Trade, Technology, and Wage Inequality: Evidence from U.S. Manufacturing, 1989-2004[1]

by

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Abstract

The roles of trade and technology in the growth of wage inequality within U.S. manufacturing have been of concern for some time. Virtually all previous papers in this area have focused on the period of the late 1970s and 1980s, with no work examining the 1990s and 2000s due to data limitations. Nevertheless, there is a general perception that the growth in wage inequality of 1990s has subsided, while evidence suggests that the 1990s and 2000s saw a dynamic growth of trade and technology. This raises skepticism of the roles of trade and technology. In this paper, I use new data and find that this perception is false and document a significant rise in wage inequality in 1990s and a decline in the 2000s. Next, I estimate the effect of trade and technology on wage inequality using standard measures of trade and fail to find a significant contribution of trade. I show that these measures suffer from measurement error, which have a downward bias on the impact of trade on relative wages. Finally, I use newly constructed and improved measures of trade, and find a very large role of trade and computer technologies on the skilled-unskilled wage gap of 1989-1996. However, neither of these factors are found to affect wages during 1997-2004. Using other measures of technological change, I find that diffusion of other high-tech equipment contributed significantly to the closing of the gap of early 2000s. This findings are indicative of a changing role of computers in U.S. manufacturing.

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I. Introduction

It has been well documented that U.S. wage inequality rose dramatically during the 1980s, when the wages of both the most skilled and moderately skilled workers increased and the wages of least skilled workers dropped. A large literature spans the debate on the determinants of this rise in the wage inequality. A common consensus points to the on-going growth of the demand for high-skilled workers, of which skill-biased technical change (SBTC) and international trade are the often cited sources. While much empirical evidence supports the hypothesis of the effect of SBTC on wages, the evidence for the impact of trade on wages is mixed. Only one U.S. study finds robust estimates of the effect of international trade, specifically, trade in intermediate inputs, on the 1980s wage inequality, and many others arrive at inconclusive evidence of the effects of trade.[3]

Surprisingly, the literature has focused almost exclusively on data from the late 1970s and the 1980s. The few studies that have examined this issue using data from the 1990s find mixed evidence on the overall patterns of wage inequality during this period and merely speculate on its determinants.[4] At the same time, there is growing evidence to suggest that both technology and trade gained further prevalence during the 1990s and early 2000s, as firms finally learned to reap the full benefits of the computer revolution and established extended networks with the low-wage countries.

Prior literature examining the effect of trade on wage inequality has two shortcomings that this chapter will focus on. First, virtually all previous papers have focused on the period of the late 1970s and 1980s, with no work examining the 1990s and 2000s. This seems primarily

3 See Feenstra and Hanson (2003) for the survey of trade's impact on wages.
4 See the survey in Autor et al. (forthcoming 2008) and Lemiuex (2007).

due to the fact that the National Bureau of Economic Research (NBER) Productivity Database used for these studies ends in 1996. Nevertheless, there is a general perception in the literature that the growth in wage inequality has subsided. This calls into question how strongly trade forces may be affecting the U.S. skilled-unskilled wage gap, since evidence suggests that the 1990s and 2000s saw a dynamic growth of trade. I find that this perception regarding the fall in the wage gap within U.S. manufacturing to be false. I document a significant rise in wage inequality in 1990s and a decline in the 2000s, which closely corresponds to the movements of trade in intermediate inputs over the same period.

A second significant shortcoming of the previous literature is its measurement of imported intermediate inputs, i.e. materials offshoring. Given available data, previous literature has used input-output relationships to determine the extent of a sector's intermediate inputs purchases from an input supplier. Then the suppliers' total imports share in the U.S. supply is used to estimate how much of the sector's input purchases are due to imports. Thus, it is assumed that total import share is a good proxy for estimating inputs import share. As shown in Appendix A of this chapter, this assumption introduces significant measurement error.

I address these shortcomings in the following fashion. First, I update the NBER Productivity Database through the year 2005. Using these data, I first document that while the gap between skilled and unskilled workers continued to rise during the 1990s, it fell significantly after 2000. Next, I use standard data construction techniques and empirical specifications utilized in product-price literature to estimate the effect of trade on the skilled-unskilled wage gap for this later period (1989-2005) and find a significant effect of materials offshoring on the wage gap. However, this effect is not robust to the inclusion of alternative measures of trade and computerization, which calls into question the validity of previous findings; e.g., Feenstra and

Hanson (1999) who find that materials offshoring explains up to 25% of the rise in the skilled-unskilled wage gap for their earlier sample covering the years, 1979-1990.

I then turn to recently constructed trade data on U.S. imports of intermediate goods to develop a refined measure of materials offshoring. Using the refined measure, I find a very large and robust effect of offshoring on the skilled-unskilled wage gap of 1989-1996 and a large, albeit insignificant, effect on wages of 1997-2004. Furthermore, offshoring of business services appears to play a large role in the widening of the wage gap during 1989-1996, although services offshoring contributes to the closing of the gap during 1997-2004.

Other findings indicate that one must take caution in interpreting all technological change as skill-biased. I find that computer adoption contributed significantly to the rise in the skilled-unskilled wage gap during 1989-1996, by increasing the non-production wages and decreasing, albeit statistically insignificantly, the production wages. On the other hand, the estimates show that office equipment diffusion has a overall neutral effect on relative wages, while other high-tech technological change is biased towards the unskilled during 1997-2004. Additionally, the failure to identify the effect of computers on the wage gap of 1997-2004 may be indicative of the diminishing role of computer technologies in U.S. manufacturing.

This work is part of the growing theoretical and empirical debate on the effects of technology and international trade on the increase in the relative demand for skill. A plethora of studies document a striking correlation between the adoption of computer-based technologies and the increased use of college-educated labor within detailed industries and firms and across plants within industries.[5] In contrast, the evidence of the impact of trade on the demand for skill

5 Katz and Autor (1999) summarize this literature.

is much more conflicting.[6] A number of studies argue that a constant trade to GDP ratio, increasing product prices of least-skilled industries, and within-industry changes in labor composition of developed countries are indicative of a relatively minor role of trade in the prediction of relative wages.[7] Proponents of trade effects, on the other hand, retaliate by pointing to a rising trade to value-added ratio, growing relative domestic prices, and aggregation issues of industry-level data on labor composition. Furthermore, recent studies argue that the growing share of trade in intermediate inputs may shift the relative demand for skill in the same manner as SBTC does (Feenstra and Hanson 1999, 2003). Recently, however, these findings have been called into question, as the alleged decline in relative wages during 1990s does not appear to coincide with the dynamic growth of technology and trade of the1990s (e.g., Card and DiNardo 2002). One of the contributions of this work is to attempt to shed more light on the roles of technology and trade in the changing nature of wage inequality of the 1990s and 2000s.

In addition to the contribution discussed above, this work also contributes to the methodology of the product-price literature (see Slaughter 1999). There are only a handful of other studies on underlying factors causing changes in prices and productivity, which then are linked to wage changes. These studies find mixed contributions of trade-related forces, i.e. materials offshoring, trade barriers, and transportation costs, on U.S. wage changes of the 1970s and 1980s (Feenstra and Hanson 1999, Haskel and Slaughter 2003). I contribute to their methods by using more recent data for 1989-2004 and exploring a broader set of causal factors, which include more refined measures of trade.

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6 See Feenstra and Hanson (2003) survey of the literature on trade and wages.

7 See Krugman (1995) for a discussion of relative magnitudes of trade; Slaughter (2000) for a discussion of literature on relative-price changes; and Berman et al. (1994) on within vs. between industry labor shift.

The chapter is organized as follows. Section II documents relative wages during 1989-2005. Section III presents empirical methodology. Section IV describes data. Section V presents empirical results. Section VI discusses sensitivity analysis and section VII concludes.

II. Old and New Evidence of Wage Inequality

The rapid growth of U.S. wage inequality of 1980s has been well documented within both U.S. manufacturing and for the U.S. as a whole. While no papers have analyzed trends in wage inequality within U.S. manufacturing during 1990s and 2000s due to data limitations, a few studies have examined the growth in relative wages using U.S.-wide micro data. These studies find conflicting evidence, suggesting a changing nature of the 1990s U.S. wage inequality, which may not correspond to the dynamic growth of trade and SBTC that occurred during the same period. In this section, I use new industry-level data to document movements of wage inequality within U.S. manufacturing over the period of 1989-2005. The new data show a significant rise in wage inequality in the 1990s and a decline in the 2000s, which correspond to the patterns of trade and SBTC referenced in the literature (e.g., Autor et al. 2003; Feenstra and Hanson 2003).

Prior studies of wage inequality rely on two primary datasets, the earnings data of workers from all U.S. industries compiled in Current Population Surveys (CPS) and the wages of workers in U.S. manufacturing available through the NBER Productivity Database (NBER PD). During the 1980s, these data show a significant rise in wage inequality. According to the CPS data, between 1979 and 1989, the real wages of workers with sixteen or more years of education rose by 3.4%, of full-time workers with twelve years of education fell by 13.4%, and of workers with less than twelve years of education fell by 20.2%.[8] Within U.S. manufacturing alone, the

8 A detailed discussion of basic facts concerning wage movements in the U.S. during 1980s is provided in Katz and Autor (1999).

total wages of nonproduction workers relative to production workers rose by an average of 0.72% per year over the period of 1979-1990 (Feenstra and Hanson 1999).[9]

The early 2000s saw a rise in the studies of wage inequality of 1990s, which paint a mixed picture of the changing nature of U.S. wage inequality and the sources of these changes. For example, Card and DiNardo (2002) explore CPS data and find no noticeable change in wage inequality between 1988 and 2000. This finding leads them to question the validity of the previously estimated effects that SBTC and trade forces have on wage inequality during 1980s. On the other hand, Autor et al. (forthcoming 2008) use similar data for 1989-2005 to show polarization in wages, where the wages in very low and very high skill occupations increased, while those in moderately skilled occupations contracted.[10] No papers document the wage inequality of 1990s and 2000s for the U.S. manufacturing, as NBER PD data ends in 1996.

In order to illustrate the trends in U.S. manufacturing wage inequality over the period of 1989-2005, I expand the NBER PD from 1997 to 2005 (see Appendix A for data and methods description). I use the wages of nonproduction and production workers, which are often used as proxies of skilled and unskilled labor wages, to construct a measure of wage inequality.[11] I follow the literature to define this measure as log of the ratio of nonproduction wages per worker to production wages, where real wages denote wages per worker.[12] Figure 1 plots 1963-2005 wage

9 In the wage literature, nonproduction and production workers are commonly used to proxy for skilled and unskilled workers in manufacturing.

10 According to Autor et al. (Forthcoming 2008) the rising wage inequality in the lower half of wage distribution was an event confined to the 1980s.

11 Nonproduction wages are constructed as total nonproduction wages divided by total nonproduction worker employment, whereas production wages are constructed as total production wages divided by total production hours worked. Data on total nonproduction hours worked is not available.

12 This is a common measure of wage inequality in labor economics studies, e.g. Autor et al. (Forthcoming 2008); Card and DiNardo (2002); etc. Other measures of wage inequality have been used in the past. For example, Feenstra and Hanson (1999), Haskel and Slaughter (2001, 2003), and others employ the ratio of total nonproduction wages to total production wages, which estimates wage inequality in nominal terms. I find little difference in my measure and this measure of wage inequality.

inequality for the entire U.S. manufacturing and as industries' average, where weights for the latter are constructed as shares of the industry wage bill in total manufacturing shipments. As can be seen, wage inequality slowly declined from the late 1960s through the 1970s, and began to increase during the 1980s. Perhaps the most rapid widening of the wage gap can be observed during the 1990s, when it was also the most steady. Wage inequality decreased dramatically during the 2001-2002 U.S. recession and fluctuated during the recovery years that followed.

Table 1 provides more detail on the growth of workers' wages over the last three decades. During the period of 1979-1990 covered in most previous studies, the wages of production workers and nonproduction workers increased at an average 4.99% and 5.42% per year, such that the relative nonproduction wage rose by an average 0.43% per year. During 1989-1996 covered in this chapter, production and nonproduction wages increased at an average 2.67% and 3.78% per year, respectively, leading to a marked rise in the relative wages of 1.11% per year. Although both wages continued to grow during 1997-2005, the average annual decline in relative wages of this period amounted to 0.74%, much of which occurred during 2001-2002.

III. Empirical Methodology

The empirical studies estimating the effect of trade and technology on wage inequality have typically used a methodology derived from the Stolper–Samuelson theorem (SS theorem), which links product price changes to changes in factor prices, under zero-profit conditions.[13] This methodology relies on the production side of the Heckscher-Ohlin model which considers an economy with multiple sectors of different factor intensities and factors with complete mobility

13 Deardorff (1994) surveys all statements of the SS Theorem that have appeared during the past 50-plus years. One of the statements is the following: "For any vector of goods price changes, the accompanying vector of factor price changes will be positively correlated with the factor intensity-weighted averages of the goods price changes."

across sectors[14]. In this framework, aggregate demand for skilled workers relative to unskilled workers is horizontal and aggregate relative labor supply is upward sloping[15]. The aggregate relative labor demand is horizontal since a change in the demanded quantity of skilled (unskilled) labor can potentially be absorbed by a change in output in an unskilled (skilled) sector, and thus may be independent of relative wages[16]. Relative wages, in turn, are determined by product prices and/or productivity under zero profit conditions, which in turn are driven by exogenous forces, i.e. trade or technological innovation. When changes in exogenous forces alter intersectoral profitability, relative wages change to restore zero profits, factors flow to other sectors, and the relative aggregate demand curve shifts.

This process can be formalized by supposing that the economy, which in this case is U.S. manufacturing, produces *I* different traded goods, associated with *I* industries. Each industry employs some combination of *J* primary factors and *M* intermediate inputs. Under constant returns to scale technology, zero profit conditions for industry *i* can be written as

$$p_i = \sum_{m \in M} p_{mi} a_{mi} + \sum_{j \in J} w_{ji} a_{ji} \qquad (1)$$

where p_i is the domestic price of one unit of output, p_{mi} is the unit cost of *m*th intermediate input, a_{mi} is the quantity of *m*th input required for production of one unit of output, w_{ji} is the unit cost of *j*th primary factor, and a_{ji} is the quantity of *j*th factor required for production of one unit of output. Totally differentiating to express everything in instantaneous changes and allowing for changes in the technology of production, equation (1) can be rewritten as

14 This is different from labor studies which assume that factors are immobile (Haskel 1999).

15 Note, that the relative demand curve in each sector is still downward-sloping, while the aggregate demand curve is flat.

16 This is the so-called Rybczynski effect (Rybczynski, 1957)

$$\dot{p}_i^{VA} = \sum_{j \in J} \dot{w}_{ji} \theta_{ji} - T\dot{F}P_i \,, \tag{2}$$

where $\dot{p}_i^{VA} = \dot{p}_i - \sum_{m \in M} \dot{p}_{mi} \theta_{mi}$ is change in value-added prices, $T\dot{F}P_i = -\sum_{j \in J} \dot{a}_{ji} \theta_{ji}$ is the primal measure of total factor productivity, and θ_{mi} and θ_{ji} are the cost shares of intermediate inputs and primal factors in total costs of industry *i*, respectively.

Since all factors are mobile across sectors, changes in wages of primary factors can be assumed to be equal across sectors. Then the existing differences between the industry wage changes and the manufacturing-wide changes are assumed to arise from the variations in factor qualities across sectors[17]. Expressing industry wage changes in equation (2) as differentials from manufacturing-wide changes, I obtain

$$\dot{p}_i^{VA} = \sum_{j \in J} \dot{\bar{w}}_j \theta_{ji} - T\dot{F}P_i + \sum_{j \in J} (\dot{w}_{ji} - \dot{\bar{w}}_j) \theta_{ji} \,, \tag{3}$$

where $\dot{\bar{w}}_j$ is the effective manufacturing-wide wage change of primary factor *j* and $\dot{w}_{ji} - \dot{\bar{w}}_j$ is industry *i*'s wage change differential of *j*th primary factor. I combine industry wage differentials with changes in TFP and refer to them as changes in effective TFP, such that

$$\Delta \ln p_{it}^{VA} + \Delta \ln ETFP_{it} = \sum_{j \in J} \Delta \ln \bar{w}_j \ \tfrac{1}{2} (\theta_{jit-1} + \theta_{jit}) \,, \tag{4}$$

where instantaneous changes are expressed in first-log-difference and primary factor cost shares are averaged over two periods.

Equation (4) shows how manufacturing-wide factor prices adjust to changes in value-added product prices and/or effective productivity to restore zero profits in all sectors. This equation captures the wage adjustments to shifts in aggregate relative labor demand described above. Value-added price and/or effective productivity increases in a sector tend to raise (reduce)

17 See Feenstra and Hanson (1999) discussion on pg. 911.

the relative wages of factors employed relatively intensively (unintensively) in that sector, where intensity is defined by $\frac{1}{2}(\theta_{jit-1}+\theta_{jit})$. Note, that productivity changes can be factor-biased or factor- neutral, as long there are changes in net productivity (or by duality net costs), which raises sectoral profitability and so necessitates wage changes[18].

In the framework discussed above, value-added prices and effective productivity changes are assumed to be exogenous. In a large country-setting, however, prices and productivity changes are determined by domestic and foreign forces. To model the endogeneity of prices and productivity changes, Feenstra and Hanson (1999) developed a two-stage procedure, in the first stage changes in prices and productivity are regressed on exogenous factors, which are then linked to changes in wages. I follow this procedure, as described it below.

In the first-stage, I regress changes in value-added price and effective productivity on a set of *K* causal factors, which are hypothesized to drive these changes over time:

$$\Delta \ln p_{it}^{VA} + ETFP_{it} = \sum_{k \in K} \gamma_k \Delta z_{ikt} + \eta_{it} \qquad (5)$$

where z_{ikt} is the *k*th causal variable, γ_k is a coefficient on *k*th causal variable, and η_{it} is a disturbance term that captures all other shocks to the value-added price and productivity, which are assumed orthogonal to z_{ikt}. Changes in a causal factor can affect changes in either only value-added prices, or both value-added prices and effective productivity. In addition to its direct effect on both prices and productivity changes, Δz_{ikt} can affect price changes indirectly through its impact on productivity changes, which are "passed through" to product prices (Feenstra and

18 This is different from labor studies focus, where only factor-biased technical change affects wages since it changes the relative productivity of factors within a sector. See Haskel (1999) for discussion.

Hanson 1999; Krugman 2000).[19] Assuming a 100% pass-through rate, effective productivity changes are neutral if one finds γ_k equal to zero.

Given the results of the first-stage regression (5), one can decompose the total change in value-added prices and effective productivity into those components due to each structural variable, namely $\gamma_k \Delta z_{itk}$. These decomposed changes, when individually regressed on the primary factor cost-shares, yield coefficients interpreted as predicted factor price changes due to that structural component. The second-stage regressions for each structural variable *k* is expressed as:

$$\gamma_k \Delta z_{ikt} = \sum_{j \in J} \delta_{jk} \frac{1}{2} (\theta_{it-1} + \theta_{it}) + u_{ikt} . \qquad (6)$$

The coefficients δ_{jk} obtained from these regressions can be seen as the economy-wide change in the price of *j*th primary factor that would have occurred if the change in *k*th structural variable had been the only source of changes in prices and effective productivity.

Only a handful of studies have used the two-stage procedure to identify causal factors of changes in prices and productivity and link them to wages. These studies find mixed contributions of trade-related variables, i.e., foreign outsourcing of materials, trade barriers, transportation costs, and changes in international product prices, on the U.S., U.K., and Mexico's wages. For example, Feenstra and Hanson (1999) find that a rise in foreign outsourcing of materials accounts for 15%-25% of the rise in U.S. wage inequality in the 1980s. On the other hand, Haskel and Slaughter (2003) fail to identify a significant impact of other trade-related variables on U.S. wages of the 1970s and 1980s, although stronger results are found for U.K. and

19 The latter result stems from the fact that productivity changes distort equilibrium in the goods market, by shifting goods supply, which in turn affect product prices (Haskel 1999). These changes in goods supply are possible either because the country in question is large in world markets or because the productivity shocks are common across countries (Krugman 2000)

Mexico's wages (Haskel and Slaughter 2001; Robertson 2004). A number of studies have also looked at the effect of technology on wage inequality, where both factor-biased, i.e. skilled-biased technological change (SBTC), and sector-biased technological changes are considered. Feenstra and Hanson (1999) find that SBTC due to office equipment and computer investment explain over 35% of the rising U.S. wage inequality in the 1980s. On the other hand, industry innovation contributed the most to the increase in the skilled-unskilled U.K. wage gap during 1996-1990 (Haskel and Slaughter 2003). I contribute to their methods by using most recent data for 1989-2004 and exploring a broader set of trade- and technological change-related factors.

IV. Data and Descriptive Statistics

I apply the estimation technique described in the previous section to U.S. manufacturing industries for the period of 1989-2004. This sample period encompasses the changing nature of the U.S. wage inequality debated in the literature, which occurred after 1989, when the wage inequality either polarized (Autor et. al. Forthcoming) or substantially declined (Card and DiNardo 2002). One feature of the sample is that the data are classified under the Standard Industrial Classification (SIC) during 1989-1996 and North America Industrial Classification System (NAICS) during 1997-2004. This forces me to split the sample along the classifications distinction and run the estimation separately on each of the subsamples. While working with shorter time-series is less ideal, this approach circumvents the differences in the definition of manufacturing embedded in the classifications.[20] It is important to note that most industry-level studies of the U.S. wage dispersion span the period of no later than early 1990s, thus I am able to go far later than the existing literature.

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20 Other than the classifications differences, I have reasons to believe that the subsamples are roughly similar, in that they contain equal time-series panels of eight years and both encompass recession and post-recession recovery periods.

The data for prices, total factor productivity, and cost shares are obtained from the Bartelsman and Gray (1996) NBER PD for the period of 1989-1996 and the extended PD for the period of 1997-2004, which I constructed for the purposes of this chapter (see Appendix A for description of the extended PD). The descriptive statistics for these variables are reported in Table 1, which also includes the data for 1979-1990 used in most previous studies as a basis of comparison. As shown in Table 1, the period of 1997-2004 experienced the slowest growth in total factor productivity and value-added prices compared to the prior periods. Services appear to have gained more prominence by early 2000s.

Now I turn to data description of trade and technology-related causal factors. The trade-related variables that I identify include offshoring of materials, offshoring of selected business services, and finished goods imports openness. The set of technology-related variables consists of computer, office equipment, and other high-tech capital shares.

To measure offshoring of materials, I rely on standard construction methods, originally proposed by Feenstra and Hanson (1996, 1999), and an alternative method, which refines the original formula by utilizing new and previously unavailable data on trade in intermediate goods. To arrive at the original measure of offshoring, I combine data on total imports with data on inputs purchases. The data on U.S. imports for the period of 1989-2004 come from Feenstra (2002) and the Census Bureau. The inputs purchases are obtained from U.S. Input-Output tables provided by the BEA. For each industry *i,* the original measure of materials offshoring is constructed as follows:[21]

21 This formula first appears in Feenstra and Hanson (1996), but has been originally used by the BEA in construction of imported input purchases for the Import Matrices.

$$\frac{\sum_j [\,purchases\,of\;interm.inputs_{ij}\,]\cdot[\frac{imports_j}{dom.output_j + imports_j - exports_j}]}{Total\ Nonenergy\ Interm.\ Purchases_i}, \qquad (7)$$

where subscript j refers to an industry supplying input j to industry i, where $i,j = 1,...N$. Each product term in the numerator of equation (7) is interpreted as industry i's estimate of imported material inputs from industry j. Then equation (7) represents an industry's share of total imported intermediate inputs in the industry's total expenditure on non-energy intermediates. This measure is commonly referred to as a broad measure of materials offshoring. One can obtain a narrow measure of offshoring, by restricting attention to only those inputs that are purchased from the same two-digit SIC industry or three-digit NAICS industry as the good being produced.[22] I will include the narrow measure of offshoring and the difference between the broad and narrow measures as separate variables in my estimation. When averaged over all industries, the original measure of offshoring, defined narrowly and as a difference, increased at an average 0.29% and 0.23% per year during 1989-1996, and declined at an average 0.19% and 0.13% per year during 1997-2004, respectively, as is apparent in Table 2.

The original measure of materials offshoring suffers from potentially serious measurement error. The measurement error arises from the inclusion of economy-wide import share to proxy for imports of intermediate goods. Since the total imports share consists of goods unrelated to intermediate inputs, the levels and changes of the offshoring measures are over or underestimated by the levels and variation of the share of the unrelated goods (see Sitchinava 2008a). Therefore, the inclusion of the original offshoring measure as an explanatory variable may bias coefficient estimates.

22 The narrow measure is assumed to capture the precise definition of foreign outsourcing, which refers to the contracting out to overseas suppliers those production activities that can be done within a company (Feenstra and Hanson 1996, 1999).

In this chapter, I make use of unique data on imports of intermediate goods to refine the currently used measure of materials offshoring. These data are made possible as a result of a recently constructed Market Structure Index of HTS Imports (the Imports Index), which classifies imports into intermediate and finished goods (see Sitchinava 2008b). I combine the Imports Index with detailed imports data obtained from Feenstra (2002) and the Census Bureau for 1989-2001 and 2002-2004, respectively, to derive imports of intermediate goods.[23] These are then incorporated into the following modified version of original measure of offshoring:

$$\frac{\sum_j [\, purchases\, of\ interm.inputs_{ij}\,] \cdot [\frac{interm.imports_j}{interm.\ dom.\ output_j + interm.imports_j - interm.exports_j}]}{Total\ Nonenergy\ Interm.\ Purchases_i} \qquad (8)$$

where subscript *j* refers to an industry from which industry *i* purchases its intermediate inputs, where $i,j = 1,...N$. This refined measure of offshoring differs from the original measure by the right term of the numerator, where I use the share of imports of intermediate goods in the domestic supply of intermediate goods in place of the share of total imports in the total domestic supply. Comparing the original with the refined measure of offshoring, there appear to be considerable differences between the measures, as shown in Table 2.

Another trade-related causal factor considered in this chapter is offshoring of services, which has recently attracted much interest in both academic and popular press circles. The services subject to offshoring commonly include information technology services; professional, scientific, and technical services; and administrative and support services (Amiti and Wei 2006). The construction of the measure follows the same formula as shown in equation (8), where intermediate inputs are now replaced with inputs of selected services. The data for services

23 The imports of intermediate goods include imports of parts, components, and raw materials, as well as final goods assemblies that go through the domestic industries before they enter the retail markets. These data provide a near perfect estimate of imports of goods subject to offshoring, in that they exclude imports of offshored assemblies of final goods, which enter the U.S. retail markets directly.

inputs and services imports come from the BLS input-output tables and are described in Appendix A. As shown in Table 2, offshoring of services grew substantially in 1989-1996, with an average change of 0.04% or roughly a ten percent growth of the average level of 0.42%. During 1997-2004, however, the average growth of services offshoring was relatively stagnant.

Following Feenstra and Hanson (1999), I expect to find positive effects of materials offshoring on changes in value-added prices and effective productivity in the first-stage and the skilled-unskilled wage gap in the second-stage. Offshoring of services is likely to have a similar effect in the first-stage, if imported services stir the technology of production away from nonproduction workers in a productivity enhancing manner. This then should lead to a negative impact of services offshoring on the skilled-unskilled wage gap in the second-stage. However, if offshoring of services is merely an alternative to domestically outsourced services, then one should find a price reducing and negative effect of services offshoring in the first stage. The skilled-unskilled wage gap will increase (decrease) if sectors experiencing declining product prices are skilled-intensive (unskilled-intensive).

The measure of openness to imports of finished goods is constructed as the finished goods imports to industry value-added ratio. During 1989-1996 imports of finished goods constituted an average of 29.89% of industry value-added, while by 1997-2004 this percentage went up to 47.16%. Competition arising from imports of finished goods is expected to put a downward pressure on domestic product prices across all sectors of the economy in the first stage estimation. The skilled-unskilled wage gap will increase (decrease) if the sectors experiencing declining product prices are skilled-intensive (unskilled-intensive).

Finally, the technology-related variables are constructed from three measures of high-technology capital stock; i.e., (1) computers, 2) office, computing, and accounting machinery (office equipment); and (3) communications equipment; science and engineering instruments; and photocopy and related equipment (other high-tech equipment).[24] Combining these capital stock measures with “ex post” and “ex ante” user costs yields “ex post” and “ex ante” measure of services rendered by office equipment, computer, and other high-tech capital, or in other words, the opportunity cost of capital possession (Berndt and Morrison 1995, 1997; Feenstra and Hanson 1999).[25] I express these measures as shares in total capital services and use the first-difference of the "ex post" capital shares as the primary technology-related explanatory variables. I check the robustness of the results to the "ex ante" measures in the sensitivity analysis. The data for the construction of the technology variables are courtesy of the BLS and more detailed discussion of the construction methods can be found in Appendix A. As shown in Table 2, the computer share increased continuously throughout the sample period. At the same time, office equipment share steadily declined, while other high-tech share rose during 1989-1996 and declined during 1997-2004. Previous studies found the technological change attributable to high-tech equipment diffusion as productivity enhancing and skill-biased (Berndt and Morrison 1995, 1997; Feenstra and Hanson 1999). I test the robustness of these findings in the section below.

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24 Previous literature incorporated investment in computer capital in the studies of the 1980s wages (Autor & Katz 1998, Feenstra and Hanson 1999, 2003). During the 1990s, these data were compiled only during 2002-2004, which makes it impossible to incorporate computer investment in this chapter. However, the inclusion of the computer services share variable should reasonably proxy for the impact of computerization on productivity, prices, and wages.

25 The *ex post user costs* reflect the internal rate of return in each industry and capital gains on each asset, and the *ex ante user costs* reflect a “safe” rate of return (the Moody rate of Baa bonds) and excludes the capital gains on each asset. Feenstra and Hanson (1999) comment that ex ante measures might be preferred because they do not reflect the capital gains on the assets and the internal rates of return in the industry.

V. Results

The estimation is performed over 458 U.S. manufacturing industries at the four-digit SIC level for the period of 1989-1996 and 473 six-digit NAICS industries for the period of 1997-2004. I utilize two methods of variable construction. The first method uses variables expressed as differences over 1989-1996 and 1997-2004 periods, divided by the number of years in each period to obtain annualized differences. The estimation then reduces to a cross-sectional analysis, which is common in the product-price literature and is motivated by the log-run nature of the Heckscher-Ohlin theory and is often used to circumvent the limited availability of yearly data (Haskel and Slaughter 2001).

I contrast the results from the "annualized differences" estimation to those where variables are expressed as first-differences. Estimation is then performed using panel estimation techniques with fixed effects to control for year-specific unobservables. As will become apparent, the differences in the magnitudes of estimates from the two methods are considerable. These differences arise from the fact that the first-difference estimation captures both industry trends in the data and the time-series variation around these trends. On the other hand, the annualized differencing approach weeds out the time-series variation by construction and evaluate the coefficients based on industry trends alone. Thus, the additional noise captured by the first-differences estimation should yield smaller coefficients, which could potentially be interpreted as short-run estimates. Then the larger estimates from the annualized differences estimation could be evaluated as long-run effects.

III.V.1. Preliminary Regression

Before turning to estimating the two-stage procedure of linking price changes to wage changes, I check the consistency of equation (4) against the data. Table 3, Part b) presents the regressions of changes in value-added prices plus effective productivity on the average cost shares of production and non-production workers and capital. Regressions are run for changes in variables measured as annualized differences and first-differences, as discussed above. The estimated coefficients can be compared with the annual average changes in the prices of these primary factors shown in Table 3, Part a). Similar to the results reported in Feenstra and Hanson (1999) for the 1980s, the estimated coefficients are extremely close to the actual factor price changes and the regressions fit nearly perfectly. The wage of nonproduction labor rises faster than production labor during 1989-1996, indicating an increase in wage inequality, and slower during 1997-2004, indicating a decrease in wage inequality.

In Table 3, Part c) I examine whether changes in value-added prices, changes in effective TFP or both are responsible for the increase in the skilled-unskilled wage gap during 1989-1996 and the decline in the wage gap during 1997-2004. Taking the differences between the predicted coefficients on non-production and production cost shares, it appears that changes in prices are concentrated in the unskill-intensive sectors in both periods, as they result in a relative decrease of the skilled-unskilled wage gap. On the other hand, changes in the effective productivity are concentrated in the skill-intensive sectors, as they result in the relative increase in the wage gap during both periods.[26] This contradicts the findings of Leamer (1998) who finds that both changes in prices and changes in productivity were concentrated in the skill-intensive sectors of U.S. manufacturing during 1980s.

26 Leamer (1998) runs similar regressions, but use changes in prices and changes in TFP to predict factor price changes for the U.S. during 1981-1991. He finds that both changes in prices and productivity are skilled-labor intensive. I rerun the regressions in Table 3, part c) using the same dependent variables, and find similar results to Table 3, part c), except that changes in TFP in fact decrease the skilled-unskilled wage gap during 1997-2004.

The results of these regressions are robust to the inclusion of market power controls, i.e. output/capital ratios and market concentration measures, and to the exclusion of the computer industry. The results of Table 3 solidify theoretical predictions of the SS theorem of the link between prices and productivity and wages.

V.2. Stage 1

In this section, I report the first stage estimation results of the two-stage procedure, where I regress changes in value-added prices plus effective productivity on trade- and technology-related causal factors. The key variables of interest are the measures of outsourcing of intermediate goods in equations (7) and (8). As it will become apparent, these measures which are comparable to those used in the existing literature produce coefficients of varying magnitudes and significance, where the estimates on the refined measure are more robust to various specifications.

There are four estimation issues to be addressed. First, while the dependent variable is available only at a highly disaggregated level, the SBTC variables are available only at two-digit SIC level and three-digit NAICS levels in the respective periods, and the outsourcing variables are available only at three-digit SIC and four-digit NAICS levels. I cluster the errors at the most aggregated groups to avoid the possibility that errors are correlated within the more aggregated industry groups (Moulton 1986; Feenstra and Hanson 1999). Second, since the dependent variables in the second-stage regressions embody the same estimated coefficients, the standard errors of the second-stage coefficient estimates need to be corrected.[27] I follow the steps outlined

27 If not corrected, the second-stage regressions provide conditional estimates of the residuals that incorporate the additional variance of the residuals from the first-stage estimation. To test the significance of the second-stage coefficients, unconditional estimates of the standard errors accounting for this additional variance have to be computed.

in Dumont et al. (2005) to correct the standard errors of the second-stage estimation.[28] Third, if industries are not perfectly competitive then the measure of total factor productivity is biased because the capital share includes pure profits. I include the log change in the output-capital ratio as a regressor to absorb the market power effect (Domowitz et al. 1988; Feenstra and Hanson 1999; Haskel and Slaughter 2001, 2003). Finally, caution needs to be taken in comparing the coefficients from the 1989-1996 and 1997-1996 data samples, due to differences in SIC and NAICS classification during the respective periods. These classification vary considerably in their definition of U.S. manufacturing, and thus may change the behavior of manufacturing-specific variables across the two periods.

Table 4 presents estimation results from the first-stage regression using the original specification proposed by Feenstra and Hanson (1999), which includes only materials offshoring and high-tech capital shares, excluding the computer share. Columns I-IV contrast estimates for original (I & III) and refined (II & IV) measures of offshoring, where variables are constructed either via annualized differences or first-differences methods using the 1989-1996 data sample. Similarly, Columns V-VIII present estimates for the period off 1997-2004. As mentioned earlier, I include year fixed effects in the estimation with first-differenced variables to account for time-varying unobservables.

As is apparent from Table 4, the signs and statistical significance of the coefficients are relatively robust to various specifications within each period. On the other hand, the magnitudes of the estimates vary considerably across specifications and sample periods. The most striking differences in magnitudes appear across annualized differences and first differences

28 Feenstra and Hanson (1997, 1999) propose a correction procedure which has been disputed in most recent work by Dumont et al. (2005), since the correction does not require that the computed variances are positive and may impose a negative bias on the standard errors. The procedure developed by Dumont et al. (2005), in turn, does guarantee positive variances of the second-stage estimates.

specifications, in particular for estimates on materials offshoring. These differences persist when year fixed effects are excluded from the first-differences estimation, not shown in Table 4, although an *F*-test confirms the necessity of year fixed effects. Additionally, the negative sign on the office equipment share comes in contrast to the findings of Feenstra and Hanson (1999). The general lack of significance of the impact of offshoring measures during 1997-2004 is troubling.

In Table 5 I present results of specifications with a full set of causal factors. The inclusion of other controls reveals the severity of the measurement error introduced in the original measure of materials offshoring. Unlike the estimates on the refined measure, the estimates on the original measure become insignificant in all specifications and shrink in magnitudes compared to those in Table 4. As a result of such poor performance, I turn my focus to the specifications using the refined measure of materials offshoring of Columns II, IV, VI, and VIII.

Turning to trade-related causal factors first, the estimates on these factors come through with mixed signs and significance. The effect of materials offshoring, per refined measure, changes across time. While offshoring, defined as a difference of broad and narrow measures, drives the growth in changes in value-added prices and effective productivity during 1989-1996, it is the narrow measure of offshoring (within closely-related industries) that appears to have a significant effect during 1997-2004. Furthermore the effect of materials offshoring changes to negative, albeit very small, in the first-difference estimation of Column VIII. Services offshoring appears to have a negative impact on changes in value-added prices and effective productivity during 1989-1996, and positive effect during 1997-2004. Openness to finished goods has a very small and insignificant coefficient.

In order to make sense of the result in Table 5, I find it useful to separate the dependent variable in the first-stage estimation into its respective components. Table 6 shows independent regressions of changes in value-added prices and changes in effective productivity on causal factors. The first-differences specifications reveal a consistent picture, where trade-related variables, with the exception of services offshoring in the 1997-2004 sample, increase productivity and reduce prices. This is consistent with prior expectations that trade-driven market competition puts a downward pressure on prices and production-related inefficiencies in the short-run. In the long-run, expressed by annualized differences, however, the results are less consistent. Thus, materials offshoring appears to mostly increase both prices and productivity, services offshoring appears to decrease productivity with mixed effect on prices, and openness to imports has mixed effects on both prices and productivity across the two sample periods. The latter results may indicate perhaps that it is hard to predict a consistent impact of trade on prices and productivity when too many things are at play, e.g.., contracting and expansion of sectors, restructuring of production technologies, etc.

Next I turn attention to the effects of technology-related causal factors on changes in value-added prices and effective productivity, as shown in Table 5. The inclusion of the computer share in the 1989-1996 specifications considerably affects the magnitudes, signs, and significance of the coefficients on other technology-related variables compared to those in Table 4. The estimates on the computer share are, in turn, large and highly significant. However, the effect of computers goes away by 1997-2004, while office equipment and other high-tech capital shares retain their signs and significance. These results may be indicative of a changing role of computer technologies in U.S. manufacturing. While the computer revolution of late 1980s-early 1990s changed the technology of production in a productivity enhancing manner during

1989-1996, the Internet revolution of the late 1990s and early 2000s may in fact have introduced little change to the existing manufacturing processes. On the other hand, by the late 1990s, advances in computerization may have penetrated other high-tech technologies leading to higher productivity gains, shown by the estimates on other high-tech share in Columns V-VIII. These interpretations are also confirmed by larger productivity gains from other high-tech capital share and lower productivity gains from computer share of Table 6.

Under zero-profit conditions, these estimated changes in value-added prices and effective productivity can be linked to changes in factor prices. In Table 7 I rerun the regressions, only retaining those causal factors that had a non-neutral impact on the dependent variable in the full specification of Table 6. Only significant coefficients signal actual changes in prices and productivity, which will then mandate changes in factor prices under the zero profit condition (Slaughter 2000). As can be seen, the coefficients on the remaining trade- and technology-related variables are robust to these changes. I use these final specifications in the second-stage analysis discussed below.

V.3. Stage 2

Before turning to the second stage of the estimation procedure, I first decompose the dependent variables of the first-stage regressions from Table 7 into those components due to each causal factor. I then use these components as dependent variables in the second-stage regressions. The second stage regressions are run without a constant and are weighted by the average industry shipment in total manufacturing shipments. The standard errors are corrected using the Dumont et al. (2005) correction procedure, as discussed above.

The results of the second-stage estimation are presented in Table 8. Consider, first, the changes in value-added product price plus effective productivity due to technological change and induced changes in factor prices. It appears that upgrading of computer capital is the only technical change variable that is skill-biased, that is it leads to a negative, albeit insignificant, change in production wages and a positive large change in the non-production wages during 1989-2004. In contrast, the office equipment share raises both the production and nonproduction wages in relatively equal amounts, while other high-tech share increases production wages and decrease non-production wages during 1997-2004. Taking the difference between the predicted changes in the nonproduction and production wages due to computerization, the relative wage of nonproduction labor increased by an astounding average 1.725% per year measured in the long-run, and 1.058% per year, measured in the short-run. In contrast, other high-tech share is responsible for an average 0.310% per year decline in relative wages measured in the long run, and 0.221% per year decline measured in the short-run during 1997-2004.

The estimates of Table 8 can, in fact, be compared with the actual increase in relative non-production wages. Recall, that the average annual change in log non-production and log production real wages is 3.839% and 2.666% during 1989-1996 measured by annualized differences and 3.784% and 2.668% measured by first differences, as reported in Table 3, Part a). The difference between these figures provides the actual increase in the relative wages of nonproduction to production workers of 1.173% and 1.116% per year, respectively over 1989-1996. Thus, computerization can individually account for over 147% and 95%, respective of the differencing approaches, of the observed annual increase in the relative wage of nonproduction labor during 1989-1996. During 1997-2004, the actual relative nonproduction wages declined by 0.256%, when measured in annualized differences, and 0.265%, when measured in first differences. Then the high-tech equipment diffusion explains over 119% and 85% of the actual decline in relative non-production wages, respectively, during 1997-2004.

Next, I consider the predicted changes in relative nonproduction wages due to changes in trade-related variables. Using the above approach of comparing the predicted wage changes to the actual wage changes, the changes in product price plus productivity due to materials offshoring explain 51% of wage changes, when measured in annualized differences, and 7% of wage changes when measured in first-differences, during 1989-1996. Materials offshoring fails to impact wages in a significant way during 1997-2004. At the same time, however, services offshoring has a strikingly large positive effect on the skilled-unskilled wage gap during 1989-1996, yet a large negative effect on the wage gap during 1997-2004. These findings are contradictory to each other and leave me puzzled, since the service offshoring comprise a very small percentage of total services outsourcing over the period of 1989-2004.

In summary, I find a very strong link between trade and technological change and relative wages. This link, however is highly sensitive to the nature of the trade and technology forces in play and the time period under inspection. I find a very strong and robust effect of materials offshoring on the skilled-unskilled wage gap during 1989-1996, but its effect during 1997-2004 appears to be statistically insignificant. Similarly, computerization is found to be the main driver of the relative wage inequality during the first half of the period, whereas other technological change plays the main role in determining wages during 1997-2004. Furthermore, one must be careful in considering all technological change as skill-biased. I find that other high-tech diffusion significantly raises wages of the unskilled and in fact lowers wages of the skilled during 1997-2004. These findings may be indicative of the diminishing role of computers in U.S. manufacturing, and a growing role of computerization of other high-tech equipment which works to enhance the productivity of the unskilled, thus raising their relative wages. The large role of services offshoring in both raising the skilled-unskilled wage gap during 1989-1996 and then reducing it during 1997-2004 is surprising due to its relatively low prevalence in manufacturing.

VI. Sensitivity Analysis

There are a number of points worth noting about my estimation in Tables 4-8. First of all it may be argued that the computer industry has experienced an unusual productivity growth over the past decades and should be excluded from the industry-level analysis (Leamer 1998, Feenstra and Hanson 1999). I rerun the estimation without the computer industry and find that the coefficients are not qualitatively different from the ones presented in Tables 4-8. Another potential concern that may arise is that trade and technology regressors in the first-stage estimation may be endogenously determined with value-added prices and productivity. I follow the previous literature in assuming that they are exogenous. Additionally, I check that the estimation is not sensitive to the weights employed in the analysis, by using employment and wage bill weights. The results are qualitatively the same. Furthermore, one may argue that both value added prices and cost shares need to be deflated by appropriate deflators to net out inflationary forces over 1989-2004. I rerun the estimation, using manufacturing wide producer price indexes to deflate product prices and wages, and find no significant changes in coefficient estimates. Finally, I check the sensitivity of the results using the alternative ex ante measures of technological change variables. The results are not qualitatively different and are available on request.

VII. Conclusion

This study is the first study of the impact of trade and technology on U.S. wages of 1990s. Using recently available data on industry statistics, I am able to document a near-continuous growth in the 1990s wage inequality within the U.S. manufacturing, where by some measures, the wage gap is growing more rapidly than that recorded in 1980s. I use these data to contribute to the on-going debate of the effects of trade and technology on U.S. wages.

My findings indicate that the relative contribution of trade is sensitive to the data and the type of variables used in the estimation. My preliminary estimation indicates that the standard measure of offshoring of materials, proposed by Feenstra and Hanson (1996, 1999) and commonly used in the literature, suffers from severe measurement errors that prohibit the estimation of the impact of trade in intermediate inputs on the wage dispersion of the 1990s. I address this issue by developing an improved measure of materials offshoring, which remarkably improves the performances of offshoring and other variables across all specifications. Furthermore, various trade-related variables have radically different effects on U.S. wage inequality of 1989-1996 and 1997-2004. Thus, I find that trade in intermediate inputs contribute dramatically to the increase in the wage inequality during 1989-1996 and 1997-2004, although the effect during the latter period is insignificant. On the other hand, trade in services inputs either raises or reduces the demand for skilled workers, and these effect are strikingly large.

Looking at the technology-related variables, I find that computerization remains the most appropriate measure of skill-biased technological change as it adversely affects the demand for the unskilled and positively impacts the demand for skilled labor. However, this effect could only be estimated in the 1989-1996 sample, as the extent of computerization failed to have a non-neutral effect on productivity during 1997-2004. Furthermore, the changes in the share of other high-tech capital, i.e., communications equipment, photocopy equipment and various scientific and engineering instruments, in fact, are found to increase wages of production workers and decrease wages of nonproduction workers during 1997-2004.

In summary, I find much support for the hypothesis that both trade and technology are some of the factors responsible for the growing wage gap during the 1990s. A different type of technological change, in turn, is responsible for the declining gap during the 2000s.

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APPENDIX A: Data Appendix

NBER Productivity Database and Productivity Database Extension

Most of the data used in construction of the non-structural variables are obtained from the NBER Productivity Database (PD). The NBER PD extends as far as 1996 on 1987 SIC basis and incorporates data on shipments, employments, materials, inventory, energy, investment, capital stock, deflators, and TFP measures for 458 industries. Since my analysis goes as far as 2004, I extend the NBER PD following the methodology outlined in Bartelsman and Grey (1996). I describe the construction of each of the variables of the PD extension and the data issues encountered on the way below. The final PD extension spans 1997-2005 and in addition to the NBER PD variables, includes two versions of output price deflators, cost of selected services, and services deflators for 473 six-digit NAICS industries.

Industry Statistics

Data on shipments, employment, materials, inventory, energy, and investment come from the Annual Survey of Manufacturers, which are currently available for 1997-2005 and can be downloaded from the Census website. I have identified two issues with the ASM data. First, while the industries in the1997-2001 ASM data follow six-digit NAICS, the industries in the 2002-2005 data follow NAICS-based code which aggregates some six-digit NAICS industries into two to five grouped Census-defined industry code. In order to break down the Census-code industries data into data for each of the embedded six-digit NAICS industries, I aggregate the data from 2001 ASM into the corresponding Census code industries. Then, for each industry statistic of six-digit NAICS industries in 2001, I calculate its share in the respective aggregated industry statistic of the corresponding Census-code industry of 2001. These shares are then used to impute the six-digit NAICS industry data from the Census-code industry data in 2002-2005. Since energy data is available as total energy, fuel and electricity purchases, I first break down fuel and electricity and then aggregate these to create the broken down total energy purchases. The break-down method for investment, which is subdivided into structures and equipment investment, is slightly different. I first used the method described above to obtain total investment for the six-digit NAICS industries. The broken down structures and equipment investment are constructed by applying the shares of equipment and structures of the corresponding Census-code industry in its total investment for 2002-2005 to the broken down total investment for the six-digit NAICS industries within the Census-code. Thus, I assume that the six-digit NAICS industries embedded in the Census-code industry invest in structures and equipment in the same proportions as the overarching Census-code industry. I justify this method by noting that since investment in structures and equipment takes place in discrete amounts, one cannot assume that proportions of 2001 will hold up during 2002-2005.

The second issue is similar to the one experienced by Bartelsman and Gray (1996), where some industries in the ASM data have missing information due to the disclosure reasons. I were able to approach the issue in two ways. For some missing observations of six-digit NAICS industries, I was able to subtract the existing data for other six-digit NAICS from the data of the overarching five-digit NAICS industries. If data for five-digit NAICS were not disclosed, I used the same method to first obtain the missing five-digit NAICS data from the overarching four-digit NAICS data. This method took care of all the missing observations but the ones due to energy and investment, where multiple industries within a five-digit NAICS would have missing information. I remedied this issue by first obtaining the aggregated data for the multiple industries with missing observations by the method of subtraction the existing data of six-digit NAICS from five-digit NAICS. Then the aggregated data were broken down for total energy, fuel, and electricity, by the average shares of these variables in the aggregated data of the nearby years, for which full data were available. The aggregated data for investment, equipment, and structures, were broken down by the share of the aggregated equipment and structures in the aggregated total investment of the same years. Once again, I did not use the data from the nearby years for the investment variables, since investment of one year does not have to follow the investment patterns of the previous year.

Shipment Price Deflators

In the NBER PD, output price deflators data come from the BEA shipments price deflator data. While the BEA produces the shipment price deflators for 1997-2005, the data come with a disclaimor about the lack of precision in the data. This is true because the BEA basis its shipment price deflator data on the BLS producer price index data for each six-digit NAICS industry, where 130 observations are missing for some industries and years. Since the changes in product prices are integral to the two-stage estimation, upon consulting the BLS, I construct my own output price deflators from the producer price indexes. I replace the missing observations with the related commodity price indexes or converting the existing SIC indexes into NAICS. While the differences between my deflators and BEA deflators exist, the TFP calculations using each of the deflators yield near identical values. The PD extension includes my version of the output price deflators as the default prices, and the BEA shipment price deflators as alternative prices.

Materials Deflators

Materials deflators are constructed for each industry as the sum of materials supplying industry PPIs weighted by the share of material purchases from that supplying industry in total material purchased of the purchasing industry. The weights are obtained from the 1997 input-output tables, since this is the only benchmark input-output table available to date. The 2002 benchmark input-output tables have been released as of the writing of this paper. The six-digit NAICS materials include materials from manufacturing and non-manufacturing sectors, where the latter includes agriculture, logging, mining and utilities. The BLS does not post PPI's for the agriculture industry. Having consulted the BLS staff, I average out the price indices of the commodities produced by each six-digit NAICS agriculture industry. While the BLS staff had provided us with the BLS commodity code – NAICS mapping, the concordance does not contain relative importance weights for multiple commodity codes mapped in the one NAICS industry. As the result, the constructed agricultural PPIs are the equally weighted average of commodity price indexes, provided by the BLS. There were a number of six-digit NAICS, for which some commodities had missing price indexes either partially or entirely.[29] A small number of NAICS had no commodity price index data, which I excluded from the material deflator calculations.[30] One drawback of the material deflator construction method described above, which is outlined in Bartelsman and Grey (1996), is that the PPI data does not contain changes in the shipment and

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29 These NAICS codes and their respective commodity codes are listed as follows: 111199:01220415; 111320:01110107; 111334:01110225; 111335:01190105; 111339:01110206; 114111:02230102, 02230103, 02230134, 02230135; 114112:02230503, 02230504.

30 The following NAICS do not have a commodity code mapping, which prevents us from constructing PPI data: 111160, 111136, 1114, 111910, 111930, 111991, 111998, 112111, 112130, 111234, 112420, 112511, 112512, 112519, 112910, 112920, 112930, 112990, 114119, 113110, 113220, 2213, 230320.

retail margin prices. This implies that the materials deflator data may not reflect the actual price changes experienced by the materials purchasing industries.

Services Deflators

Services deflators are constructed for each industry as the sum of services supplying industry PPI's weighted by the share of services purchases from that supplying industry in total services purchases of the purchasing industry. The weights are obtained from the 1997 input-output table, since this is the only benchmark input-output table available to date. I restrict services to only those related to the information services (NAICS 5112, 518, 514); professional scientific support services (NAICS 5411-5119); and administrative and support services (NAICS 5614). PPIs are available for only a limited number of these services (5112, 518, 514, 5411, 5412, 5413, and 5418). Services deflators are not available in the NBER PD and could not be constructed for years prior to 1997.

Capital Stock and Investment Deflators

As described in the NBER Productivity Database, the starting point for the process of creating real capital stock series is a set of less aggregated industry capital stock estimates. I use FRB 4-digit NAICS net capital stocks as the basis for my 6-digit NAICS estimates.[31] The FRB 4-digit net capital stock data are based on 4-digit investment series for plant, equipment, and software of the Annual Survey of Manufacturers, and the 1997 industry-asset type investment flow matrix, producer durable equipment deflators, and a table of mean service lives by asset type from the BEA. The 4-digit data are converted to the 6-digit level by assuming that the industry-asset type flows are the same for all 6-digit industries within a 4-digit. With this assumption in mind, I are able to use the FRB 4-digit data on real and nominal investment by asset type (structures, equipment, software) and create investment deflators, which I use to create real investment at 6-digit NAICS level. The initial 6-digit real capital stocks for 1997 are created using the ratio of 6-digit to 4-digit real (net capital) from the Annual Survey of Manufacturers. I construct the implied "depreciation" from the 4-digit capital stock and and real investment data by using $K_{it}=(1-\delta_i) K_{it-1}+I_{it}$. Now I can successively add real investment in equipment and structures and subtract the "depreciation" to create real net capital stocks from 1997-2005.

Non-Structural Variables

Factor Cost-Shares

I calculate factor cost-shares by dividing payment to each factor by the value of shipments, in nominal terms. The factor cost-share of services cannot be derived from the ASM data. I assume that six-digit NAICS industries have the same share of services costs as the over-arching four-digit NAICS. The data for the latter comes from the BLS input-output tables for 1997-2004, which are provided on four-digit NAICS levels. The services cost-shares for years prior to 1997 are obtained at three-digit SIC level from the BLS input-output table for 1989-1996. In the paper analysis, factor cost-shares appear as an average cost-share between the first and last year of each period.

Factor Prices

I proxy prices of unskilled and skilled labor by the ratio of production and nonproduction

31 I thank John Stevens of FRB for providing us with these data.

wages to the number of production and nonproduction workers employed, respectively. The price of capital is calculated by dividing the payments to capital in each industry (which equals value of shipments less payments to labor and materials) by the quantity of capital. In the specifications where services are netted out from value added prices and TFP calculations, payments to services are also netted out from the payments to capital. Materials, energy, and services price deflators are used to calculate log change in the respective prices.

Value-added product prices

The log change value-added product price is measured by the formula provided in the text, $\Delta \ln p_{it}^{VA} \equiv [\Delta \ln p_{it} - \frac{1}{2}(r_{it-1} + r_{it})' \Delta \ln p_{it}^{m}]$, where r_{it-1} and r_{it} are the materials cost-shares of industry i=1, ..., N, averaged over the two periods and $\Delta \ln p_{it}^{m}$ is the change in log price of intermediates. The product price data comes from the output deflator data, and the price of intermediates comes from the materials deflator data from the NBER PD and PD extension An alternative specification of value-added prices is the change in log product price net of the average cost-share weighted change in log price of intermediates and services.

Primal TFP

Primal total factor productivity is constructed as the difference in the growth of value added (log change) and cost-share weighted growth of primary factors (log change). The value-added is calculated as the growth in real shipments (log change) minus the average cost-share weighted growth in real materials payments (log change). In the alternative specification of TFP net of services, the growth of value-added is constructed as the growth of real shipments net of weighted growth of real materials and services payments.

Aggregated Value-Added Prices and Primal TFP

In the sensitivity analysis, the two-stage procedure relies on aggregate values of the dependent variable, Value-Added Prices + Effective Primal TFP. These values are constructed constructed at three-digit SIC and four-digit NAICS industry levels for periods of 1989-1996 and 1997-2004, respectively. The aggregate prices were calculated by initially aggregating the output and intermediates deflators as a Divisia index, with each inflation rate weighted by the average of previous and current-year's output and intermediates shares in total respective values. Then value-added prices were recalculated at aggregate levels using the formula discussed above, with internal weights derived from the aggregated industry intermediates cost shares. The aggregate TFP measure was derived as a weighted average of industry productivity growth rates, where weights are Domar weights equal to the ratios of industry shipments to aggregate value-added (Domar 1961; Jorgenson and Stiroh 2000).

Structural Variables

Technology

The data I use for technology variables, i.e., *office equipment share, other high-technology share,* and *computer share*, have been supplied to us by Randal Kinoshita of the BLS. These data are available in 2000 constant dollars and distinguish capital by asset type for 1948-2002 on 2-digit SIC level and 1987-2005 on 3-digit NAICS level.

Berndt and Morrison (1995) define high-technology capital to include office, computing, and accounting machinery; communications equipment; science and engineering instruments; and photocopy and related equipment. This definition of high-technology capital does not incorporate computers. The data currently available to us breaks assets up slightly differently. On the SIC level, the high-technology capital is broken up into the following: office, computing, and accounting machinery (asset 14) and communications equipment (asset 16) had stayed the same, while instruments category is broken up into photocopy and related equipment (asset 27); medical equipment and related (28); electromedical (29); and other medical (30). On the NAICS level, the high-tech capital is broken up into the following: office and accounting machinery (asset 4); communications equipment (6), photocopying and related equipment (26); medical equipment and related equipment (27); electromedical instruments (28); nonmedical instruments (29). Similarly to Berndt and Morrison (1995), I separate high-technology capital into office equipment (SIC asset 14 and NAICS asset 4), and other high-tech capital. I also define computer capital to include SIC assets 32-42 and NAICS assets 33-43, which is not considered in Berndt and Morrison (1995).

To calculate the technology shares, I first calculate the capital services incurred from each type of high technology capital (office equipment, computer, and other high-tech capital) by summing the production of the productive stock of assets and the assets' user costs over all assets in each type of high-technology capital. I then divide the office equipment, computer, and other high-tech capital services by the total capital services, obtained using the same method. I use two measures of use costs, ex post and ex ante user costs. The ex post user cost (or internal rental price) is provided by the BLS and are calculated as in Hall and Jorgenson (1967). This reflects the internal rate of return in each industry and capital gains on each asset. On the other hand, the ex ante user cost used by Berndt and Morrison (1995) reflect a “safe” rate of return and excludes capital gains on each asset. The “safe” rate of return is measured by Moody's Baa Corporate Bond rate, which I obtain from St. Louise FRB on monthly basis and average out to get the annual rate.

A practical problem arises when capital income in national accounts (gross operating surplus) becomes negative or assets undergo a very high revaluation. In such cases, the measured rental prices using internal rate of return may also become negative, which is theoretically inconsistent. One way of eliminating such negative rental prices is to employ an external rate of return. Following Harper, Berndt and Wood (1989) I take a constant rate at 3.5%, which is the difference between nominal discount rate and inflation rates in the US as calculated by Fraumeni and Jorgenson (1980) (see Harper et al. 1989 or Erumban 2004, pg 13). Thus I substitute internal rate of return in rental price formula (13) with a 3.5. Note that the 3.5 rate of return is assumed to be a real rate of return (net of capital gains).

Outsourcing and Import Openness

The construction of these measures of outsourcing and import openness follows the descriptions provided in Sections IV and V. The data for the measures come from the BLS input-output tables, U.S. imports from Feenstra (2000) and the Census Bureau, and the Market Classification of HTS Imports provided by Sitchinava (2008b). Foreign services outsourcing is constructed using the services inputs and imports information from the BLS input-output tables. The services are limited to information; professional, scientific, and technical; and administrative and support services. The corresponding NAICS and SIC industries are provided in the Table A.1.

Table A.1. Selected services

Services Break-Down on 2002 NAICS-basis	
Information	
Software publishers	5112
Internet and other	518 [1]
Professional, scientific, and technical services	
Legal	5411
Accounting, tax preparation, bookkeeping, & payroll	5412
Architectural, engineering, & related	5413
Specialized design	5414
Computer systems design & related	5415
Management, scientific, & technical consulting	5416
Scientific research & development	5417
Advertising	5418
Other professional, scientific, & technical	5419
Administrative and support	
Business support services	5614
Services Break-Down on 1987 SIC- basis	
Information; professional, scientific, and technical services; administrative and support	
Legal	81
Accounting, auditing, & related	872, 89
Engineering, architectural, & related	871
Computer, data processing, & related	737
Management & public relations	874
Research & testing	873
Advertising	731
Miscellaneous business	732, 733, 738

[1]*Note, that this 2002 NAICS translates to 514 1997 NAICS*
Price data found for 5112, 518, 5411, 5412, 5413, 5418 only

APPENDIX B: Figures and Tables

Figure 1. U.S. Wage Inequality, 1963-2005

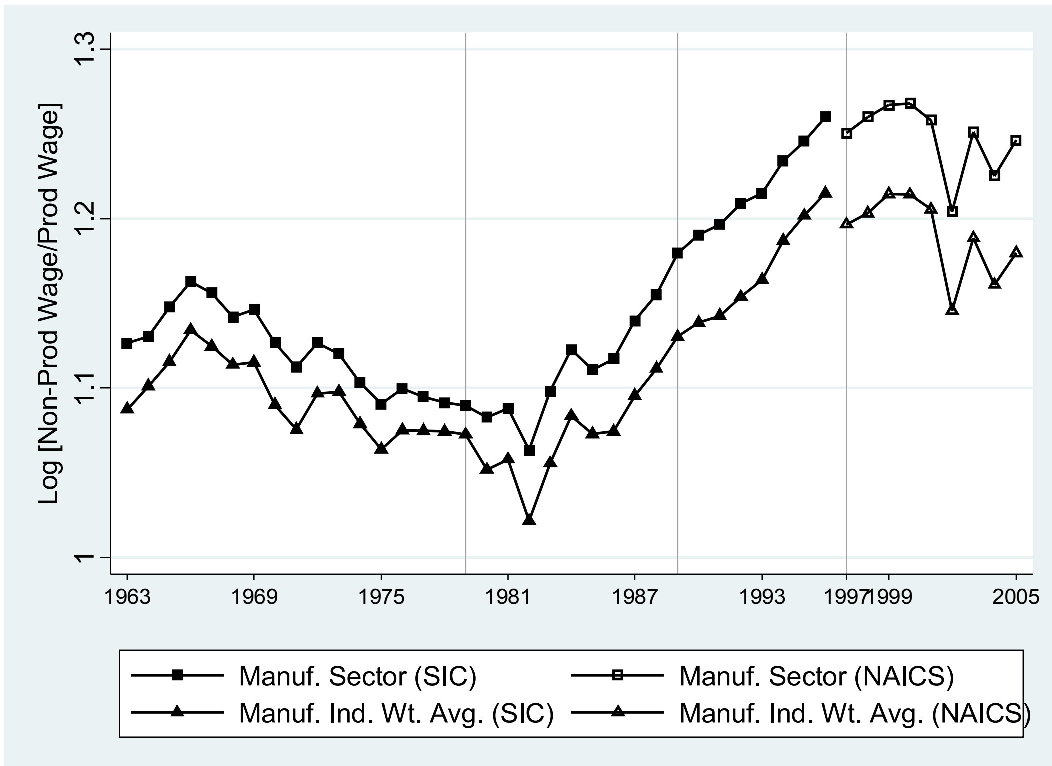

Table 1. Summary Statistics of Non-Structural Variables

	1979 – 1990		1989 – 1996		1997-2004	
	Average (percent)	Annual change	Average (percent)	Annual change	Average (percent)	Annual change
Change in log factor prices						
Production labor		4.99		2.67		3.02
Nonproduction labor		5.42		3.78		2.76
Capital		3.98		2.91		0.27
Materials		3.29		0.88		1.66
Energy		3.31		2.00		4.55
Selected Services						2.62
Factor cost-shares:						
Production labor	13.41	-0.18	12.03	-0.17	11.44	-0.12
Nonproduction labor	10.66	0.01	10.14	-0.15	8.91	0.01
Capital	32.06	0.33	35.12	0.32	38.30	0.25
Materials	53.41	-0.06	52.95	-0.02	50.55	-0.08
Energy	2.45	-0.01	1.86	-0.02	1.83	0.03
Selected Services			2.53	0.02	4.38	0.19
Change in productivity						
Primal TFP		0.80		0.70		0.43
Primal ETFP		0.78		0.68		0.40
Change in product prices						
Value-added		1.53		0.67		0.12

Note: Both averages and changes are weighted by the industry share of total manufacturing shipments, except changes in log primary factor prices, which are weighted by the industry share of total manufacturing payments to that factor. All variables are computed over 452 four-digit SIC industries in 1979-1988 and 1989-1996 and 472 six-digit industries in 1997-2004. The data come from the NBER PD (Bartelsman and Gray 1996) and the PD extension of it for 1997-2005 based on the data from Annual Survey of Manufacturers, Federal Reserve Board, and Bureau of Labor Statistics.

Table 2. Summary Statistics for Structural Variables

	1979-1990		1990 – 1996		1998 – 2004	
	Average (percent)	Annual change	Average (percent)	Annual change	Average (percent)	Annual change
Trade						
Materials Offshoring						
Original measure (Br)			14.98	0.52	15.73	-0.32
Original measure (Nr)			7.64	0.29	8.35	-0.19
Original measure (Br – Nr)			7.34	0.23	7.38	-0.13
Refined measure (Br)			14.56	0.46	17.54	-0.06
Refined measure (Nr)			7.68	0.23	9.71	-0.02
Refined measure (Br – Nr)			6.88	0.23	7.84	-0.04
Services Offshoring						
Selected Business Services			0.42	0.04	0.51	0.0003
Openness to Imports						
Finished Goods Imports/VA			29.89	0.87	47.16	4.61
Technology						
With Ex Post User Costs						
Computer Share	4.75	0.32	7.17	0.16	12.20	0.48
Office Equipment Share	0.83	-0.05	0.45	-0.03	0.10	-0.03
Other Hi-Tech Share	4.01	0.20	5.12	0.03	4.76	-0.11
With Ex Ante User Costs						
Computer Share	2.87	0.23	5.14	0.19	9.67	0.48
Office Equipment Share	0.48	-0.03	0.33	-0.01	0.08	-0.02
Other Hi-Tech Share	3.01	0.18	4.32	0.07	4.23	-0.08

Note: Both averages and changes are weighted by the industry share of total manufacturing shipments. All variables are computed over 453 four-digit SIC industries in 1989-1996 and 473 six-digit industries in 1997-2004. The data come from the BLS input-output tables and Ray Roshita of BLS.

Table 3. Consistency of Data with Equation (4)

a) Descriptive Statistics: Mean Changes in Log Factor Prices

	1989-1996		1997-2004	
	Annualized Diff.	First Diff.	Annualized Diff.	First Diff.
Production labor	2.666	2.668	3.025	3.022
Nonproduction labor	3.839	3.784	2.769	2.758
Capital	2.900	2.771	0.418	0.274

b) Regression of $\Delta p_i^{VA} + \Delta ETFP_i$ **on primary factor cost shares**

	1989-1996		1997-2004	
	Annualized Diff.	First Diff.	Annualized Diff.	First Diff.
Prod. Cost Share	2.631***	2.667***	3.010***	3.032***
	[0.022]	[0.013]	[0.015]	[0.012]
Non-Prod. Cost Share	3.689***	3.644***	2.777***	2.744***
	[0.172]	[0.161]	[0.040]	[0.025]
Capital Cost Share	2.941***	2.798***	0.422***	0.275***
	[0.030]	[0.029]	[0.008]	[0.005]
Observations	458	3206	473	3311
R-squared	1.00	0.99	1.00	0.99

Note: Standard errors are in parenthesis. All regressions are weighted by the industry share of total manufacturing shipments.

Table 3. Consistency of Data with Equation (4) (Cont.)

c) Regression of $\Delta\, p_i^{VA}$ and $\Delta\, ETFP_i$ on primary factor cost shares

	1989-1996				1997-2004			
	Annualized Diff.		First Diff.		Annualized Diff.		First Diff.	
	$\Delta\, p_i^{VA}$	$\Delta\, ETFP_i$	$\Delta\, p_i^{VA}$	$\Delta\, ETFP_i$	$\Delta\, p_i^{VA}$	$\Delta\, ETFP_i$	$\Delta\, p_i^{VA}$	$\Delta\, ETFP_i$
Prod. Cost Share	11.516	-8.885	10.317**	-7.650*	4.986	-1.976	5.099*	-2.067
	[9.095]	[9.110]	[4.396]	[4.397]	[6.256]	[6.251]	[2.956]	[2.953]
Non-Prod. Cost Share	-4.037	7.725	-0.970	4.614	-2.713	5.490	-6.781*	9.525***
	[8.659]	[8.684]	[3.715]	[3.719]	[4.834]	[4.828]	[3.675]	[3.672]
Capital Cost Share	-0.482	3.423	-0.628	3.426	-0.204	0.626	0.601	-0.325
	[2.757]	[2.765]	[2.087]	[2.087]	[2.529]	[2.524]	[1.395]	[1.393]
Observations	458	458	3206	3206	473	473	3311	3311
R-squared	0.06	0.09	0.03	0.03	0.02	0.03	0.01	0.01

Note: Standard errors are in parenthesis. All regressions are weighted by the industry share of total manufacturing shipments.

Table 4. Stage I – Original Feenstra and Hanson (1999) Specification

	1989-1996				1997-2004			
	Annualized Difference		First Difference		Annualized Difference		First Difference	
	Original Measure	Refined Measure	Original Measure	Refined Measure	Original Measure	Refined Measure	Original Measure	Refined Measure
	I	II	III	IV	V	VI	VII	VIII
Trade								
Materials Offsh. (Nr)	0.067	-0.021	0.016	0.000	0.136	0.135	0.002	-0.001
	[0.083]	[0.077]	[0.012]	[0.017]	[0.151]	[0.184]	[0.003]	[0.001]
Materials Offsh. (Br-Nr)	0.440**	0.533*	0.081*	0.061*	0.133	0.296	0.001	0.010*
	[0.208]	[0.263]	[0.046]	[0.030]	[0.348]	[0.218]	[0.007]	[0.005]
Technology								
Office Equip. Share	-3.820*	-4.835**	-3.337**	-3.476**	-2.903**	-2.975***	-1.749***	-1.754***
	[2.095]	[2.277]	[1.530]	[1.595]	[1.067]	[0.799]	[0.569]	[0.557]
Other Hi-Tech Share	-0.322	-0.415	-0.251	-0.262	0.440**	0.560***	0.332*	0.334*
	[0.386]	[0.423]	[0.325]	[0.333]	[0.186]	[0.193]	[0.163]	[0.164]
Other Controls								
Year Fixed Effects	-	-	Yes	Yes	-	-	Yes	Yes
Constant	1.167***	1.150***	1.038***	1.020***	0.554***	0.542***	0.476***	0.476***
	[0.113]	[0.137]	[0.151]	[0.161]	[0.072]	[0.045]	[0.069]	[0.069]
Observations	458	458	3206	3206	473	473	3311	3311
R^2	0.18	0.17	0.08	0.07	0.14	0.18	0.08	0.08

Note: Standard errors in brackets are robust to heterosckedasticity and correlation in the errors within two-digit SIC industries for 1989-1996 and three-digit NAICS industries for 1997-2004. Variables expressed as annualized differences are constructed as differences over end-years of each period, divided by the number of years in the period. Variables expressed as first-difference are constructed as differences over year *t* and *t-1*. Regressions are weighted by an average industry share of the manufacturing shipments.

Table 5. Stage I – Full Specification

	1989-1996				1997-2004			
	Annualized Difference		First Difference		Annualized Difference		First Difference	
	Original Measure	Refined Measure	Original Measure	Refined Measure	Original Measure	Refined Measure	Original Measure	Refined Measure
	I	II	III	IV	V	VI	VII	VIII
Trade								
Materials Offsh. (Nr)	-0.030	-0.030	0.010	0.001	0.153	0.361**	-0.004	-0.004***
	[0.066]	[0.044]	[0.010]	[0.015]	[0.174]	[0.137]	[0.005]	[0.001]
Materials Offsh. (Br-Nr)	0.260	0.510**	0.066	0.057*	0.071	0.103	-0.007	0.006
	[0.171]	[0.186]	[0.039]	[0.031]	[0.339]	[0.162]	[0.008]	[0.006]
Services Offsh.	-17.100**	-17.263**	-0.993***	-1.039***	-0.115	5.932**	0.755	0.686
	[6.834]	[6.136]	[0.276]	[0.281]	[2.493]	[2.341]	[0.676]	[0.639]
Import Openness	0.001	-0.001	0.000	0.000	-0.001	-0.001	0.000	0.000
	[0.004]	[0.004]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]
Technology								
Office Equip. Share	0.004	-0.129	-1.848	-1.914	-2.438**	-2.300***	-1.710***	-1.714***
	[2.798]	[2.827]	[1.519]	[1.527]	[0.903]	[0.701]	[0.545]	[0.534]
Other Hi-Tech Share	-0.358	-0.424	-0.280	-0.285	0.372*	0.491***	0.326*	0.326*
	[0.310]	[0.283]	[0.289]	[0.290]	[0.191]	[0.159]	[0.171]	[0.171]
Computer Share	0.567*	0.603**	0.323***	0.330***	0.085	0.077	0.013	0.015
	[0.281]	[0.242]	[0.103]	[0.101]	[0.088]	[0.074]	[0.028]	[0.027]
Other Controls								
Market Power	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	-	-	Yes	Yes	-	-	Yes	Yes
Observations	458	458	3206	3206	473	473	3311	3311
R^2	0.33	0.36	0.16	0.16	0.24	0.30	0.09	0.09

Note: Standard errors in brackets are robust to heterosckedasticity and correlation in the errors within two-digit SIC industries for 1989-1996 and three-digit NAICS industries for 1997-2004. Variables expressed as annualized differences are constructed as differences over end-years of each period, divided by the number of years in the period. Variables expressed as first-difference are constructed as differences over year *t* and *t-1*. Regressions are weighted by an average industry share of the manufacturing shipments.

Table 6. Stage I – Decomposed Dependent Variable (Refined Measure)

	1989-1996				1997-2004			
	Annualized Difference		First Difference		Annualized Difference		First Difference	
	Δp_i^{VA}	$\Delta ETFP_i$	Δp_i^{VA}	$\Delta ETFP_i$	Δp_i^{VA}	$\Delta ETFP_i$	Δp_i^{VA}	$\Delta ETFP_i$
	I	II	III	IV	V	VI	VII	VII
Trade								
Materials Offsh. (Nr)	-1.603***	1.573***	-0.008	0.009	0.093	0.268	-0.175	0.171
	[0.404]	[0.424]	[0.153]	[0.147]	[1.204]	[1.250]	[0.113]	[0.114]
Materials Offsh. (Br-Nr)	0.070	0.440	-0.698*	0.755*	0.403	-0.300	-0.356	0.362
	[0.846]	[0.789]	[0.390]	[0.395]	[1.032]	[1.078]	[0.339]	[0.344]
Services Offsh.	-8.693	-8.570	-3.014	1.975	155.304***	-149.372***	81.825***	-81.139***
	[24.890]	[23.649]	[7.457]	[7.396]	[23.045]	[22.050]	[10.553]	[10.104]
Import Openness	0.015	-0.015	-0.019	0.019	-0.012**	0.011**	-0.003	0.003
	[0.031]	[0.031]	[0.012]	[0.012]	[0.006]	[0.004]	[0.005]	[0.005]
Technology								
Office Equip. Share	3.183	-3.312	2.686	-4.600	1.943	-4.243	-3.457	1.742
	[10.265]	[9.614]	[7.123]	[6.231]	[3.401]	[3.484]	[3.004]	[3.222]
Other Hi-Tech Share	-2.301*	1.877*	0.912	-1.197	-1.225	1.716	-1.178	1.505
	[1.133]	[0.912]	[1.667]	[1.426]	[1.632]	[1.625]	[1.219]	[1.264]
Computer Share	0.112	0.491	-0.324	0.654	-0.099	0.176	0.349	-0.334
	[0.615]	[0.519]	[0.561]	[0.491]	[0.342]	[0.369]	[0.245]	[0.249]
Other Controls								
Market Power	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	-	-	Yes	Yes	-	-	Yes	Yes
Observations	458	458	3206	3206	473	473	3311	3311
R^2	0.72	0.73	0.22	0.23	0.43	0.42	0.15	0.14

Note: Standard errors in brackets are robust to heterosckedasticity and correlation in the errors within two-digit SIC industries for 1989-1996 and three-digit NAICS industries for 1997-2004. Variables expressed as annualized differences are constructed as differences over end-years of each period, divided by the number of years in the period. Variables expressed as first-difference are constructed as differences over year *t* and *t-1*. Regressions are weighted by an average industry share of the manufacturing shipments.

Table 7. Stage I – Final Specification (Refined Measure)

	1989-1996		1989-1996	
	Annualized Difference	First Difference	Annualized Difference	First Difference
	I	II	III	IV
Trade				
Materials Offsh. (Nr)[1]			0.390**	-0.003***
			[0.178]	[0.001]
Materials Offsh. (Br-Nr)[2]	0.433**	0.056*		
	[0.164]	[0.028]		
Services Outs.	-16.158**	-1.086***	6.120**	
	[6.933]	[0.344]	[2.751]	
Technology				
Office Equip. Share			-2.394***	-1.722***
			[0.650]	[0.549]
Other Hi-Tech Share			0.484***	0.327*
			[0.154]	[0.166]
Computer Share	0.668***	0.373***		
	[0.166]	[0.067]		
Other Controls				
Market Power	Yes	Yes	Yes	Yes
Year Fixed Effects	-	Yes	-	Yes
Constant	1.774***	1.209***	0.526***	0.476***
	[0.222]	[0.090]	[0.040]	[0.068]
Observations	458	3206	473	3311
R^2	0.33	0.12	0.28	0.09

Note: [1,2] Materials Offshoring measures are constructed using the refined formula. Standard errors in brackets are robust to heterosckedasticity and correlation in the errors within two-digit SIC industries for 1989-1996 and three-digit NAICS industries for 1997-2004. Variables expressed as annualized differences are constructed as differences over end-years of each period, divided by the number of years in the period. Variables expressed as first-difference are constructed as differences over year *t* and *t-1*. Regressions are weighted by an average industry share of the manufacturing shipments.

Table 8. Stage II – (Refined Measure)

Dependent Variable: $\Delta \ln p_i^{VA} + \Delta \ln ETFP_i$ **explained by causal variables**

	1989-1996			1997-2004			
	Materials Offsh. (Br-Nr)	Services Offsh.	Computer Share	Materials Offsh. (Nr)	Service Offsh.	Office Equip. Share	Other Hi-Tech Share
Annualized Difference							
Prod. Cost Share	0.305**	-2.413***	-0.237	-0.119	0.182	0.243**	0.270***
	[0.122]	[0.288]	[0.326]	[0.161]	[0.125]	[0.110]	[0.073]
Non-Prod. Cost Share	0.898***	0.546	1.488**	0.066	-0.159	0.234***	-0.040
	[0.224]	[0.499]	[0.656]	[0.242]	[0.169]	[0.090]	[0.095]
Capital Cost Share	0.013	-1.131***	0.137	-0.028	-0.002	0.122***	-0.221***
	[0.044]	[0.146]	[0.132]	[0.052]	[0.035]	[0.022]	[0.030]
Observations	458	458	458	473	473	473	473
R^2	0.59	0.86	0.36	0.04	0.03	0.63	0.61
Net Coefficient[1]	**0.593***	**2.959***	**1.725***	**0.185**	**-0.341**	**-0.009**	**-0.310***
	[0.180]	**[0.407]**	**[0.518]**	**[0.206]**	**[0.149]**	**[0.100]**	**[0.085]**
First Difference							
Prod. Cost Share	0.031	-0.172***	-0.112	0.001		0.198***	0.160***
	[0.025]	[0.034]	[0.105]	[0.008]		[0.041]	[0.023]
Non-Prod. Cost Share	0.113**	-0.004	0.946***	-0.005		0.174***	-0.061*
	[0.058]	[0.052]	[0.202]	[0.014]		[0.038]	[0.032]
Capital Cost Share	0.005	-0.062***	0.041	0.001		0.079***	-0.139***
	[0.007]	[0.015]	[0.034]	[0.002]		[0.010]	[0.009]
Observations	3206	3206	3206	3311		3311	3311
R^2	0.11	0.23	0.20	0.00		0.44	0.50
Net Coefficient[1]	**0.082***	**0.168***	**1.058***	**-0.006**		**-0.024**	**-0.221***
	[0.045]	**[0.044]**	**[0.161]**	**[0.011]**		**[0.040]**	**[0.028]**

Note: [1]Net coefficient refers to the difference between the coefficients on non-production and production cost shares. Coefficient estimates used to construct the dependent variable for 1989-1996 and 1997-2004 are those from respective columns of Table 6. Standard errors are in brackets and are adjusted using Dumont et al. (2005) method described in the text. All regressions are weighted by an average industry share of total manufacturing shipments.