. The fixed cost of importing material inputs, F_k^M, and the fixed cost of importing service inputs, F_k^S, vary by industry k. This assumption reflects that the type of services or materials required are different for each industry, and hence importing will involve different amounts of search costs depending on the level of the sophistication of the inputs.

2.2. Estimation

Taking the log of equation 2.1, and denoting first differences by Δ, the estimating equation becomes

$$\begin{aligned}\Delta \ln Y_{it} &= \alpha_0 + \alpha_1 \Delta oss_{it} + \alpha_2 \Delta osm_{it} \\ &\quad + \beta_1 \Delta \ln L_{it} + \beta_2 \Delta \ln K_{it} + \beta_3 \Delta \ln M_{it} + \beta_4 \Delta \ln S_{it} + \delta_t D_t + \delta_i D_i + \varepsilon_{it}.\end{aligned} \tag{2.2}$$

This first difference specification controls for any time invariant industry specific effects such as industry technology differences. In this time differenced specification, we also include year fixed effects, to control for any unobserved time-varying effect common across all industries that affect productivity growth, and in some specifications we also include industry fixed effects. Some industries may be pioneering industries that are high growth industries and hence more likely to outsource; and some industries might be subject to higher technical progress than others. Adding industry fixed effects to a time differenced equation takes account of these factors, provided the growth or technical progress is fairly constant over time. We estimate equations 2.2 using ordinary least squares, with robust standard errors corrected for clustering. We hypothesize that α_1 and α_2 are positive. We also include one period lags of the offshoring variables to take account that productivity effects may not be instantaneous.[11]

There are a number of econometric issues that will need to be addressed. First, the choice of inputs is endogenous. To address this, we estimate the total factor productivity equation using the Arrellano-Bond (1991) GMM estimator, which uses all possible lags of each variable as instruments. An alternative way to address the endogeneity of inputs is to estimate productivity as value added per worker. Since the dependent variable is redefined as real output less materials and services, divided by labor, the inputs would not be included as explanatory variables.

Second, there may also be a problem of potential endogeneity of offshoring, which is not adequately addressed with lagged values as instruments. More productive industries might self select into offshoring, or conversely, firms that expect a fall in productivity growth might increase their level of offshoring in the hope of increasing their productivity. Hence the bias could go either way. In addition, the extent of offshored activities are likely to be measured with errors which also contributes to the downward bias. We use two-stage least squares to address this concern, as well as the Arellano-Bond GMM analysis, with additional exogenous instruments, which we describe below.

3. Data and measurement of offshoring

We estimate the effects of offshoring on productivity for the period 1992 to 2000. The offshoring intensity of services ($oss_{i,t}$) for each industry i at time t is defined as the share of

[11] Longer lags were insignificant.

imported service inputs, and is calculated analagously to the material offshoring measure in Feenstra and Hanson (1996, 1999), as follows:

$$oss_i = \sum_j \left[\frac{\text{input purchases of service } j \text{ by industry } i, \text{ at time } t}{\text{total non-energy inputs used by industry } i, \text{ at time } t} \right] * \left[\frac{\text{imports of service } j, \text{ at time } t}{\text{production}_j + \text{imports}_j - \text{exports}_j \text{ at time } t} \right]. \tag{3.1}$$

The first square bracketed term is calculated using annul input/output tables from 1992 to 2000 constructed by the Bureau of Labor Statistics (BLS), based on the Bureau of Economic Analysis (BEA) 1992 benchmark tables. The BEA use SIC 1987 industry disaggregation, which consist of roughly 450 manufacturing industries. These are aggregated up to 96 input/output manufacturing codes by the BLS.[12] We also include the following five service industries as inputs to the manufacturing industries: telecommunications, insurance, finance, business services, and computing and information. These service industries were aggregated up to match the IMF Balance of Payments statistics. Business services is the largest component of service inputs with an average share of 12% in 2000; then finance (2.4%); telecommunications (1.3%); insurance (0.5%); and the lowest share is computing and information (0.4%).

The second square bracketed term is calculated using international trade data from the IMF Balance of Payments yearbooks. Unfortunately, imports and exports of each input by industry are unavailable so an economy wide import share is applied to each industry. As an

[12] We were unable to use the more disaggregated BEA I/O tables because the next available year is 1997 and this is under a different classification system, called NAICS. Unfortunately, the concordance between SIC and NAICS is not straightforward, thus there would be a high risk that changes in the input coefficients would reflect reclassification rather than changes in input intensties. In contrast, the BLS I/O tables use the same classification throughout this period.

example, the US economy imported 2.2 percent of business services in 2000 – we then assume that each manufacturing industry imports 2.2 percent of its business service that year. Thus, on average, the offshoring intensity of business services is equal to 0.12*0.022=0.3 percent. We aggregate across the five service inputs to get the average service offshoring intensity for each industry, oss_i. An analogous measure is constructed for material offshoring, denoted by osm_i.

Table 1 presents averages of offshoring intensities of materials and services, weighted by industry output. The average share of imported service inputs in 2000 is only 0.3 percent whereas the average share of imported material inputs is 17.4 percent. Both types of offshoring have been increasing over the sample period, with higher growth rates for service offshoring at an annual average of 6.3 percent compared to an average growth rate of 4.4 percent for materials.

The breakdown of the two components of the offshoring intensity ratio for each service category is provided for 1992 and 2000 in Table 2. The first column shows the average intensity of each service category (the first term in equation 3.1), and the last column gives the average import intensity of each service category (the second term in equation 3.1). We see from column 1 that business services is the largest service category used across manufacturing industries, and this has grown from an average of 9.7 percent in 1992 to 12 percent in 2000. There is also much variation between industries. For example, in 2000, in the "household audio and video equipment" industry business services only accounted for 2 percent of total inputs whereas in the "greeting cards" industry it was 45 percent. From the last column, we see that the import share of all service category, except communications, increased over the period.

There are a number of potential problems with these offshoring measures that should be noted. First, they are likely to under-estimate the value of offshoring because the cost of importing services is likely to be lower than the cost of purchasing them domestically. While it would be preferable to have quantity data rather than current values this is unavailable for the United States. Second, applying the same import share to all industries is not ideal, but given the unavailability of imports by industry this is our "best guess". The same strategy was used by Feenstra and Hanson (1996, 1999) to construct measures of material offshoring. This approach apportions a higher value of imported inputs to the industries that are the biggest users of those inputs. Although this seems reasonable, without access to actual import data by industry it is impossible to say how accurate it is. Despite these limitations, we believe that combining the input use information with trade data provides a reasonable proxy of the proportion of imported inputs by industry.

The BLS data sources are used for estimation of productivity to match the level of aggregation of the offshoring ratios. However, capital stock was only available from the Annual Survey of Manufacturers (ASM) at the SIC level so needed to be aggregated up to the BLS I/O level. We adopt the perpetual inventory method to extend the capital stock series beyond 1996, using average depreciation rates that were applied in the NBER (Bartelsman and Gray, 1996) database: 7.7 percent depreciation for equipment and 3.5 percent for structures. Productivity is estimated at the more aggregate BLS I/O industry level because service inputs by industry are only available from the I/O tables and these need to be subtracted from gross output in order to ensure that productivity growth is not inflated in service-intenstive industries as an artifact of an omitted variable. All the summary statistics are provided in Table 3.

4. Results

We estimate equation 2.2 at the industry level for the period 1992 to 2000. All variables are entered in log first differences, except offshoring which is the change in the offshoring intensity. All estimations include year fixed effects and some specifications also include industry fixed effects. The errors have been corrected for heteroskedasticity by clustering at the industry level.

4.1. Total Factor Productivity

The results from estimating equation 2.2 using OLS are presented in Table 4. Columns 1 to 4 include year fixed effects, and columns 5 to 9 include year and industry fixed effects. All columns show that service offshoring has a positive significant effect on total factor productivity. That is, holding all factors of production constant (total services, materials, labor and capital stock), increasing the share of service offshoring leads to higher output. In the first column we only include the change in offshoring in period t; in the second column we only include the lagged value $(t-1)$; whereas in the third column we include both the contemporaneous and lagged values of offshoring. In column 4, we split employment by production and non-production workers (proxies for unskilled and skilled workers respectively, to ensure that changes in skill composition are not driving the results.[13] We find this breakdown hardly affects the size of the offshoring coefficients. In each specification, service offshoring

[13] This was the most detailed skill level data available.

is individually significant in the current and lagged periods, and jointly significant, with a p-value less than 0.01. Similarly, service offshoring is positive and significant in columns 5 to 8 with industry effects, with the coefficients now larger. The coefficient on material offshoring is positive and significant only in some of the specifications.

The endogeneity of input choices could result in biased estimates using OLS estimation. In addition, offshoring may be measured with errors. To address these issues, we re-estimate equation 2.2 using the Arrellano-Bond dynamic panel estimation technique in column 9. In this specification, all possible lags of each variable are used as instruments, and the lagged dependent variable is also included but this is insignificant. The coefficient on service offshoring remains positive and significant, with the size of the joint effect of the current and lagged offshoring variables a little smaller than the coefficients in the OLS estimation. The effect of material offshoring is now higher, with the lagged coefficient positive and significant.

4.2. Labor Productivity

An alternative way to address the endogeneity of labor, material and service inputs is to estimate the effect of offshoring on labor productivity. This is measured by value added per worker, calculated by taking the difference between real output and real materials and services, divided by employment. The results are presented in Table 5.[14] In columns 1 to 3, with only year fixed effects, we see that lagged service and material offshoring are positive and significant in columns 2 and 3. Once we add industry effects in columns 4 to 6, the size of the coefficients on service offshoring become larger, and both the contemporaneous and

[14] All specifications include capital stock as an explanatory variable. However, estimates without capital stock produce the same results.

lagged variables are significant, however material offshoring becomes insignificant.

4.2.1. Additional Controls

There may be concern that the service offshoring measure is correlated with omitted variables such as high-technology capital or total imports, which may be inflating the coefficients on service offshoring. To address this we include two measures of high technology capital as in Feenstra and Hanson (1999); and the share of imports by industry. The data for high-technology capital stock are estimates of the real stock of assets within two-digit SIC manufacturing industries, from the BLS. High-technology capital includes computers and peripheral equipment, software, communication equipment, office and accounting machinery, scientific and engineering instruments, and photocopy and related equipment. Each capital asset is then multiplied by its ex post rental price to obtain the share of high-tech capital services for each asset within each two-digit SIC industry (also estimated by BLS), and reflects the internal rate of return in each industry and capital gains on each asset. As an alternative, the capital stock components are multiplied by an ex ante measure of rental prices used by Berndt and Morrison(1995), where the Moody rate of Baa bonds is used to measure the ex ante interest rate and the capital gains term is excluded.

The high-tech capital share measured with ex post rental prices is included in column 1 of Table 6; and the high-tech capital share with ex ante rental prices in column 2. Neither of these measures are significant. Import share, defined as the ratio of total imports to output by industry, is included in column 3. This shows that tougher import competition has a positive effect on labor productivity, but its inclusion leaves the effect of service offshoring unchanged.

Again, we find that the service offshoring coefficients are significant and larger with industry effects in columns 4, 5 and 6, and lagged material offshoring is also significant with fixed industry effects. We see from column 4 that the ex post measure of high-tech capital becomes significant at the 10% level whereas the ex ante measure remains insignificant. The import share with industry fixed effects, in column 6, also becomes insignificant. Although the high-tech capital share, with industry fixed effects, has a positive effect on productivity it does not affect the size of the service offshoring coefficients (comparing column 4, Table 6 with column 6, Table 5).

4.2.2. Sensitivity: Measurement Error

There is a risk that taking first time period differences could induce measurement error, particularly when the variables are aggregated at the industry level.[15] To address this concern, we re-estimate the equations using longer time differences to help wash out measurement error. In columns 1 to 3 of Table 7, all variables are in two period differences, and include industry fixed effects. We see that as in the previous table service offshoring is positively correlated with labor productivity and material offshoring is insignificant. The ex post high-tech capital measure is significant at the 5 percent level and import share has a negative significant effect on productivity.[16] In the next three columns, all variables are calculated as the difference between the average of the last three years less the average of the first three years.[17] This averaging and differencing helps reduce measurement error and having only

[15] See Griliches and Hausman (1986).

[16] The ex ante measure is insignificant in all specifications so we only include the ex post measure in all subsequent tables to conserve space.

[17] Two outliers, computer and electronics industries, were dropped from the long difference estimations because they had unusually high growth in value added that was unrelated to outsourcing. The computing

one observation per industry avoids any serial correlation, but this is at the cost of a smaller number of observations. The technology and import share variables are now insignificant. Interestingly, in all of the specifications service offshoring is positively correlated with labor productivity, and in these long differenced specifications so is material offshoring but with much smaller coefficients.

4.2.3. Sensitivity: Outliers

With industry level data and a short time series there is concern that outlier industries might be driving the results. To check that this is not the case here we reestimate the equations, both in one period and two period differences, using robust regressions in columns 1 (one period differences) and 3 (two period difference) – this uses an iterative process, giving less weight to outlier observations.[18] The service offshoring coefficients are still significant but the point estimates are now smaller. Inspection of the data reveals that the tobacco industry is the main outlier. Omitting tobacco from the estimation (in columns 2 and 5) provides similar results to the robust regressions. However, omitting the two high-tech industries, computing and electronics, in columns 3 and 6 makes almost no difference to the results. To ensure that no one industry is driving the results, we drop tobacco from the subsequent estimations.

industry experienced growth in labor productivity 6 standard deviations higher than the mean and the electronics industry 5 standard deviations higher than the mean.

[18] Using the rreg command in STATA, an intial screening is performed based on Cook's distance >1 to eliminate gross outliers before calculating starting values, followed by an iterative process: it performs a regresssion, calculates weights based on absolute residuals, and regresses again using those weights, beginning with Huber weights followed by biweights as suggested by Li (1985).

4.3. Endogeneity

Which industries engage in more offshoring may not be random, and hence could lead to biased estimates. If the industries that self-select into offshoring do not change over time then the industry effects should take account of this. However, if there is some time varying effect, then the bias might persist. In order to address this potential problem, we re-estimate the equations using instruments for service offshoring and material offshoring. An instrumental variables approach can also mitigate potential bias from measurement error. A good instrument is one that would only affect productivity through its effect on offshoring.

New technologies that have led to an increase in service offshoring can be related to the level of internet development in foreign countries, which can be measured by the number of internet hosts or internet users in the countries that supply the largest share of imported services to the US. Of course, there are also other technological changes that affect service offshoring, such as changes in digital telephone technology. It turns out that all of these measures are highly correlated so could not all be included in one estimation, and when included in separate estimations they produced similar results. Thus the number of internet hosts can be thought of as a proxy for technology changes more generally.

Industries that rely heavily on service inputs are more likely to respond to technology changes that reduce the cost of service offshoring. To capture this idea, we interact the number of internet hosts in each country c at time t, (IH_{ct}) with total services as a share of output at the beginning of the sample for each industry in the first stage regression, thus

$$\Delta oss_{it} = f\left(\sum_c \gamma_c * \left(\Delta \ln IH_{c,t} * \frac{services_{i,1992}}{output_{i,1992}}\right)\right),$$

which provides us with c instruments that vary by industry and time. Although the offshoring measure is not by country, firms respond to technological changes in different countries when making their importing decisions. The $\gamma_c' s$ will be estimated in the first stage regression of the two-stage least squares estimation. We would expect that industries would respond to technological developments in different ways as each country differs in its technology and the type of services they provide.

The number of internet users are from the International Telecommunication Union (2003) Yearbook. To determine which countries' internet developments to include we turn to the BEA bilateral services trade statistics to identify the countries that the US imports the largest shares of its services. For the year 2000, these countries are UK (21%), Canada (10%), Japan (7%), and Germany (7%). We also include the number of internet hosts in India. Even though the US share of service imports from India are only 1.5% as reported by the BEA, Indian statistical sources show this number to be much higher.[19]

For material offshoring, we use the average freight and insurance rate, FI_{it}, on US imports, averaged across all partner countries, from import data at the fob and cif basis provided by the US Census Bureau. Then for each industry i, this is weighted by the share of input j used in industry i, using weights from the I/O tables, a_{ij} at the beginning of the sample (1992).

$$\Delta \ln FI_{i,t} = \Delta \ln \left(\sum_j a_{ij,1992} * FI_{j,t} \right)$$

The results for the one period differenced variables are presented in the first four columns

[19] See Wedding, 2005.

of Table 9; and for two period difference variables in columns 4 to 8. In all of the specifications, the instruments for service offshoring provide a good fit in the first stage regressions. In column 1, where only one endogenous variable is included, lagged service offshoring, the $F(5, 44) = 14.27$ with a p-value less than 0.01. When there is more than one endogenous variable, the Shea partial R-squared provides an indication of the goodness of fit, taking into account the collinearity between the endogenous variables.[20] In all specifications, this statistic indicates a good fit for the first stage regression of service offshoring, with values ranging between 0.31 to 0.43, however the instrument for material offshoring does not provide such a good fit.

The first stage regression results for lagged service offshoring are provided in panel B of Table 9. All the internet coefficients are significant. Note that the first stage regression also includes all the other variables from the second stage, including year and industry effects, which are suppressed to save space. In all cases, they pass the overidentification tests. The p-values are higher when only the lagged offshoring variable is included ranging from 0.11 to 0.59, indicating that these are statistically valid instruments. One might expect that the coefficients on the interactive internet host variables would be positive, however some of these coefficients are actually negative. This is likely due to collinearity of the internet measures across countries. Since our main interest is in the aggregate effect, rather than individual country effects, this does not invalidate the instruments.

The net effect of service offshoring on productivity remains positive in all columns, however, in column 1 with only the lagged offshoring variable included the coefficient is insignif-

[20] For further details, see Shea (1997).

icant with a z-statistic equal to 1.52. Column 2 shows that the contemporaneous and lagged service offshoring variables are jointly significant at the 10 percent level but not individually significant. Once we control for high-tech capital and import share, the lagged service offshoring becomes significant at the 10 percent level in column 4. It may be that these variables are not highly significant because the instruments are not able to take care of all the errors in measuring offshoring, and the errors possibly induced by first differencing.

The two period differenced results using instrumental variables are presented in columns 4 to 8, and the OLS two-period differenced results are included in column 9 for comparison. We see that the lagged service offshoring variable is positive and significant in all of these specifications, with the coefficient larger than the OLS estimates (comparing columns 8 and 9). In the two-period difference results, using internet users or the number of digital telephone users produces the same results as internet hosts.

A more general specification would allow for a lagged dependent variable, but this would result in a correlation with the error term, which is particularly problematic in a fixed effects model. Thus, as a final robustness check on the labor productivity estimates we re-estimate the equations using Arrellano-Bond GMM analysis. We also include the high-tech capital share and import share variables in all estimations. In the first three columns of Table 10 we use all lagged variables as instruments. In the next three columns we also include the number of internet hosts by most important partner country, interacted with service intensity at the beginning of the period, as well as freight costs. The results show that service offshoring and high-tech capital have a positive significant effect on labor productivity, material offshoring has a positive insignificant effect, and imports have a negative effect. In all of the specifications, service offshoring has a positive and significant effect on productivity whereas the positive effect from material offshoring is not robust across all specifications.

4.4. Discussion of Results

To get an idea of the magnitude of the effects, we calculate the total effect of service offshoring on productivity using the coefficients from the IV estimates. These range from 0.3 using the Arellano-Bond estimates in column 6, Table 10, to 0.38 using one period differences two-stage least squares estimates (column 4, Table 9) and 0.46 using two-period differenced variables in column 8 of Table 9. Service offshoring increased by 0.1 percentage point over the sample period, from 0.18 to 0.29 (see Table 1) so this implies that service offshoring led to an increase of 3 to 4.5 percent in labor productity over the sample period. Given that value added per worker increased by an average of 35 percent over the sample period, this suggests that service offshoring accounted for 11 to 13 percent of the average growth in labor productivity.

5. Conclusion

Sourcing service inputs from abroad by US firms is growing rapidly. Although the level of service offshoring is still low compared to material offshoring, this business practice is expected to grow as new technologies make it possible to access cheaper foreign labor and different skills. Thus it is important to understand its effects on the domestic economy. In this paper, we analyzed the effects of service and material offshoring on productivity in manufacturing industries in the US between 1992 to 2000. We found that offshoring has a positive effect on productivity: service offshoring accounts for 11 to 13 percent of labor productivity growth over this period; and material offshoring for 3 to 6 percent of labor productivity.

The positive effect of service offshoring on productivity is robust to the inclusion of industry fixed effects, high-technology capital share and import shares. The key econometric issue in this analysis is finding a valid instrument for service offshoring. We used the number of internet hosts in the countries that supply the largest shares of services to the US. These reflect changes in new technologies that would only affect US productivity through their effect on offshoring. These time varying measures are interacted with the service intensity at the beginning of the period to reflect that those industries that rely heavily on services are more likely to respond to new technologies that affect offshoring costs. We find the positive effect of service offshoring on productivity is robust across all specifications, however the material offshoring effect is only significant in some of the specifications.

Our analysis suggests a number of possible avenues for future research. First, data limitations have prevented us from identifying the channels through which service offshoring has increased productivity. Improvements in the collection of data at the firm level with information distinguishing between domestic input purchases from imports, combined with detailed skill level data would be a major step forward in making this type of analysis possible. Second, as well as productivity effects, offshoring is likely to have terms of trade and income distribution effects. Feenstra and Hanson (1999) found that material outsourcing explained about 40 percent of the increase in the skill premium in the US in the 1980s. Given that service offshoring is likely to be more skill intensive than material offshoring, it will be interesting to see what effects, if any, service offshoring has on the wage skill premium.

References

[1] Amiti, Mary (2005). Location of Vertically Linked Industries: Agglomeration versus Comparative Advantage. *European Economic Review*, 49(4), 809-832.

[2] Amiti, Mary and Shang-Jin Wei (2005a). Fear of Outsourcing: Is it Justified?. *Economic Policy*, April issue, 308-348.

[3] Amiti, Mary and Shang-Jin Wei (2005b). Service Offshoring, Productivity and Employment: Evidence from the US. International Monetary Fund Working Paper.

[4] Antras, Pol and Elhanan Helpman (2004). Global Sourcing. *Journal of Political Economy* 112(3), 552-580.

[5] Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies* 58, 277-297.

[6] Bartelsman, Eric J. and Wayne Gray (1996). The NBER Manufacturing Productivity Database, NBER Technical Working Paper No. 205.

[7] Berndt, Ernst R. and Catherine J. Morrison (1995). High-Tech Capital Formation and Labor Composition in U.S. Manufacturing Industries: An Exploratory Analysis. *Journal of Econometrics*, 65(1), 9-43.

[8] Cordella, Tito and Isabel Grilo (1998). 'Globalization' and Relocation in a Vertically Differentiated Industry. CEPR Discussion Paper No. 1863.

[9] Deardorff, Alan V. (2001). Fragmentation in Simple Trade Models. *North American Journal of Economics and Finance* 12(2), 121-137.

[10] Deardorff, Alan V. (1998). Fragmentation Across Cones, Research Seminar. International Economics Discussion Paper No. 427.

[11] Dixit, Avinash K. and Gene M. Grossman (1982). Trade and Protection with Multistage Production. *Review of Economic Studies*, 49(4), 583-594.

[12] Egger, Hartmut and Peter Egger (2005). International outsourcing and the productivity of low-skilled labour in the EU. Forthcoming in *Economic Inquiry.*

[13] Ekholm, Karolina and Katariina Hakkala (2005). Effect of Offshoring on Labor Demand: Evidence from Sweden. IUI Working Paper No. 654.

[14] Ethier, W. (1982). National and International Returns to Scale in the Modern Theory of of International Trade. *American Economic Review* 72(3), 389-405.

[15] Feenstra, Robert C. and Gordon H. Hanson (1999). The Impact of offshoring and High Technology Capital on Wages: Estimates for the United States, 1979-1990. *Quarterly Journal of Economics,* 114(3), 907-40.

[16] Feenstra, Robert C. and Gordon H. Hanson (1996). Globalization, offshoring, and Wage Inequality. *American Economic Review*, 86(2), 240-245.

[17] Freund, C. and D. Weinhold (2002). The internet and international trade in services, *American Economic Review*, 92(2), 236-240.

[18] Girma, S. and H. Gorg (2004). Outsourcing, Foreign Ownership and Productivity: Evidence from UK establishment level data. *Review of International Economics*, 12(5), 817-832.

[19] Gorg H. and A. Hanley (2005). Offshoring, Foreign Ownership, Exports and Productivity: An Empirical Investigation with Plant Level Data. University of Nottingham, unpublished manuscript.

[20] Gorg H. and A. Hanley (2003). International outsourcing and productivity: evidence from plant level data. Research Paper 2003/20, 1-23. University of Nottingham.

[21] Griliches, Z. and J. A. Hausman (1986). Errors in variables in panel data. *Journal of Econometrics*, 31(1), 93-118.

[22] Harrison, Anne E. and Margaret S. McMillan (2005). US Multinational Activity Abroad and US Jobs: Substitutes or Complements? Unpublished mimeo. University of California, Berkeley.

[23] Hummels, D., Jun Ishii and Kei-Mu Yi (2001). The nature and growth of vertical specialization in world trade. *Journal of International Economics*, 54(1), 75-96.

[24] International Monetary Fund (2003). *Balance of Payments Statistics Part 1*: Country Tables Yearbook.

[25] International Telecommunication Union, (2003). Yearbook of Statistics, Telecommunication Services 1992-2001, Geneva, Switzerland.

[26] Jones, Ronald and Henryk Kierzkowski (2001). A framework for fragmentation, in Cheng and Kierzkowski (eds), *Fragmentation and International Trade*, Oxford University Press.

[27] Jones, Ronald and Henryk Kierzkowski (1999). Globalization and the consequences of international fragmentation, in R. Dornbusch, G. Calvo and M.Obstfeld (eds), *The Festschrift in Honor of Robert Mundell*, MIT Press, Cambridge.

[28] Jones, Ronald W. and Henryk Kierzkowski (1990). The Role of Services in Production and International Trade: A Theoretical Framework, Ch. 3 in Jones and Krueger (eds), *The Political Economy of International Trade*, Blackwells.

[29] Keller, Wolfgang and Stephen Yeaple (2003). Multinational Enterprises, International Trade, and Productivity Growth: Firm-Level Evidence from the United States. NBER Working Paper 9504..

[30] Li, G. (1985). Robust Regression. In (ed.) D.C. Hoaglin, F. Mosteller, and J.W. Turkey, *Exploring Data Tables, Trends, and Shapes,* New York. Wiley, 281-340.

[31] Mann, Catherine L. (2004). Globalization of IT Services and White Collar Jobs: The Next Wave of Productivity Growth, *International Economics Policy Briefs* 3-11. Institute of International Economics.

[32] Murray, Michael P. (2005). The Bad, the Weak and the Ugly: Avoiding the Pitfalls of Instrumental Variables Estimation. Forthcoming in *Journal of Economic Perspectives.*

[33] Samuelson, Paul (2004). Where Ricardo and Mill Rebut and Confirm Arguments of Mainstream Economists Supporting Globalization. *Journal of Economic Perspectives*, 18(3), 135-146.

[34] Shea, J. (1997). Instrument Relevance in Multivariate Linear Models: A Simple Measure. *Review of Economics and Statistics* (79), 348-52.

[35] Ten Raa, T. and E. N. Wolff (2001). Outsourcing of Services and the Productivity Recovery in U.S. Manufacturing in the 1980s and 1990s, *Journal of Productivity Analysis*, 16, 149-65.

[36] Wedding (2005). U.S. and India Data on Offshoring Show Significant Differences. Unites States Government Accountability Office. Report to Congressional Committees. GAO-06-116.

Table 1 Offshoring intensity: 1992-2000

	share of imported material inputs - OSM		share of imported service inputs - OSS	
Year	%	%Δ	%	%Δ
1992	11.72		0.18	
1993	12.68	5.25	0.18	4.88
1994	13.41	5.06	0.20	6.39
1995	14.18	4.65	0.20	4.10
1996	14.32	1.75	0.21	6.64
1997	14.55	1.75	0.23	6.97
1998	14.94	2.97	0.24	6.57
1999	15.55	3.49	0.29	16.73
2000	17.33	10.12	0.29	-2.23
1992-2000		4.38		6.26

Table 2 Offshoring of Services, by type: 1992 and 2000

Services	Share of Service Inputs (%)				Import of Services (%)
	Mean	Std Dev	Min	Max	
(1992)					
Communication	1.16	0.79	0.25	4.82	2.47
Financial	1.91	0.63	0.93	4.72	0.25
Insurance	0.43	0.18	0.16	1.39	1.82
Other business service	9.69	7.16	1.87	37.93	1.47
Computer and Information	0.55	0.44	0.02	2.53	0.16
(2000)					
Communication	1.27	0.94	0.28	5.45	1.18
Financial	2.37	0.86	0.71	5.28	0.51
Insurance	0.47	0.22	0.10	1.36	2.84
Other business service	12.02	8.55	1.89	44.99	2.23
Computer and Information	0.38	0.31	0.01	2.01	0.62

Source: BLS, Input-Output Tables and IMF, Balance of Payments Statistics Yearbook.

Table 3 Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
$oss_{i,t}$	864	0.239	0.162	0.040	1.071
$\Delta oss_{i,t}$	768	0.016	0.032	-0.145	0.411
$osm_{i,t}$	864	14.949	9.808	1.220	69.255
$\Delta osm_{i,t}$	768	0.694	1.950	-16.173	21.220
ln(value-added per worker)$_{i,t}$	864	-2.591	0.480	-4.034	-0.526
Δln(value-added per worker)$_{i,t}$	768	0.043	0.070	-0.231	0.364
ln(real output)$_{i,t}$	864	10.112	0.953	6.549	12.979
Δln(real output)$_{i,t}$	768	0.036	0.074	-0.256	0.443
ln(materials)$_{i,t}$	864	9.032	1.034	5.577	12.498
Δln(materials)$_{i,t}$	768	0.031	0.103	-0.567	0.544
ln(services)$_{i,t}$	864	7.060	1.025	3.892	9.875
Δln(services)$_{i,t}$	768	0.045	0.075	-0.316	0.418
ln(labor)$_{i,t}$	864	11.834	0.847	8.618	13.836
Δln(labor)$_{i,t}$	768	-0.001	0.038	-0.165	0.139
ln(capital stock)$_{i,t}$	844	9.175	1.030	5.979	11.701
Δln(capital stock)$_{i,t}$	748	0.029	0.043	-0.809	0.301
htech (*ex post*)$_{i,t}$	864	10.070	6.302	2.574	24.112
Δhtech (*ex post*)$_{i,t}$	768	0.265	0.959	-2.899	4.410
htech (ex ante)$_{i,t}$	860	9.738	5.961	2.508	23.149
Δhtech (*ex ante*)$_{i,t}$	764	0.107	0.338	-0.729	1.512
import share$_{i,t}$	855	0.257	0.486	0.000	3.408
Δ(import share)$_{i,t}$	760	0.014	0.050	-0.375	0.579

Note: 1) htech is defined as (high-tech capital services / total capital services)

Table 4 Total Factor Productivity

Dependent variable: $\Delta\ln(\text{real output})_{i,t}$									
					OLS				*GMM*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta oss_{i,t}$	0.235***		0.249***	0.241***	0.341***		0.331***	0.335***	0.258***
	(0.059)		(0.042)	(0.045)	(0.051)		(0.071)	(0.073)	(0.043)
$\Delta oss_{i,t-1}$		0.094**	0.079*	0.065		0.082***	0.097***	0.093***	0.098***
		(0.036)	(0.040)	(0.041)		(0.030)	(0.027)	(0.027)	(0.019)
$\Delta osm_{i,t}$	0.001*		0.001*	0.001*	0.001		0.001*	0.001*	0.0005
	(0.001)		(0.001)	(0.001)	(0.001)		(0.001)	(0.0005)	(0.0004)
$\Delta osm_{i,t-1}$		-0.0004	0.0002	0.0002		-0.0003	0.0001	0.0001	0.0004*
		(0.0003)	(0.0003)	(0.0003)		(0.0003)	(0.0003)	(0.0003)	(0.0002)
$\Delta\ln(\text{materials})_{i,t}$	0.389***	0.358***	0.404***	0.406***	0.432***	0.365***	0.443***	0.445***	0.432***
	(0.041)	(0.038)	(0.033)	(0.033)	(0.047)	(0.040)	(0.042)	(0.043)	(0.019)
$\Delta\ln(\text{services})_{i,t}$	0.563***	0.592***	0.548***	0.546***	0.508***	0.566***	0.496***	0.495***	0.506***
	(0.048)	(0.042)	(0.036)	(0.036)	(0.047)	(0.043)	(0.042)	(0.042)	(0.022)
$\Delta\ln(\text{labor})_{i,t}$	0.059***	0.056**	0.056**		0.013	0.017	0.006		
	(0.021)	(0.022)	(0.022)		(0.025)	(0.028)	(0.026)		
$\Delta\ln(\text{skilled labor})_{i,t}$				0.029**				0.006	-0.0004
				(0.015)				(0.018)	(0.015)
$\Delta\ln(\text{unskilled labor})_{i,t}$				0.008				-0.007	-0.003
				(0.013)				(0.013)	(0.010)
$\Delta\ln(\text{capital})_{i,t}$	0.013	0.010	0.009	0.579*	0.001	-0.005	-0.002	0.007	-0.007
	(0.021)	(0.025)	(0.021)	(0.032)	(0.012)	(0.010)	(0.010)	(0.051)	(0.040)
$\Delta\ln(\text{real output})_{i,t-1}$									0.009
									(0.008)
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry fixed effects	no	no	no	no	yes	yes	yes	yes	no
Joint significance tests:									
$\Delta oss_t + \Delta oss_{t-1}=0$			F(1,95)=27.99	F(1,95)=20.71			F(1,95)=21.70	F(1,95)=20.24	$\chi^2(1)$=31.81
			p-value=0.00	*p-value*=0.00			*p-value*=0.00	*p-value*=0.00	*p-value*=0.00
$\Delta osm_t + \Delta osm_{t-1}=0$			F(1,95)=2.57	F(1,95)=2.36			F(1,95)=2.19	F(1,95)=2.12	$\chi^2(1)$=0.64
			p-value=0.11	*p-value*=0.13			*p-value*=0.14	*p-value*=0.15	*p-value*=0.42
Observations	748	652	652	640	748	652	652	640	541
R-squared	0.96	0.97	0.97	0.97	0.97	0.98	0.98	0.98	

Note: Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%; Sargan overidentification test in column (9) estimation $\chi^2(20)$=23.08, *p-value*=0.28; and H_0: no autocorrelation z =1.85 Pr> z = 0.064.

Table 5 Labor Productivity

Dependent variable: Δln(value added per worker)$_t$						
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta oss_{i,t}$	0.214		0.236	0.298**		0.386**
	(0.150)		(0.162)	(0.143)		(0.167)
$\Delta oss_{i,t-1}$		0.310*	0.292*		0.414**	0.418***
		(0.174)	(0.154)		(0.164)	(0.150)
$\Delta osm_{i,t}$	0.001		0.003	-0.001		0.001
	(0.002)		(0.003)	(0.003)		(0.004)
$\Delta osm_{i,t-1}$		0.003*	0.003**		0.001	0.002
		(0.001)	(0.001)		(0.001)	(0.001)
Δln(capital)$_{i,t}$	0.166*	0.186*	0.196*	0.099	0.108***	0.129***
	(0.097)	(0.101)	(0.100)	(0.063)	(0.033)	(0.036)
Year fixed effects	yes	yes	yes	yes	yes	yes
Industry fixed effects	no	no	no	yes	yes	yes
Joint significance tests:						
$\Delta oss_t + \Delta oss_{t-1}=0$			F(1,95)=3.84			F(1,95)=10.53
			p-value=0.05			*p-value*=0.00
$\Delta osm_t + \Delta osm_{t-1}=0$			F(1,95)=2.45			F(1,95)=0.38
			p-value=0.12			*p-value*=0.54
Observations	748	652	652	748	652	652
R-squared	0.06	0.07	0.08	0.39	0.41	0.42

Note: Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6 Labor Productivity and Additional Controls

Dependent variable: $\Delta\ln(\text{value added per worker})_t$	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta oss_{i,t}$	0.222	0.243	0.227	0.383**	0.399**	0.394**
	(0.171)	(0.162)	(0.158)	(0.171)	(0.164)	(0.159)
$\Delta oss_{i,t-1}$	0.289*	0.299*	0.306**	0.425***	0.428***	0.426***
	(0.150)	(0.156)	(0.150)	(0.138)	(0.148)	(0.136)
$\Delta osm_{i,t}$	0.003	0.003	0.005	0.001	0.002	0.003
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
$\Delta osm_{i,t-1}$	0.003**	0.003**	0.003**	0.001	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta\ln(\text{capital})_{i,t}$	0.196*	0.201**	0.202**	0.130***	0.131***	0.129***
	(0.100)	(0.101)	(0.101)	(0.037)	(0.035)	(0.036)
$\Delta(\text{htech})_{i,t}$	0.001			0.003		0.003
(ex post rental prices)	(0.003)			(0.003)		(0.003)
$\Delta(\text{htech})_{i,t-1}$	0.005			0.008*		0.008*
(ex post rental prices)	(0.005)			(0.004)		(0.004)
$\Delta(\text{htech})_{i,t}$		-0.007			-0.010	
(ex ante rental prices)		(0.018)			(0.015)	
$\Delta(\text{htech})_{i,t-1}$		-0.001			-0.001	
(ex ante rental prices)		(0.011)			(0.012)	
$\Delta(\text{impshare})_{i,t}$			-0.142			-0.274
			(0.128)			(0.182)
$\Delta(\text{impshare})_{i,t-1}$			0.158**			-0.012
			(0.065)			(0.059)
Year fixed effects	yes	yes	yes	yes	yes	yes
Industry fixed effects	no	no	no	yes	yes	yes
Joint significance tests:						
$\Delta oss_t + \Delta oss_{t-1}=0$	$F(1,95)=3.44$	$F(1,95)=3.96$	$F(1,94)=4.03$	$F(1,95)=11.56$	$F(1,95)=11.64$	$F(1,94)=13.47$
	p-value=0.07	*p-value*=0.05	*p-value*=0.05	*p-value*=0.00	*p-value*=0.00	*p-value*=0.00
$\Delta osm_t + \Delta osm_{t-1}=0$	$F(1,95)=2.16$	$F(1,95)=2.27$	$F(1,94)=4.49$	$F(1,95)=0.22$	$F(1,95)=0.65$	$F(1,94)=1.97$
	p-value=0.15	*p-value*=0.14	*p-value*=0.04	*p-value*=0.64	*p-value*=0.42	*p-value*=0.16
$\Delta(\text{htech})_t+\Delta(\text{htech})_{t-1}=0$	$F(1,95)=0.67$			$F(1,95)=3.09$		$F(1,94)=3.45$
(ex post rental prices)	*p-value*=0.42			*p-value*=0.08		*p-value*=0.07
$\Delta(\text{htech})_t+\Delta(\text{htech})_{t-1}=0$		$F(1,95)=0.17$			$F(1,95)=0.49$	
(ex ante rental prices)		*p-value*=0.68			*p-value*=0.48	
$\Delta(\text{impshare})_t+\Delta(\text{impshare})_{t-1}=0$			$F(1,94)=0.02$			$F(1,94)=2.52$
			p-value=0.88			*p-value*=0.12
Observations	652	648	645	652	648	645
R-squared	0.08	0.08	0.09	0.43	0.44	0.45

Note: Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 7 Labor Productivity – Long Period Differences

Dependent variable: $\Delta\ln(\text{value-added per worker})_t$ - $\Delta\ln(\text{value-added per worker})_{t\text{-}k}$	2 period difference			long difference[1]		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta oss_{i,t}$	0.035	0.064	0.076	0.546*	0.535*	0.529*
	(0.248)	(0.259)	(0.254)	(0.287)	(0.292)	(0.292)
$\Delta oss_{i,t-1}$	0.607***	0.582***	0.588***			
	(0.117)	(0.111)	(0.102)			
$\Delta osm_{i,t}$	0.001	0.001	0.003	0.031***	0.031***	0.029***
	(0.004)	(0.004)	(0.003)	(0.007)	(0.007)	(0.010)
$\Delta osm_{i,t-1}$	0.001	0.000	0.000			
	(0.002)	(0.002)	(0.002)			
$\Delta\ln(\text{capital})_{it}$	0.111**	0.101*	0.089	0.135	0.136	0.146
	(0.054)	(0.060)	(0.054)	(0.091)	(0.092)	(0.092)
$\Delta(\text{htech})_{i,t}$		-0.003	-0.003		0.308	0.110
(ex post rental prices)		(0.005)	(0.005)		(0.976)	(1.071)
$\Delta(\text{htech})_{i,t-1}$		0.011*	0.012**			
(ex post rental prices)		(0.005)	(0.005)			
$\Delta(\text{impshare})_t$			-0.321**			0.044
			(0.141)			(0.110)
$\Delta(\text{impshare})_{t-1}$			-0.000			
			(0.085)			
Year fixed effects	yes	yes	yes	n/a	n/a	n/a
Industry fixed effects	yes	yes	yes	n/a	n/a	n/a
Joint significance tests:						
$\Delta oss_t + \Delta oss_{t-1}=0$	F(1,95)=4.53	F(1,95)=4.39	F(1,94)=4.92			
	p-value=0.04	*p-value*=0.04	*p-value*=0.03			
$\Delta osm_t + \Delta osm_{t-1}=0$	F(1,95)=0.09	F(1,95)=0.03	F(1,94)=0.40			
	p-value=0.76	*p-value*=0.86	*p-value*=0.53			
$\Delta(\text{htech})_t+\Delta(\text{htech})_{t-1}=0$		F(1,95)=0.90	F(1,94)=1.15			
(ex post rental prices)		*p-value*=0.35	*p-value*=0.29			
$\Delta(\text{impshare})_t+\Delta(\text{impshare})_{t-1}=0$			F(1,94)=2.94			
			p-value=0.09			
Observations	556	556	550	89	89	88
R-squared	0.64	0.65	0.68	0.19	0.19	0.19

Notes: 1) Variables in columns (4) to (6) are the difference between the average of the first three and the last three years. Two industries, electronic components and computer and office equipment, were dropped – these were large outliers with unusually high labor productivity growth unrelated to offshoring. Note that the taking difference between 2000 and 1992 produces similar sized coefficients but much higher standard errors. 2) Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%; 3) Import shares for metal coating and engraving (I/O code=36) are missing.

Table 8 Labor Productivity – Outliers

Dependent variable: Δln(value-added per worker)$_t$						
	One period difference			Two period difference		
	Robust regression	Without tobacco industry	Without tobacco and high-tech	Robust regression	Without tobacco industry	Without tobacco and high-tech
	(1)	(2)	(3)	(4)	(5)	(6)
Δoss_t	0.342***	0.235	0.240	0.013	-0.119	-0.104
	(0.077)	(0.217)	(0.218)	(0.117)	(0.258)	(0.260)
Δoss_{t-1}	0.266***	0.266**	0.267**	0.369***	0.438***	0.429***
	(0.075)	(0.116)	(0.116)	(0.091)	(0.145)	(0.146)
Δosm_t	0.004***	0.003	0.003	0.004***	0.002	0.002
	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.004)
Δosm_{t-1}	0.002*	0.002	0.002	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
$\Delta \ln(capital)_t$	0.110**	0.122***	0.124***	0.055	0.073	0.072
	(0.048)	(0.038)	(0.039)	(0.051)	(0.056)	(0.058)
$\Delta(htech)_t$	0.004*	0.003	0.002	-0.001	-0.005	-0.006
(ex post rental prices)	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
$\Delta(htech)_{t-1}$	0.009***	0.008*	0.008*	0.010***	0.012**	0.014**
(ex post rental prices)	(0.003)	(0.004)	(0.005)	(0.003)	(0.005)	(0.005)
$\Delta(impshare)_t$	-0.186***	-0.270	-0.283	-0.159***	-0.322**	-0.341**
	(0.040)	(0.187)	(0.190)	(0.050)	(0.145)	(0.146)
$\Delta(impshare)_{t-1}$	0.124***	-0.011	-0.007	0.280***	0.007	0.012
	(0.042)	(0.058)	(0.059)	(0.055)	(0.088)	(0.091)
Year fixed effects	yes	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes	yes
Joint significance tests:						
$\Delta oss_t + \Delta oss_{t-1}=0$	F(1,535)=31.53	F(1,93)=6.03	F(1,91)=6.29	F(1,441)=10.89	F(1,93)=1.66	F(1,91)=1.73
	p-value=0.00	*p-value*=0.02	*p-value*=0.01	*p-value*=0.00	*p-value*=0.20	*p-value*=0.19
$\Delta osm_t + \Delta osm_{t-1}=0$	F(1,535)=10.41	F(1,93)=1.09	F(1,91)=1.12	F(1,441)=7.36	F(1,93)=0.08	F(1,91)=0.07
	p-value=0.00	*p-value*=0.30	*p-value*=0.29	*p-value*=0.01	*p-value*=0.78	*p-value*=0.79
$\Delta(htech)_t + \Delta(htech)_{t-1}=0$	F(1,535)=9.20	F(1,93)=2.79	F(1,91)=2.58	F(1,441)=4.90	F(1,93)=0.93	F(1,91)=0.83
(ex post rental prices)	*p-value*=0.00	*p-value*=0.10	*p-value*=0.11	*p-value*=0.03	*p-value*=0.34	*p-value*=0.36
$\Delta(impshare)_t+\Delta(impshare)_{t-1}=0$	F(1,535)=1.14	F(1,93)=2.14	F(1,91)=2.20	F(1,441)=5.66	F(1,93)=2.56	F(1,91)=2.70
	p-value=0.29	*p-value*=0.15	*p-value*=0.14	*p-value*=0.02	*p-value*=0.11	*p-value*=0.10
Observations	645	638	624	550	544	532
R-squared	0.60	0.44	0.29	0.81	0.67	0.48

Note: Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 9: Labor Productivity - Instrumental Variables

A. Dependent variable : Δln(value added per worker)$_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		One period differences				Two period differences			OLS
Δoss_t		0.226				-0.078			
		(0.146)				(0.168)			
Δoss_{t-1}	0.277	0.266	0.328	0.380*	0.382*	0.418*	0.467*	0.457*	0.380***
	(0.182)	(0.189)	(0.201)	(0.206)	(0.213)	(0.220)	(0.251)	(0.250)	(0.132)
Δosm_{t-1}			0.006	0.008			0.007	0.006	-0.0001
			(0.006)	(0.006)			(0.007)	(0.008)	(0.002)
Δln(capital)$_t$	0.111***	0.122***	0.104***	0.100*	0.105***	0.100***	0.103***	0.078*	0.080*
	(0.027)	(0.028)	(0.029)	(0.031)	(0.032)	(0.035)	(0.034)	(0.041)	(0.048)
Δ(htech)$_{t-1}$				0.006**				0.011**	0.012**
(*ex post rental prices*)				(0.003)				(0.004)	(0.005)
Δ(impshare)$_{t-1}$				-0.045				-0.200**	-0.183*
				(0.144)				(0.098)	(0.100)
$\Delta oss_t + \Delta oss_{t-1} = 0$		$\chi^2(1)=3.29$				$\chi^2(1)=2.08$			
		p-value=0.07				*p-value*=0.15			
B. First Stage Results	***Dependent variable:***								
Service intensity$_{i,1992}$ interacted with:	Δoss_{t-1}				Δoss_{t-1}				
$\Delta(IH)_{Canada,t}$	0.017***				0.024**				
	(0.004)				(0.011)				
$\Delta(IH)_{Germany,t}$	-0.024***				-0.028***				
	(0.005)				(0.007)				
$\Delta(IH)_{India,t}$	-0.020***				-0.013**				
	(0.004)				(0.005)				
$\Delta(IH)_{Japan,t}$	0.018***				0.012*				
	(0.005)				(0.006)				
$\Delta(IH)_{UK,t}$	-0.012***				-0.009				
	(0.004)				(0.006)				
Shea Partial R^2 : Δoss_t		0.37				0.43			
Δoss_{t-1}	0.32	0.31	0.31	0.32	0.35	0.37	0.31	0.32	
Δosm_t									
Δosm_{t-1}			0.04	0.04			0.04	0.03	
Hansen J statistic	4.03	7.90	2.83	2.90	7.62	7.61	7.24	6.69	
	$\chi^2(4)=0.40$	$\chi^2(4)=0.10$	$\chi^2(4)=0.59$	$X^2(4)=0.58$	$\chi^2(4)=0.11$	$\chi^2(3)=0.05$	$\chi^2(4)=0.12$	$\chi^2(4)=0.15$	
Observations	645	645	645	638	550	550	550	544	544

Note: All columns include year and industry fixed effects. Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; ***; * significant at 1% level.

Table 10: Labor Productivity - GMM Analysis

Dependent variable: Δln(value-added per worker)$_t$						
Additional Instruments:					Δln(Internet users)$_{c,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δoss_t	0.330*	0.320	0.266*	0.248	0.241	0.219
	(0.193)	(0.201)	(0.140)	(0.200)	(0.206)	(0.196)
Δoss_{t-1}	0.378***	0.387***	0.294*	0.296**	0.320***	0.301**
	(0.122)	(0.122)	(0.164)	(0.125)	(0.121)	(0.14)
Δosm_t	-0.002	-0.002	0.002	-0.002	-0.002	0.002
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
Δosm_{t-1}	0.000	0.000	0.002*	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Δln(capital)$_t$	0.116***	0.134***	0.136***	0.111***	0.131***	0.126***
	(0.027)	(0.028)	(0.029)	(0.026)	(0.027)	(0.027)
Δ(htech)$_t$		0.005	0.003		0.005	0.003
(*ex post rental prices*)		(0.003)	(0.002)		(0.003)	(0.0026)
Δ(htech)$_{t-1}$		0.009**	0.006		0.009**	0.008*
(*ex post rental prices*)		(0.004)	(0.004)		(0.004)	(0.004)
Δ(impshare)$_t$			-0.341**			-0.339*
			(0.171)			(0.182)
Δ(impshare)$_{t-1}$			-0.150*			-0.131
			(0.079)			(0.086)
Δ(vaw)$_{t-1}$	-0.199***	-0.196***	-0.276***	-0.204***	-0.202***	-0.281***
	(0.063)	(0.063)	(0.063)	(0.062)	(0.062)	(0.063)
Joint significance tests						
$\Delta oss_t + \Delta oss_{t-1} = 0$	$\chi^2(1)$= 10.80	$\chi^2(1)$= 9.75	$\chi^2(1)$= 6.71	$\chi^2(1)$= 4.98	$\chi^2(1)$= 5.13	$\chi^2(1)$= 4.06
	p-value=0.00	*p-value*=0.00	*p-value*=0.01	*p-value*=0.03	*p-value*=0.02	*p-value*=0.04
$\Delta osm_t + \Delta osm_{t-1} = 0$	$\chi^2(1)$= 0.04	$\chi^2(1)$= 0.07	$\chi^2(1)$= 0.64	$\chi^2(1)$= 0.05	$\chi^2(1)$= 0.10	$\chi^2(1)$= 0.48
	p-value=0.85	*p-value*=0.79	*p-value*=0.42	*p-value*=0.82	*p-value*=0.76	*p-value*=0.49
Δ(htech)$_t$ +Δ(htech)$_{t-1}$ = 0		$\chi^2(1)$= 4.69	$\chi^2(1)$= 2.18		$\chi^2(1)$= 4.16	$\chi^2(1)$= .3.31
(*ex post rental prices*)		*p-value*=0.03	*p-value*=0.14		*p-value*=0.04	*p-value*=0.07
Δ(impshare)$_t$ + Δ(impshare)$_{t-1}$ = 0			$\chi^2(1)$= 4.73			$\chi^2(1)$= 3.74
			p-value=0.03			*p-value*=0.05
Sargan test	$\chi^2(20)$= 28.65	$X^2(20)$= 29.09	$\chi^2(20)$= 29.19	$\chi^2(29)$= 37.77	$\chi^2(29)$= 38.63	$\chi^2(29)$= 39.61
	p-value=0.10	*p-value*=0.09	*p-value*=0.08	*p-value*=0.13	*p-value*=0.11	*p-value*=0.09
H_0 : no 2nd order autocorrelation	z =-0.22	z =-0.40	z =0.40	z =-0.46	z =-0.60	z =0.22
	p-value=0.83	*p-value*=0.69	*p-value*=0.69	*p-value*=0.65	*p-value*=0.55	*p-value*=0.83
Observations	550	550	544	550	550	544

Note: Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%