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Outsourcing, Demand and Employment Loss In US Manufacturing, 1990 – 2005

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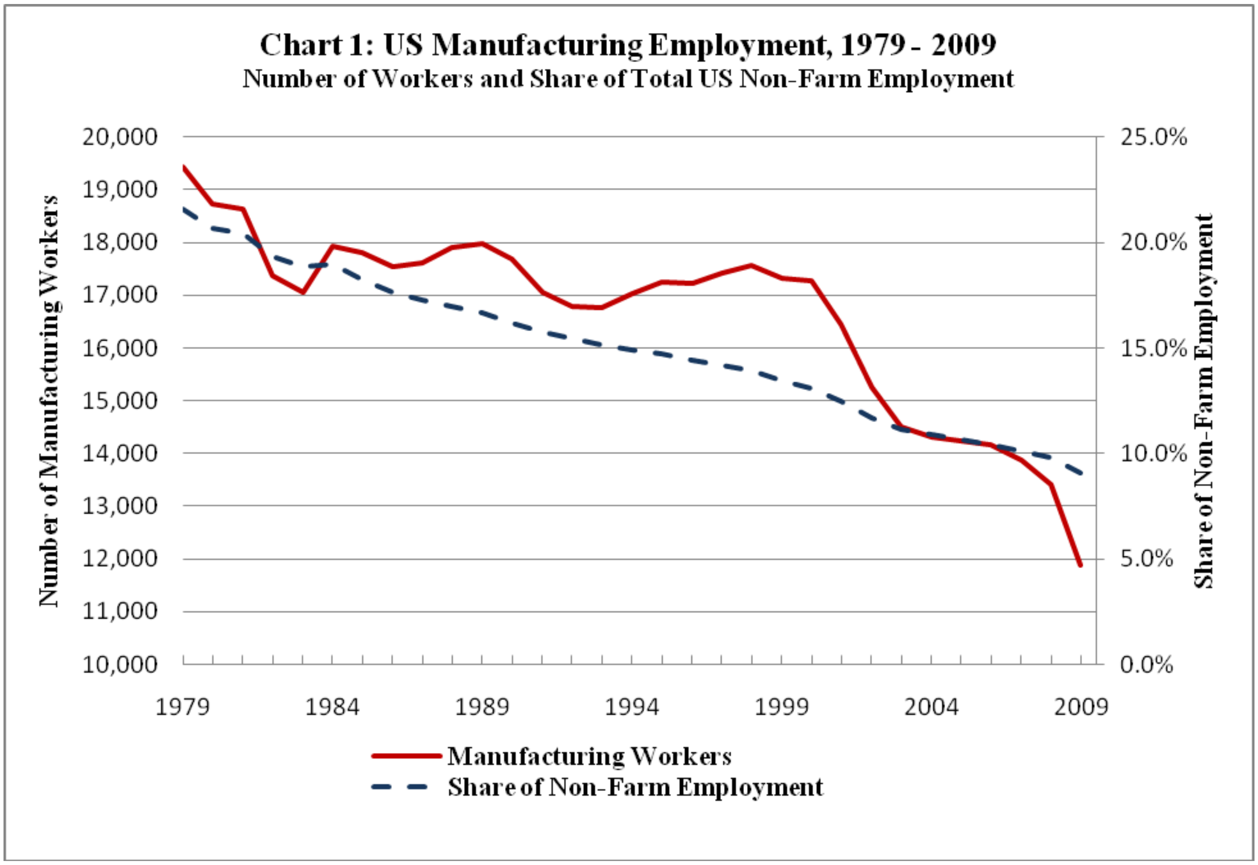
I. Introduction

In this paper, we focus on new measures of foreign outsourcing to track changes in the offshoring of manufacturing activity and to explore how offshoring along with other factors are related to the dramatic dislocation of workers in the US manufacturing sector in recent years. Employment in the US manufacturing sector has been declining over the last three decades with the most rapid job loss taking place in the past ten years. The manufacturing sector labor force in the US, which peaked at 19.4 million workers in 1979, had by 2009 fallen off to 11.9 million workers; during this same period the share of manufacturing jobs in total non-farm employment fell from 21.6 percent to 9.1 percent (Chart 1). The most rapid loss of manufacturing jobs has taken place in the past ten years – between 1999 and 2009 the manufacturing workforce contracted by 31 percent with a fall of almost five and a half million jobs. There is considerable debate among economists and policy makers about the causes of this steep loss of manufacturing jobs in recent decades.[1] Among international factors, rising import competition and the growth of foreign outsourcing are put forward as playing a substantial role. Rising labor productivity and structural changes leading to less demand for manufactured goods in the economy are also pointed to as factors drawing down US manufacturing employment in recent years. The current economic crisis that began in 2008 has had an especially harsh impact on the manufacturing sector – employment in manufacturing fell by nearly three times the rate of employment decline in the economy as a whole between the end of 2007 and the end of 2009.[2]

Public concern over job loss due to foreign outsourcing has generated heated debate in both government policy and academic arenas. In recent years, the threat of offshoring to US service sector and white collar jobs has augmented longer standing anxieties about the loss of

[1] See Bivens 2004; Bailey and Lawrence 2004, and Fisher 2004.

[2] US Bureau of Labor Statistics. While non-farm employment in the economy as a whole fell by about 5 percent during the period, employment in manufacturing fell by about 14 percent.



Source: US Bureau of Labor Statistics

manufacturing and blue collar jobs to the movement of production to foreign sites.[3] There appears to be a broad consensus among economists that offshoring disproportionately lowers domestic demand for less skilled workers and so increases wage inequality between higher and lower skilled labor.[4] However, the impact of outsourcing on the overall employment level and national welfare is a more contentious issue.[5] Mankiw and Swagel (2006) state the main

[3] A 2004 survey by the University of Maryland's Program on International Policy Attitudes found that support for free trade fell in most income groups from 1999 to 2004, but dropped most rapidly among high-income respondents as this group has come to perceive their own jobs threatened by white-collar workers in China, India and other countries.

[4] See, for instance, Feenstra 1998, Feensta and Hanson 1996, 1999 for the United States, Hijzen, Gorg, and Hine 2005 for the United Kingdom, and Ekholm and Hakkala 2006 for Sweden.

[5] For contrasting conclusions on the impact of offshoring on employment levels, see, for example, Bhagwait, Panagariya, and Srinivasan (2004), Schultze (2004), Falk and Wolfmayr (2005), Mankiw and Swagel (2006), Hijzen and Swaim (2007), and Leamer (2007).

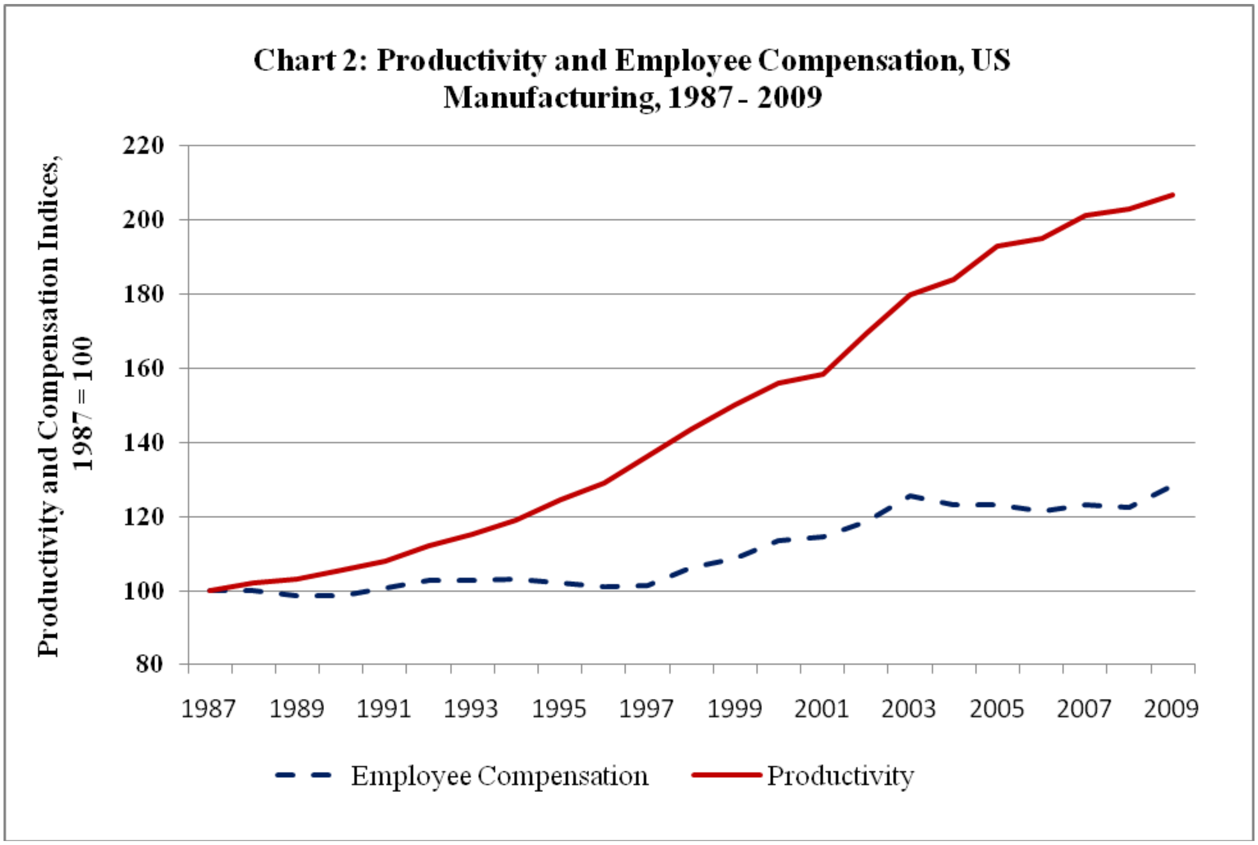
argument for those who see the overall impact of foreign outsourcing as positive: "outsourcing is simply a new form of trade, which as usual, creates winners and losers but involves gains to overall productivity and incomes". According to this view, foreign outsourcing has two positive impacts in terms of employment and productivity (and, through productivity, on the real wage). First, as less productive, low-technology production activities are increasingly sent abroad, resources are freed up to finance the expansion of high-technology and high value-added activities in the US economy. The job loss caused by foreign outsourcing is thus not a serious problem for the US economy because the lost employment can be replaced by new and better jobs created in the expanded high technology and high value-added production activities into which workers will be reallocated. Technological innovation in these expanded industries allows workers to be more productive and so able to earn higher wages. Second, according to this view, even though foreign outsourcing increases inequality between low and high skilled workers, the higher productivity generated by outsourcing leads to lower prices for goods and services and so lifts the absolute real wage for both groups of workers.

Other researchers, including ourselves, have a less sanguine view of the effects of off-shoring and instead see it as a phenomenon that is potentially quite harmful to the US economy and its workers. We believe that the assumptions underlying the argument that foreign offshoring has a positive impact on employment – namely, that the economy persists at full employment with a low cost of job switching – are unrealistic most of the time. In an economy which falls short of full employment and in which job dislocation is costly for most workers, foreign outsourcing can have lasting negative effects.[6] If newly created high-technology and high value-added employment does arise to replace outsourced production jobs in the US economy, these jobs are likely to be allocated to more educated workers and not to the less skilled workers most directly displaced by outsourcing in the manufacturing sector. Instead, workers dislocated from manufacturing jobs by offshoring are likely to experience prolonged periods of unemployment before moving on to jobs with significantly lower wages than they earned in their previous jobs.[7] Furthermore, in a world in which full employment is not automatic, less outsourcing-prone

[6] See Crotty, Epstein and Kelly (1998) for a description of the dynamic relationship between offshoring and the labor market in a economy that operates at less than full employment.
[7] See Farber (2005) and Kletzer (1998) for evidence of lower earnings in new jobs for displaced US manufacturing workers in recent years.

industries may not absorb all the employment displaced by the offshoring of production, resulting in a negative impact on the economy's overall employment level that can persist over long periods.

While a number of studies claim that there is a positive relationship between foreign outsourcing and productivity at home, the gap between growth in employee compensation and



Source: US Bureau of Labor Statistics

productivity in recent years raises fundamental questions about the claim that workers in the US economy stand to gain from productivity increases generated by foreign outsourcing.[8] Between 1987 and 2009, productivity (measured as output per hour) for the civilian labor force as a whole rose by over 100 percent while employee compensation (wages and benefits per hour) grew by less than a third as much over this time period (see Chart 2). With compensation growth

[8] For studies that link foreign outsourcing to productivity growth at home, see Amiti and Wei (2006), Egger and Egger (2006), and Mann (2004).

unlinked from rising labor productivity, increases in productivity brought about through the offshoring of domestic production can be expected to flow towards capital as profits while workers bear the costs of dislocation.[9] As we discuss, the threat of foreign outsourcing itself partly explains, along with other factors, the very erosion of labor's bargaining power that leaves workers unable to either lessen the costs of dislocation, moderate the rate of offshoring of production, or claim much benefit from rising productivity.

In the section below we discuss past studies that have explored the impact on workers of growing offshoring in manufacturing industries. In the next section, we introduce our measure of imported inputs and examine the growth of foreign outsourcing activity in manufacturing industries from 1987 to 2002. Next, we present a counterfactual analysis as a way to show the loss of manufacturing industry employment resulting from rising foreign outsourcing between 1987 and 2005. We then explore the effect of foreign outsourcing on employment in US manufacturing industries for the period 1990 to 2005 using a regression analysis of industry data.

II. Measuring the growth and impact of foreign outsourcing: past findings

One of the major challenges in empirically studying the growth and impact of US offshoring is the deficiency in direct government data on this activity. There are three sources of data from the US government that allow empirical yet incomplete observation of offshoring behavior: the Mass Layoff Statistics, the US Direct Investment Abroad Survey, and US trade data. Beginning in January of 2004, the Bureau of Labor Statistics added questions on the movement of work to the Mass Layoff Statistics survey for the first time.[10] The Mass Layoff Statistics survey identifies firms that over a five-week period had layoffs involving more than 50 workers out of work for 30 days. These firms are contacted by phone and along with other interview questions are directly asked if jobs were moved abroad. According to the Mass Layoff Statistics, in 2007 only 2 percent of laid off private, nonfarm workers in the survey had their jobs outsourced to a foreign location. However, there are several limitations in the Mass Layoff Statistics survey that lead us to question the small size for offshoring effects indicated in the data. First, as mentioned,

[9] Housman (2007) suggests that offshoring can result in inflated and misleading increases in US productivity statistics, providing an alternative explanation for some part of the gap between wage growth and growing production figures.
[10] See Brown (2004) for a description of the movement of work questions in the Mass Layoffs Survey.

the survey only looks at job loss from layoffs of 50 workers or more taking place at a firm within a five week period; a substantial part of total job loss is thus not included in the data. Further, the Mass Layoff Statistics data does not capture situations where firms might reduce hiring (rather than lay off workers) as a result of offshoring production or may move work abroad and not immediately lay off workers at a rate of 50 or more over five weeks. The Mass Layoff data defines outsourcing (domestic or foreign) narrowly as pertaining to movement of work within the company (in another location) or to movement of work to another company under contractual arrangements. Replacing parts of the production process with purchased inputs is thus not considered outsourcing under this definition if the firm deals with the provider of these inputs as a supplier rather than as an outside contractor. In many cases where the BLS determines that movement of work was a possible reason for layoffs, employers did not provide enough detail to count the job loss as either domestic or foreign outsourcing. Finally, it seems likely that many firms, sensitive to the political sensitivity surrounding foreign outsourcing, give another reason for layoffs when offshoring in fact played a major role.

The US Direct Investment Abroad Survey is another source of information on the foreign outsourcing of production. The Direct Investment Abroad Survey is compiled by the Bureau of Economic Analysis from information provided by US firms that carry out some production in foreign affiliates. Several studies have made use of these surveys of US multinational firms to study the relationship between foreign outsourcing and employment. Brainard and Riker (1997) and Riker and Brainard (1997), using the BEA survey of US direct investment abroad for the years from 1982 to 1992, find that manufacturing employment in foreign affiliates has a small substitution effect on manufacturing employment by parents in the US. Harrison and McMillan (2006) use the data for US multinational corporations' parent and affiliate employment data to separate the effect of these firms' horizontal versus vertical foreign direct investment. Using firm-level data from 1982 to 1999, they show that for US manufacturing corporations most likely to perform the same tasks in foreign affiliates and at home ("horizontal" foreign investment), foreign and domestic employees appear to be substitutes. For these firms, lower wages in affiliate locations are associated with lower employment in the US. In contrast, for US manufacturing firms which do significantly different tasks at home and abroad ("vertical" foreign investment), foreign and domestic employment are complements. Using the same data, Harrison, McMillan and Null (2007) find that foreign affiliate employment in developing countries is a substitute for employment by US manufacturing parents at home. While manufacturing employment in affiliates based in high-income countries is shown to complement employment in US parents, this relationship is driven by contraction in both locations. Also making use of the BEA survey of US manufacturing multinational firms for the years 1982 to 1999, Desai, Foley, and Hines (2005) conclude that an increase in employment compensation in foreign affiliates is associated with an increase in employee compensation at home. It is important to note some limitations to using the BEA surveys of direct investment abroad to capture the effects of offshoring. As Mankiw and Swagel (2006) point out, it is not possible to know from the BEA data how much of foreign affiliate employment represents jobs that either formerly existed or would have existed in the US if firms didn't have the option of basing production abroad. Also, the measure of foreign outsourcing is overly narrow; only foreign production that is internal to US multinational firms (that is, carried out in US foreign affiliates) is considered in studies that focus on the BEA surveys of US multinationals. Finally, the BEA survey data only represents the approximately 55 percent of US manufacturing workers who are employed by US multinational firms.

Other studies have focused on US trade data to measure foreign outsourcing activity by US firms. By fragmenting production internationally, foreign outsourcing leads to a rise in the international trade of intermediate goods.[11] As inputs produced globally take the place of intermediate stages of production at home, we witness an increased flow of intermediate goods across country borders. For this reason, several studies have measured the intensity of outsourcing activity in an industry by calculating the ratio of imported intermediate goods to either total intermediate goods used in that industry or to total industry output. While the share of imported intermediate goods will not fully capture the extent of globalization outsourcing in an industry – some foreign outsourcing activity by US firms will show itself as a displacement of US production of final goods or exports rather than an increase in imports of intermediate goods – it does provide a measurable indicator that allows foreign outsourcing to be defined less

[11] Feenstra (1998) presents data showing that between 1980 and 1995 products were imported into the United States at increasingly advanced stages of processing, suggesting that U.S. firms were substituting away from these processing activities at home.

narrowly than studies utilizing the BEA's Mass Layoff Statistics or the Direct Investment Abroad Survey .[12]

Feenstra and Hanson (1999) find that imported intermediate goods have increased from 5.3 percent of total non-energy intermediate purchases for U.S. manufacturing industries in 1972 to 7.3 percent in 1979, and 12.1 percent in 1990. Campa and Goldberg (1997), looking more narrowly at just manufacturing goods as inputs in production, find that imported inputs have increased from 4.1 percent of total intermediate goods in 1975 to 6.2 percent in 1985, and 8.2 percent in 1995 for U.S. manufacturing industries. Amiti and Wei (2005b) report that the share of imported inputs of materials and services for the US manufacturing sector has increased from 11.7 percent in 1992 to 17.4 percent in 2000. In our analysis, as we discuss below, we find that the ratio of imported intermediate manufactured goods in total purchases of intermediate manufactured goods in the US manufacturing sector has risen from 11.2 percent in 1987 to 20.8 percent in 2002.

Using the ratio of imported to total intermediate inputs as a measure of outsourcing intensity for the years between 1995 and 2000, Falk and Wolfmayr (2005) investigate the impact of foreign outsourcing on total employment for twenty-two manufacturing industries for seven EU countries.[13] They find that imported inputs from low-wage countries have a negative effect on total industry employment for EU countries amounting to an approximate reduction of 0.25 percentage points in employment per year. Imported inputs from high-wage countries, on the other hand, are found to have a positive impact on industry employment, thus suggesting that imports from high-wage countries and domestic employment are complements. Feenstra and Hanson (1999) present results showing that growing foreign outsourcing in manufacturing industries, measured as rising imported inputs ratios, have contributed to the falling relative wage of US manufacturing production workers between the years 1979 and 1990. Using the measure of imported intermediate goods or services, Amiti and Wei (2006) show that foreign

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[12] In addition to outsourcing, there are other possible sources of rising imported inputs in US production by US firms. First, if foreign firms set up production in US sites, they are likely to use more intermediate goods shipped from their home countries relative to domestic firms. Second, a rise in the relative price of foreign versus domestic inputs can lead to a rise in the value share of imported inputs without actually representing a shift in the location of production abroad. In future work, we will test the size of some of these effects but we assume for now that these effects are small compared to the effect of outsourcing activity.

[13] Austria, Denmark, Finland, Germany, Italy, Netherlands, and Sweden.

outsourcing had a positive effect on productivity growth in US manufacturing industries between 1992 and 2000.

III. Foreign outsourcing and intermediate goods trade

We measure imported intermediate goods used by a US manufacturing industry by finding the value of each manufacturing commodity used in the production process of the industry as well as the import share of these commodities (the share of the commodity used in the US economy that is imported). We then multiply the value of each commodity by its import share to find the value of imports of the commodity used as an input by the industry. By summing up the imported inputs of each manufacturing commodity used by that industry, we can find the industry's total imported manufactured inputs used in production. We arrive at the industry imported input ratio by dividing the value of imported intermediate goods to total intermediate goods used in production by each industry group.[14] Thus, the imported inputs for an industry can be denoted:

$$\text{Imported Inputs}_i = \Sigma_J[\text{inputs of good j by industry i*imports of good j}/(\text{shipments}_j + \text{imports}_j - \text{exports}_j)];$$

and the imported input ratio for an industry is:

$$\text{Imported Input Ratio}_i = \text{Imported Inputs}_i/\text{Total Inputs}_i.$$

A basic assumption of this method of calculating the value of imported inputs is that the import share of the commodity when it is used as an intermediate good in each particular industry is the same as the import share of the commodity in the economy as a whole. The industry data that we use to carry out these calculations (that is, industry inputs, shipments and

[14] The question arises of whether to construct our outsourcing measure as the ratio of imported inputs to total industry inputs or as the ratio of imported inputs to industry output. Because intermediate goods as a share of total production differs across industry groups, for different industry groups the same imported to total inputs ratio might reflect that outsourced inputs are 10 percent of industry output for one industry group and 20 percent for another. On the other hand, because the share of intermediate goods in total production can change over time, changes in the ratio of imported inputs to total output may not accurately reflect the change in outsourcing behavior. For example, if both the share of imported and total inputs in industry output increase by 25 percent, the imported inputs to industry output ratio will rise. However, because the ratio of imported to total inputs doesn't rise in this example, this change doesn't represent an increase in outsourcing behavior. Although it is somewhat arbitrary, because a change in the imported to total inputs ratio more consistently represents a change in outsourcing behavior, we will use this measure in our paper.

trade) and some additional details on how we compute the imported input ratio are described in the Data Appendix.

An important distinguishing feature of our study is that we are able to construct a long period data set of imported input ratios for disaggregated manufacturing industry groups, covering the years from the late 1980s through to 2005. The transition of the US industry classification system from the Standard Industrial Classification (SIC) to the North American Industrial Classification System (NAICS) in the late 1990s presents a major hurdle for researchers in compiling a set of disaggregated manufacturing industry group data that spans these years. Due in large part to the switch-over from the SIC to NAICS classification system, empirical studies of foreign outsourcing using industry group data have tended to focus on time periods that either begin or end in the late 1990s or are limited to more aggregated industry groups for which the change in industry classification systems are less important. The NAICS, adopted by most US government departments and agencies around 1997, created newly defined industry classifications to reflect a changing economy (in particular, the growth of service industries) and provide a more closely harmonized industry classification system for NAFTA members Canada, Mexico, and the United States. In contrast to the SIC, the NAICS began assigning firms to industry groups based on the production processes taking place within the firms rather than the goods or services the firms primarily produced. Because the conversion from one to the other industrial classification system involved assigning firms to industry groups in new ways, we needed to devote much time and care to create continuous industry group data across the years separated by the two different systems.[15] The procedures we followed to arrive at a data set with a high degree of continuity over the SIC–NAICS break are described in the Data Appendix.

In addition to examining how industries use imported intermediate goods in production, we also measure the degree to which imported inputs compete with the production of intermediate goods by US manufacturing industry groups. That is, we look at the phenomenon of foreign outsourcing from the perspective of the industry *making* intermediate goods as well as the perspective of the industry *using* intermediate goods in production. We do this because we are interested in data that will allow us to explore links between foreign outsourcing and industry employment at home. Because firms often use intermediate goods that are not produced in their

[15] See Yuskavage (2007) for a description of the issues surrounding converting historical industry data from SIC to NAICS.

own industry group, foreign outsourcing that involves shifting purchases of intermediate goods from domestic to foreign suppliers can raise the share of imported inputs used in production in an industry while not directly displacing production or employment in that industry group. Instead, the demand for production and workers may fall in other industries as a result of this kind of foreign outsourcing activity. We describe in the Data Appendix how we use the "make tables" of the BEA's Input-Output Accounts to allocate production of each manufactured intermediate good to individual industry groups. We can then calculate another kind of imported inputs ratio that indicates the import share of the intermediate goods produced by each manufacturing industry group.

Imports of intermediate goods in manufacturing industry production, 1987 to 2002

The BEA has released benchmark input/output tables at five year intervals from 1987 to 2002 based on surveys of the firms in the economy. We use these four I/O benchmark surveys together with trade and shipments data to calculate the ratios of imported to total manufactured inputs in the manufacturing sector. As mentioned above, the BEA switched from grouping industries using the SIC classifications to the NAICS classifications. In order to report across a consistent set of industries over the whole period, we convert the imported and total inputs reported for SIC industry groups at the four digit level in 1987 and 1992 into NAICS six digit level groupings using the NAICS – SIC bridge developed by the US Census Bureau for the 1997 Economic Census.[16] We then aggregate these converted NAICS values up to three digit NAICS groupings to calculate the imported inputs ratios in the tables below. Due to the limits of exact one-to-one matching of SIC and NAICS groups, a relatively small number of industry groups are dropped in the process of conversion for the years 1987 and 1992.[17]

Table 1 shows the share of imported inputs used in production for each 3-digit NAICS manufacturing industry and for the sector as a whole. The imported inputs ratio for the manufacturing sector rose by 9.6 percent during the period from 11.2 percent in 1987 to 20.8

[16] The conversion of industry data from SIC to NAICS codes is described in the Data Appendix.
[17] Table A-8 in the Appendix shows the magnitude of industry loss due to the SIC-NAICS conversion. As Table a-8 shows, for 1987 there is slightly more loss in the conversion of total inputs than there is for imported inputs. This results in somewhat over-reporting the size of the imported inputs/total inputs ratio for the manufacturing sector in 1987 and thus understating slightly the growth in the outsourcing measure over the 1987 to 2002 period.

Table 1: Imported inputs as a share of total inputs used in production, 1987 – 2002					
NAICS	**1987**	**1992**	**1997**	**2002**	***% Change, 1987-2002***
All Manufacturing	11.2%	12.9%	18.7%	20.8%	*9.6%*
Food	3.6%	4.3%	6.0%	7.1%	*3.5%*
Beverage and Tobacco	2.8%	2.6%	5.4%	9.3%	*6.5%*
Textile Mills	8.2%	4.7%	12.5%	17.0%	*8.8%*
Textile Product Mills	8.1%	5.8%	15.3%	20.3%	*12.2%*
Apparel	12.7%	11.3%	20.9%	22.9%	*10.2%*
Leather and Allied Product	15.2%	16.1%	25.3%	23.8%	*8.6%*
Wood Product	8.0%	8.4%	18.9%	20.1%	*12.1%*
Paper	13.5%	11.9%	20.7%	21.2%	*7.7%*
Printing and Related Support Activities	8.2%	7.6%	12.9%	15.3%	*7.1%*
Petroleum and Coal Products	9.2%	8.1%	12.7%	15.7%	*6.5%*
Chemical	9.6%	10.8%	15.1%	20.5%	*10.9%*
Plastics and Rubber Products	6.2%	8.2%	13.6%	15.8%	*9.6%*
Nonmetallic Mineral Product	9.6%	8.1%	13.1%	16.6%	*7.0%*
Primary Metal	20.1%	21.7%	26.3%	28.2%	*8.1%*
Fabricated Metal Product	10.9%	12.0%	14.7%	16.4%	*5.5%*
Machinery	12.4%	13.6%	17.2%	20.8%	*8.4%*
Computer and Electronic Product	17.6%	25.8%	36.3%	39.1%	*21.5%*
Electrical Equipment, Appliances, and Components	11.6%	13.1%	18.1%	22.2%	*10.6%*
Transportation Equipment	12.8%	14.7%	19.9%	23.3%	*10.5%*
Furniture and Related Product	9.9%	7.5%	13.5%	18.1%	*8.2%*
Miscellaneous	18.1%	22.5%	19.3%	22.5%	*4.4%*

Table 2: Imported inputs as a share of total inputs produced by industry, 1987 – 2002					
NAICS	**1987**	**1992**	**1997**	**2002**	***% Change, 1987-2002***
All Manufacturing	11.2%	12.9%	18.7%	20.8%	*9.6%*
Food	4.1%	5.3%	5.4%	5.6%	*1.5%*
Beverage and Tobacco	5.4%	6.1%	8.0%	12.1%	*6.7%*
Textile Mills	8.9%	3.0%	11.8%	15.2%	*6.3%*
Textile Product Mills	8.3%	16.5%	14.5%	18.4%	*10.1%*
Apparel	25.6%	35.0%	42.9%	52.7%	*27.1%*
Leather and Allied Product	27.1%	25.7%	47.0%	65.4%	*38.3%*
Wood Product	14.1%	13.0%	19.8%	21.2%	*7.1%*
Paper	10.5%	9.4%	13.2%	13.2%	*2.7%*
Printing and Related Support Activities	1.1%	1.1%	3.1%	5.7%	*4.6%*
Petroleum and Coal Products	10.2%	8.2%	10.9%	14.4%	*4.2%*
Chemical	8.3%	10.7%	14.8%	19.3%	*11.0%*
Plastics and Rubber Products	2.6%	2.6%	7.7%	10.2%	*7.2%*
Nonmetallic Mineral Product	8.9%	9.3%	12.2%	15.8%	*6.9%*
Primary Metal	16.2%	18.0%	20.6%	22.7%	*6.5%*
Fabricated Metal Product	6.8%	5.7%	7.6%	9.5%	*2.7%*
Machinery	17.5%	21.8%	23.7%	27.1%	*9.6%*
Computer and Electronic Product	23.4%	30.1%	42.5%	45.3%	*21.9%*
Electrical Equipment, Appliances, and Components	11.6%	16.3%	22.4%	31.5%	*19.9%*
Transportation Equipment	13.1%	16.2%	21.6%	26.7%	*13.6%*
Furniture and Related Product	10.6%	12.5%	14.4%	16.3%	*5.7%*
Miscellaneous	20.5%	30.5%	25.8%	29.4%	*8.9%*

percent in 2002. Foreign outsourcing activity increased in all industry groups during the period. The most rapid growth in the outsourcing measure for the manufacturing sector during the period was for the years between the 1992 and 1997 benchmarks in which the imported inputs ratio increased from 12.9 to 18.7 percent. The industry group with the largest increase in the share of imported inputs used in production was Computer and Electronic products, growing by 21.5 percent, from an imported input share of 17.6 percent in 1987 to 39.1 percent in 2002.

Table 2 presents the share of imported inputs in the total inputs produced by industry groups. The size and growth of the imported share of inputs *produced* by industry groups range more widely than the ratios presented in Table 1 for inputs *used* by industry groups. The Leather and Allied Products group stands out in Table 2 with its share of imported inputs growing from 27.1 percent in 1987 to 65.4 percent in 2002, an increase of nearly 40 percent over the period. Other industry groups that witnessed rapid growth in the import share of the inputs they produce over the period are Apparel (rising from 25.6 to 52.7 percent), Computer and Electronic Products (from 23.4 to 45.3 percent), and Electrical Equipment, Appliances and Components (growing from 11.6 percent to 31.5 percent).

IV. Employment loss from foreign outsourcing: A counterfactual analysis

In this section we present a counterfactual analysis to isolate the effects of foreign outsourcing on employment in the manufacturing sector between 1987 and 2005. We modify a model set out by Jeffrey Sachs and Howard Shatz in a 1994 paper in which they use a counterfactual analysis to analyze the relationship between trade and employment. Our investigation differs from Sachs and Shatz (1994) in that we focus on the relationship between foreign outsourcing (rather than trade) and employment during the period from 1987 to 2005. For this analysis, we utilize a counterfactual for 2005 in which foreign outsourcing (as measured by the imported input ratio) in each industry group is assumed to be constant at the level of 1987, while other industry values remain equal to their actual 2005 levels. Keeping foreign outsourcing at the 1987 level, the share of imported inputs for each industry group in the 2005 counterfactual year will tend to be lower than its actual level in 2005. Since we are keeping total output in the counterfactual year at its actual 2005 level, each industry's domestic inputs must change by the difference between the actual and counterfactual imported inputs to maintain the same amount of overall inputs required to produce industry output. Therefore, in the case of rising foreign outsourcing over the period, the counterfactual would require more domestic industry production and employment to satisfy the increase in demand for domestic inputs. The counterfactual analysis allow us to decompose the actual percentage change in industry employment between 1987 and 2005 into two parts – industry employment change purely caused by foreign outsourcing and employment change caused by all other factors. The model that we use is presented below.

Variables:

Q_j^t = total demand for output of industry j (shipments) ,

TF_j^t = demand for final goods produced by industry j at time t.

MF_j^t = demand for imported final goods produced by industry j at time t.

DF_j^t = demand for domestic final goods produced by industry j at time t.

TI_j^t = demand for intermediate goods produced by industry j at time t.

MI_j^t = demand for imported intermediate goods produced by industry j at time t.

DI_j^t = demand for domestic intermediate goods produced by industry j at time t.

O_j^t: foreign outsourcing index of industry j at time t.

Subscript c = counterfactual year

The model begins with a formula that states that total demand for an industry's output is equal to the demand for final goods produced by the industry plus the demand for intermediate goods produced by that industry.

$Q_j^t = TI_j^t + TF_j^t$, where $TI_j^t = MI_j^t + DI_j^t$ and $TF_j^t = MF_j^t + IF_j^t$.

Thus, $Q_j^t = MI_j^t + DI_j^t + MF_j^t + IF_j^t$.

Define a new variable $Q^*{}_j^t$, domestic output of industry j, as $Q^*{}_j^t = DI_j^t + DF_j^t = Q_j^t - MI_j^t - MF_j^t$.

As in previous sections, we define the foreign outsourcing measure for an industry as the ratio of imported inputs to total inputs: $O_j^t = MI_j^t/TI_j^t$. Since we assume that in the counterfactual everything is the same as 2005 except for the foreign outsourcing structure, imported inputs is the only factor that changes. We calculate the counterfactual imported inputs for industry j, MI_j^c, as the level that would preserve the same ratio of imported inputs to total inputs as existed in 1987, so $MI_j^c = O_j^{87} TI_j^{05}$.

We denote the difference between counterfactual and actual values using Δ so that $\Delta M_j^{05} = M_j^c - M_j^{05}$. Note that by the counterfactual assumed in the model, total output and imported final goods is unchanged at the level of 2005, so $\Delta Q_j^{05} = \Delta MF_j^{05} = 0$, and we have $\Delta Q^*{}_j^{05} = -\Delta M_j^{05}$. Assuming that average labor productivity within an industry group in 2005 is unaffected by the counterfactual, the percentage difference between the actual and counterfactual values of employment is equal to the percentage difference between actual and counterfactual Q*, $\Delta L^{05}/L^{05} = \Delta Q^{*05}/Q^{*05}$. By multiplying this percentage change by 2005 employment levels, we can get the counterfactual change in employment levels.

We use our calculated values of imported inputs produced by industry groups as MI in the model and find the other needed industry values for 1987 and 2005 (shipments, employment, and total inputs) from sources described in the data appendix. As in the analysis of the last section, due to the inability to completely match some industries from SIC to NAICS in the conversion process, we needed to drop some industry groups in 1987 that together made up 7.7 percent of total employment that year. This conversion loss is detailed in Table 3 below. Examination of the data indicated that the conversion loss doesn't greatly alter the proportions of imported to total inputs in the aggregated four digit NAICS industry groups or the manufacturing sector as a whole in 1987.[18] This allows us to find the 1987 outsourcing ratios, O_j^{87}, needed to calculate the counterfactual employment levels for 2005 in our model.

[18] For the manufacturing sector as a whole, the imported inputs ratio for the unconverted SIC data in 1987 is 11.4% while for the converted NAICS data in that year the imported inputs ratio is 11. 2%.

Table 3. Conversion loss in 1987 sample due to SIC to NAICS conversion	
	Employment (thousands)
Original SIC Benchmark Data for 1987	17,715.9
Converted NAICS Four Digit Data for 1987	16,345.6
Loss from SIC –NAICS Conversion for 1987	-7.7%

Results of the counterfactual analysis

Our counterfactual analysis shows job loss from the change in offshoring in the whole U.S. manufacturing sector as 3.6 percent of total employment in 2005 or about 515,000 less manufacturing jobs. During the period from 1987 to 2005 actual employment fell by 3.3 million manufacturing jobs, so that job loss associated with growth in our global outsourcing measure amounts to about one-sixth (15.6 percent) of the total loss of jobs over the period. Put another way, the job loss from the growth in offshoring by 2005 lowered manufacturing employment by about 3.1 percent from the 1987 level.

In Table 4, we present the results of the counterfactual analysis for the twenty-one 3-digit NAICS industry groups that make up the manufacturing sector. The third column indicates the percent decline in employment in 2005 for each group attributed to increased offshoring between 1987 and 2005. According to the counterfactual analysis, some of the industry groups were significantly more affected than others by increases in offshoring. The industry groups for which growing offshoring between 1987 and 2005 accounted for the largest amounts of lost employment include the Transportation Equipment Manufacturing group with an employment fall of 6.7 percent (140,000 jobs), the Plastics and Rubber Manufacturing group with an employment loss of 9.4 percent (76,000 jobs), the Chemical group with a loss of 7.0 percent (61,000 jobs), the Computer and Electronic Equipment group with a loss of 4.6 percent (61,000 jobs), and the Primary Metal Manufacturing group with a loss of 10.3 percent of employment (48,000 jobs).

Table 4: Foreign outsourcing effect on manufacturing industry employment: counterfactual analysis

NAICS code	Industry	Change in employment in 2005 due to increase in offshoring from 1987 to 2005, percent	Change in employment in 2005 due to increase in offshoring from 1987 to 2005, number of jobs.
311	Food	-0.3%	-5,100
312	Beverage and Tobacco	-1.3%	-2,500
313	Textile Mills	-5.8%	-12,700
314	Textile Product Mills	-1.9%	-3,300
315	Apparel	-2.6%	-6,700
316	Leather and Allied Product	-5.1%	-2,000
321	Wood Product	-1.9%	-10,500
322	Paper	-0.7%	-3,200
323	Printing and Related Support Activities	-2.2%	-14,500
324	Petroleum and Coal Products	-1.7%	-1,900
325	Chemical	-7.0%	-61,000
326	Plastics and Rubber Products	-9.4%	-75,700
327	Nonmetallic Mineral Product	-1.1%	-5,600
331	Primary Metal	-10.3%	-47,800
332	Fabricated Metal Product	-1.9%	-29,600
333	Machinery	-1.7%	-19,700
334	Computer and Electronic Product	-4.6%	-61,000
335	Electrical Equipment, Appliance, and Component	-4.4%	-18,900
336	Transportation Equipment	-7.9%	-140,100
337	Furniture and Related Product	-0.3%	-1,600
339	Miscellaneous	-1.2%	-8,500

V. Employment loss from foreign outsourcing: Regression analysis

In this section we present a regression analysis to explore the relationship between industry offshoring and employment in the manufacturing sector between 1990 and 2005. We look to a simple model of firm and industry behavior to arrive at the expected values of the regression coefficients in our analysis. We assume that over time industry values tend to be determined by the long run profit maximization behavior of the firms that make up the industry group as these firms are influenced by domestic and foreign demand, labor costs, technology and international competition as well as the extent of foreign outsourcing. We thus look for revenues and costs to move towards equality for industries as profit maximization guides behavior over the medium and long term. [19]

First, we expect the size of domestic and foreign demand for the industry's output to be positively related to the size of total revenues for the industry and we expect imports of produced inputs (our outsourcing measure) and the import penetration ratio to be negatively related to revenues:

TR = Domestic Demand (DD) + Foreign Demand (Exp) – Imported Inputs (ImpInp) – Import Penetration Ratio(ImpPen).

On the cost side, we include the wage bill (the average wage multiplied by industry employment) and expect it to be positively related to the size of costs. We also include two measures of production technology in the cost equation: labor productivity (output per labor hour) and the size of the capital share (the size of the capital stock in relation to industry output). We expect increases in labor productivity to lower the costs of production, and we expect that the size of the capital share may either lower or raise industry costs depending on the role of capital equipment and plant in the production process. Higher levels of the capital share may indicate greater investments in new technology and equipment that allow the industry to be more cost efficient in

[19] Although we realize that many manufacturing industries don't operate in competitive markets, we rely on a model of profit maximization in a competitive market to indicate the tendency of different forces to influence the behavior of the firms that make up an industry group.

the production process. However, a higher capital share may also reflect greater operating and overhead costs. For the cost equation, we then have:

> TC = Wage Bill (W*Emp) - Labor Productivity Growth (LnProd) +/- Capital Share (CapShare).

Setting total revenues and total costs equal for long run profit maximization, we have:

> DD + Exp – ImpInp – ImpPen = (W*Emp) – Prod +/- CapShare,

and

> W*Emp = DD + Exp – ImpInp – ImpPen +/- Prod +/- CapShare.

We want to note at this point that although we expect productivity growth to lower the costs of production, it may do so in part through the adoption of labor-saving technologies and so lower employment and the wage bill. However, it is also possible that rising productivity may increase the wage bill by either lifting wages as the value of a labor hour rises or by allowing the industry to expand employment as it becomes more competitive. In light of these considerations, in taking the wage bill to the left-hand side we will leave the sign on productivity growth indeterminate. In this general equation, we can carry out log transformations on various variables without changing any of the relationships:

> LnW + LnEmp = LnDD + LnExp –ImpInp – ImpPen +/- LnProd +/- CapShare.

The log transformations allow us to re-arrange the equation as an industry employment change equation in this general form:

> LnEmp = LnDD + LnExp – LnW – ImpInp – ImpPen +/- LnProd +/- CapShare.

In particular we note the expected negative relationship in our model between the offshoring variable (imported inputs) and employment growth as the outsourcing activity of manufacturing firms displaces domestic employment. The employment change equation to be estimated is written as:

$$\mathrm{LnEmp}_{it} = \alpha + \beta_1(\mathrm{LnDD})_{it} + \beta_2(\mathrm{LnExp})_{it} - \beta_3(\mathrm{LnW})_{it} +/- \beta_4(\mathrm{CapShare})_{it} +/- \beta_5(\mathrm{LnProd})_{it}$$
$$- \beta_6(\mathrm{Outsourcing})_{it} - \beta_7(\mathrm{ImpPen})_{it} + \varepsilon_{it},$$

where Emp_{it} = employment for industry i in year t;

DD_{it} = domestic demand, or shipments + imports – exports for industry i in year t;

Exp_{it} = exports for industry i in year t;

W_{it} = hourly wage rate for production workers for industry i in year t;

$\mathrm{CapShare}_{it}$ = capital stock/shipments for industry i in year t;

Prod_{it} = labor productivity index for industry i in year t;

$\mathrm{Outsourcing}_{it}$ = import share of total inputs produced for industry i in year t;

ImpPen_{it} = imports/domestic demand for industry i in year t.

In our regression analysis we treat the sample as a panel data set with industry fixed effects to control for characteristics of individual industry groups that effect employment growth over time.[20] Time period fixed effects were also added in some of our estimations to allow for year specific influences on employment changes. We ran the regression with an AR(1) disturbance after the results of a Woolridge test indicated the need to correct for autocorrelation. We separately regressed total industry employment and employment of just those workers categorized as production workers. In particular, we were interested in testing if offshoring had a stronger effect on the employment of production workers (assumed to be less skilled than non-production workers) in contrast to workers as a whole.

Data and results

In the Data Appendix we describe the creation of the data set we use in the regression, including how we dealt with the issues involved in converting data between industry classification systems that changed across time periods and the matching of data between various data sources. As we discuss in the Data Appendix, a large number of industry groups needed to be dropped from our sample or bundled with other industry groups. In the end, we were left with about 245 six-digit NAICS industry groups bundled into 91aggregated manufacturing industry

[20] Both a Hausman test and a Breusch-Pagan Lagrangian multiplier test on our data rejected a random effects model as providing inconsistent estimates.

groups. This final regression data set comprised about 56 percent of total employment in the manufacturing sector in 2005 (see Table A-10 in data appendix).

The 91 bundled industry groups in our regression sample vary widely in employment size (see Table A-10 and Chart A-1 in the Data Appendix). In 2005, the average employment size of an industry group in our sample was about 87 thousand workers, with a minimum industry size of about 11 thousand and a maximum size of about 1 million workers. Taking the range of industry group sizes into account, we carried out both a frequency weighted regression, in which groups were weighted in proportion to their relative employment sizes, as well as an unweighted regression.

Table 5 presents the results for the unweighted regression analysis of changes in total industry group employment and employment of production workers. Table 6 presents the results for these regressions when the data are weighted by the industry group employment size. For many of the variables, there turns out to be little difference in the estimated coefficients between regressions using the weighted and unweighted data. Adding the year fixed effects to the model creates a greater difference in the estimated coefficients for a number of the variables.

As we expected when we set out our model of industry employment, we find strongly significant and positive coefficients in each of the regressions for the domestic demand variable. Increases in domestic demand for an industry's output appears to be a clear impetus for employment growth for that industry. Increases in foreign export demand for an industry's goods also emerges as an important source of employment growth. In Tables 5 and 6, the coefficient on exports is strongly significant and positive in each regression equation we estimate. The coefficient on our other foreign trade variable, the import penetration ratio, is negative and statistically significant in six of our eight regressions; in one regression the coefficient is negative but only significant at the ten percent level, and in one regression it is not significantly different from zero . In six of the eight regressions, then, this variable has the negative coefficient we expected, indicative of foreign import competition displacing jobs in domestic manufacturing.

We were uncertain when laying out our model about the direction in which productivity growth would effect employment growth. In all our regression equations in Tables 5 and 6, we find a strongly significant and negative effect on industry employment growth. Our results strongly

Table 5: Manufacturing industry employment regression, 1991-2005

Dependent Variable:	**Ln(Total Employment)**		**Ln(Production WorkerEmployment)**	
	(1)	(2)	(3)	(4)
Ln(Domestic Demand)	0.144***	0.108***	0.152***	0.112***
	[0.014]	[0.014]	[0.018]	[0.018]
Ln(Exports)	0.049***	0.036***	0.056***	0.039***
	[0.006]	[0.006]	[0.008]	[0.008]
Ln(Productivity Index)	-0.278***	-0.176***	-0.260***	-0.125***
	[0.022]	[0.024]	[0.028]	[0.030]
Ln(Wage)	-0.119**	-0.086	-0.141*	-0.073
	[0.059]	[0.055]	[0.076]	[0.071]
Capital Stock/Shipments Ratio	-0.254***	-0.187***	-0.317***	-0.201***
	[0.029]	[0.029]	[0.037]	[0.037]
Import Penetration Ratio	-0.107***	-0.062*	-0.106**	-0.048
	[0.039]	[0.038]	[0.050]	[0.049]
Imported Inputs Ratio (Make)	-0.431***	-0.221***	-0.522***	-0.238**
	[0.067]	[0.068]	[0.085]	[0.086]
Constant	4.324***	4.028***	3.849***	3.315***
	[0.041]	[0.042]	[0.055]	[0.057]
Industry Effects	Yes	Yes	Yes	Yes
Year Effects	No	Yes	No	Yes
Observations	1365	1365	1365	1365
NAICS industry groups	91	91	91	91
R-squared	0.47	0.46	0.40	0.39
F-test	79.8***	45.3***	60.6***	37.7***

Standard errors in brackets. Significance Level: * 10% level, ** 5% level, *** 1% level

Table 6: Manufacturing industry employment regression, weighted by industry group employment size, 1991-2005

Dependent Variable:	Ln(Total Employment)		Ln(Production Worker Employment)	
	(1)	(2)	(3)	(4)
Ln(Domestic Demand)	0.187***	0.145***	0.186***	0.134***
	[0.005]	[0.005]	[0.006]	[0.006]
Ln(Exports)	0.056***	0.045***	0.062***	0.047***
	[0.002]	[0.002]	[0.003]	[0.002]
Ln(Productivity Index)	-0.248***	-0.180***	-0.217***	-0.113***
	[0.007]	[0.008]	[0.009]	[0.009]
Ln(Wage)	-0.184***	-0.030	-0.254***	-0.031
	[0.023]	[0.021]	[0.028]	[0.026]
Capital Stock/Shipments Ratio	-0.176***	-0.110***	-0.243***	-0.126***
	[0.009]	[0.009]	[0.011]	[0.011]
Import Penetration Ratio	-0.223***	-0.162***	-0.222***	-0.155**
	[0.013]	[0.013]	[0.016]	[0.016]
Imported Inputs Ratio (Make)	-0.351***	-0.216***	-0.409***	-0.182***
	[0.024]	[0.024]	[0.030]	[0.030]
Constant	4.557***	4.212***	4.240***	3.598***
	[0.015]	[0.016]	[0.018]	[0.019]
Industry Effects	Yes	Yes	Yes	Yes
Year Effects	No	Yes	No	Yes
Observations	1365	1365	1365	1365
NAICS industry groups	91	91	91	91
R-squared	0.67	0.66	0.63	0.59
F-test	675.3***	395.6***	515.1***	331.0***

Standard errors in brackets. Significance Level: * 10% level, ** 5% level, *** 1% level suggest that productivity growth in these manufacturing industries has involved a large degree of labor saving changes in production technology. In all our specifications without a year effect, the results show a significant and negative effect of higher wages on employment as expected. In the regressions that include the year fixed effect, however, the wage coefficient is not significantly different from zero. The historically slow growth in manufacturing wages over the period may explain why a stronger wage effect is not evident and may be washed out by the addition of the year effect to the regression.[21] We were unsure about the direction in which the capital share (capital stock/shipments) variable would influence industry costs and employment growth. In all eight specifications of our regression, the coefficient on the capital share variable is strongly significant and negative. These results suggest that the effect of increased industry capital share tends to be higher overhead costs which lowers industry supply and thus lowers employment.

For our offshoring variable, the ratio of imported to total inputs produced by an industry, the coefficient is strongly significant and negative in each of the equations presented in Tables 5 and 6. This result is consistent with our expectation that offshoring displaces domestic employment as US firms look to foreign production sites and workers to replace manufactured inputs previously produced domestically. For our regression specifications without year effects, we find that the coefficients on the offshoring variable is somewhat higher for production worker employment in Tables 5 and 6. When year effects are included, there is little difference between the estimated effects of offshoring on production worker employent and employment for all workers.

Table 7 takes the coefficients from Tables 5 and 6 to estimate a range of employment impacts in the manufacturing sector as a whole for the 1990 to 2005 period due to the different variables from the regression analysis. The estimated employment change over the 1990 to 2005 time period due to a variable is the 1990 to 2005 change in the value of the variable for the sector multiplied by the variable coefficient. We use the lowest and the highest values for the variable coefficients from Tables 5 and 6 to arrive at the ranges for estimated employment changes due to each variable.

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[21] Real wages in the manufacturing sector grew by less than five percent between 1990 and 2005 according to US Bureau of Labor Statistics data.

According to the results presented in Table 7, domestic and foreign demand for industry output are the two strongest factors promoting employment growth in our analysis. The growth of domestic demand added between 2.9 percent and 5.1 percent to total manufacturing sector employment growth between 1990 and 2005 and added 3.0 percent to 5.0 percent to employment growth of manufacturing production workers over the period. Growth in foreign demand for manufacturing sector exports between 1990 and 2005 contributed between 3.0 percent and 4.7 percent to total 1990 – 2005 manufacturing employment growth and between 3.3 percent and 5.2 percent to production workers employment growth in the manufacturing sector over this time. The capital share variables showed positive but smaller contributions to manufacturing sector employment according to our analysis. Over the 1990 to 2005 period, the capital share for the manufacturing industries in our whole sample declined so that, given the negative coefficient on this variable, the effect on employment was positive. The change in the capital share variable in the manufacturing sector contributed between 0.7 percent and 1.5 percent to total 1990 – 2005 manufacturing employment growth and between 0.8 percent and 1.9 percent to production worker employment growth. These results suggest that the decline in the capital share over time may represent lower costs of production, allowing an increase in industry supply and expanded employment .

Change in the import penetration ratio variable results in a negative effect on employment in the manufacturing sector over the time period. Over the 1990 to 2005 period, the change in the import penetration ratio variable in the manufacturing sector lowered total manufacturing employment by between 0.4 percent and 1.4 percent and production worker employment between 0.3 percent and 1.4 percent. The strongest negative impact on employment seen in Table 7 comes from the increase in worker productivity during the period. The growth in productivity between 1990 and 2005 resulted in a fall in total employment in the manufacturing sector of between 14.6 percent and 23.1 percent during those years and a fall in production worker employment growth in the range of 9.4 percent to 21.6 percent. The small increase in the average wage rate in the manufacturing sector during this period did not have a strong impact on employment levels. Over the period, the rise in the wage rate resulted in a fall of total employment of between zero and 0.7 percent and a drop in production worker jobs of zero to 0.9 percent in the sector.

Table 7: Estimated manufacturing employment effects of regression variables, 1990– 2005

Variable	Estimated 1990 – 2005 change in employment due to variable*
Total manufacturing employment change, 1990 – 2005: -19.6%	
Domestic Demand	2.9% to 5.1%
Exports	3.0% to 4.7%
Productivity Index	-23.1% to -14.6%
Wage	0% to -0.7%
Capital Stock/Shipments Ratio	0.7% to 1.5%
Import Penetration Ratio	-1.4% to -0.4%
Imported Inputs Ratio (Make)	-4.4% to -2.2%
Production worker manufacturing employment change, 1990 – 2005: -20.6%	
Variable	Estimated 1990 – 2005 change in employment due to variable*
Domestic Demand	3.0% to 5.0%
Exports	3.3% to 5.2%
Productivity Index	-21.6% to -9.4%
Wage	-0.9% to 0%
Capital Stock/Shipments Ratio	0.8% to 1.9%
Import Penetration Ratio	-1.4% to -0.3%
Imported Inputs Ratio (Make)	-5.3% to -1.9%

* Estimated change in employment due to variable is 1990 – 2005 change in variable value multiplied by variable coefficient. The lowest and highest estimated variable coefficients from Tables 9 and 10 above are used to find the range of estimated employment changes. Insignificant coefficient values are treated as zeros.

Finally, the increase in the imported inputs ratio over the period is shown to have led to a decline in employment for all workers in the manufacturing sector over the 1990 to 2005 period of between 2.2 and 4.4 percent and a drop in production worker employment in the range of 1.9 percent to 5.3 percent between 1990 and 2005. It is noteworthy that our estimate of the impact of offshoring on total manufacturing employment by 2005 from the counterfactual analysis above (a fall of 2.9 percent from the 1987 level) is close to the midpoint of the range from our regression analysis (a drop of 3.3 percent from the 1990 level).

In summary, for employment change in US manufacturing between 1990 and 2005 the biggest factors that emerge from our analysis are the levels of both domestic and foreign demand, the rise in labor productivity, and the growing offshoring of manufacturing activities by US firms. Increases in demand from both domestic and foreign sources have kept employment in US manufacturing jobs from falling even further during this period of steep decline. Changes in technology, as manifested by rapidly rising indices of labor productivity, have put significant downward pressure on the employment level. It appears that technological innovation and new work processes in the 1990s and the first half of the 2000s have worked to displace very large numbers of workers in US manufacturing production. Foreign outsourcing of parts of the production process have also significantly displaced workers in US production in the manufacturing sector during this period. Taking the mid-point of the range of results in our regression analysis, we arrive at an estimate of a fall in employment in the US manufacturing sector of about 3.3 percent from the rise in offshoring during the 1990 to 2005 period. This amounts to 584,000 jobs or 17 percent of the total drop of 3.5 million jobs in the US manufacturing sector over the period. While we have explored the factors which explain the dramatic contraction of US manufacturing employment, the stagnation of manufacturing wages during this period has also been striking. We suspect that the impact of actual and potential implementation of labor saving technology and foreign outsourcing as threat effects in the wage bargaining process are key to explaining the phenomenon of flat wage growth as well as the decline in manufacturing sector employment.

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Data Appendix

In section 1 of this appendix we will describe the processes which allowed us to draw upon data from multiple sources and years, in particular the conversion of industry data from multiple industry classification codes into common matched codes. We will also describe the industry samples that resulted after carrying out these conversions and the aggregation and dropping of data that is sometimes necessary. In section 2, we will discuss some details of how we carried out the analyses and calculations presented in the text.

1. Compiling the data

In compiling the data used to create our outsourcing measures and to carry out our counterfactual and regression analyses, challenges arose from the need to draw upon sources using different industry groupings and years to report their data items. The task of matching data from an array of different sources is complicated further by the fact that many of the data sources switched during our analysis period from reporting industry data using the Standard Industry Classification (SIC) to the North American Industry Classification System (NAICS). See Table A-1 below for sources and industry code formats of our data variables. Variable data prior to the late 1990s tend to be reported using SIC codes while data from later years are reported using NAICS. To bridge the whole period of our analysis, we thus needed to convert SIC data from the earlier years to NAICS classifications. In some cases, the lack of one-to-one correspondence between SIC and NAICS groups required aggregating multiple groups to maintain consistency over time; in other cases, industry groups needed to be dropped altogether because SIC to NAICS matching across time periods could not be achieved. In general, less difficulty arose from the use of multiple data sources and SIC to NAICS matching when analyses were carried out at more highly aggregated industry group levels. In addition, data presented in the U.S. Input-Output Accounts (which are central to our analyses) are reported using industry codes, called I-O Classification Codes, that are different from the standard SIC or NAICS industry codes in a relatively small number of cases. Thus, we also need to account for these I-O Classification Codes in matching our data to a common industry classification code.

Table A-1: Data Sources			
Variable	**Years**	**Source**	**Number of industry groupings**
Employment	1987-1989	NBER[1]	459 (SIC) 340 (After conversion to NAICS)
	1990-2006	BLS[2]	238 (NAICS)
Shipments	1987-1997	BEA[3]	458 (SIC) 339 (After conversion to NAICS)
	1998-2005	BEA[3]	434 (NAICS)
Imports and Exports	1987-1988	NBER[4]	450 (SIC - 1972 basis) 336 (After conversion to SIC – 1987 basis)
	1989-1996	USITC[5]	389 (SIC) 282 (After conversion to NAICS)
	1997-2006	USITC[5]	386 (NAICS)
Productivity Index	1987 - 2004	BLS[6]	86 (4-digit NAICS)
Capital Stock	1987 - 2002	NBER[7]	459 (SIC) 340 (After conversion to NAICS)
Intermediate Goods	1987, 1992	BEA[8]	349 (IO/SIC)
	1997, 2002	BEA[8]	256 (IO/NAICS)

1. **NBER: National Bureau of Economic Research; *NBER-CES Manufacturing Industry Database (1958-1996)*-** *http://www.nber.org/nberces/*
2. BLS: Bureau of Labor Statistics, U.S. Department of Labor; *Current Employment Statistics* - *http://www.bls.gov/ces/home.htm*
3. BEA: Bureau of Economic Analysis, U.S. Department of Commerce; *GDP by Industry Data* - *http://www.bea.gov/industry/gdpbyind_data.htm*
4. NBER: National Bureau of Economic Research; *NBER Trade Database* – *http://www.nber.org/data/*
5. USITC: United States International Trade Commission; *Trade Dataweb* - *http://www.dataweb.usitc.gov/*
6. BLS: Bureau of Labor Statistics, U.S. Department of Labor; *Industry Productivity and Costs* - *http://stats.bls.gov/lpc/home.htm*
7. **NBER: National Bureau of Economic Research; *NBER-CES Manufacturing Industry Database (1958-2005)* -** http://www.nber.org/data/nbprod2005.html
8. BEA: Bureau of Economic Analysis, U.S. Department of Commerce; *Benchmark Input-Output Accounts* - *http://www.bea.gov/industry/io_benchmark.htm*

The 1997 Economic Census Bridge Between NAICS and SIC

To allow researchers to convert industry values from earlier years reported using SIC codes into the new NAICS codes (or vice versa), the U.S. Census Bureau's 1997 Economic Census assigned census records both SIC and NAICS codes, thus making a concordance possible. From this data the Census Bureau produced the "1997 Economic Census: Bridge Between NAICS and SIC" (found online at http://www.census.gov/epcd/ec97brdg/). We make use of Table 1 ("1987 NAICS Matched to 1997 SIC") and Table 2 ("1987 SIC Matched to 1997 NAICS") of the concordance to find how each NAICS group corresponds to percent shares of 1997 shipments in different SIC groups. For instance, shipments for the NAICS group 311421 (Fruit and vegetable canning) in 1997 matched to 100 percent of the shipments from SIC group 2033 (Canned fruits and vegetables) together with 21 percent of the shipments for SIC group 2035 (Pickles, sauces, and salad dressings). We apply these shares to translate SIC values from earlier years to NAICS values. Basic assumptions underlying this process of SIC to NAICS conversion include: 1) that the match of shipments shares between SIC and NAICS groups in earlier years do not differ greatly from the match of shipment shares in 1997, and 2) that the matching of shares between SIC and NAICS groups for other variables such as employment, trade and capital stock do not differ greatly from the matching of shares for shipments.

In accordance with Federal law governing census reports, some industry data are not published so that the operations of an individual establishment or company are not disclosed. The 1997 SIC to NAICS bridge includes many instances where the shipments by an SIC group are undisclosed (denoted by a "D" in Table 2 of the bridge) for this reason.[22] Due to this suppressed data, there are some SIC groups for which we do not have percentage shares of shipments assigned to NAICS groups (the percentage shares along with the shipments value are denoted by "D") and as a result in many cases we cannot convert SIC codes into NAICS codes. Whether we need to then drop the NAICS industry group from our analyses depends on how difficult it is to attain the NAICS group's shipments due to the undisclosed data. Below are the decision rules that we use to determine if we will retain a NAICS group in our sample when the SIC share of shipments is suppressed.

[22] None of the NAICS groups in the SIC-NAICS bridge were reported with undisclosed shipments data.

1) When a small percentage of the NAICS group shipments is made up of the suppressed shipments of an SIC group in 1997 (less than 5 percent of the total NIACS group shipments), then we drop the SIC-NAICS bridge for the undisclosed SIC group but keep the NAICS group in the sample.
2) When a significant percentage of the NAICS group shipments is made up of the suppressed shipments of an SIC group in 1997 (generally, greater than 5 percent of the NAICS group shipments) we then apply these two rules:
    a. If we can determine that all or almost all of the SIC group shipments go into the NAICS group, then we keep the SIC-NAICS bridge, converting 100 percent of the SIC group into the NAICS group. The NAICS group is kept in the sample.
    b. If we cannot determine that all or almost all of the SIC group shipments go into the NAICS group, then we drop the NAICS group from the sample.

Table A-2 presents the SIC groups that are dropped from our analyses due to data being suppressed by the BEA but for which we did not drop the corresponding NAICS group according to Rule 1 above. Table A-3 lists the SIC and NAICS groups that are dropped from our analyses due to data suppression according to Rule 2b above.

Table A-2
Suppressed SIC Data: NAICS Groups Remain in Sample by Rule 1

SIC Group (suppressed data)	NAICS Group (not dropped from sample)
2077	311225
2077	311711
2077	311712
2299	313111
2299	313210
2299	313221
2259	313249
2284	313312
2299	313312
2259	315191
2259	315192
2341	315211
2384	315211
2385	315211
2385	315222

Table A-2, cont.

2361	315223
2385	315228
2385	315234
2385	315239
3999	316110
3131	321999
3999	321999
3999	322299
3999	323110
3999	323111
3999	323112
3999	323113
3999	323119
2819	325131
2899	325199
2819	325998
3999	326199
3523	332212
3524	332212
3699	332212
3799	332212
3999	332212
3429	332919
3499	332919
3524	333112
3699	333293
3699	333314
3699	333315
3523	333922
3699	333992
3699	334119
3699	334511
3699	334516
3699	334519
3699	335129
3639	335212
3711	336211
3519	336399
3944	336991
3999	337127
3699	339114
3131	339993

Table A-3 Suppressed SIC Data: NAICS Groups Dropped from Sample by Rule 2b	
SIC Group (suppressed data)	**NAICS Group (dropped from sample)**
2077	311613
2087	311930
2087	311942
2095	311942
2899	311942
2032	311999
2087	311999
2284	313113
2299	313113
2385	315999
2819	325188
2869	325188
3559	333220
3559	333295
3559	333298
3639	333298
3559	333319
3699	333319
3519	333618
3699	333618
3495	334518
3711	336992
3579	339942

For the manufacturing sector, the BEA's SIC to NAICS bridge includes twenty-eight cases in which the percentage share of the SIC group matched to a NAICS group is given as "0", in almost all instances signifying that a very small amount of this SIC group should be translated into the NAICS group for 1997. We do not use any of these SIC to NAICS bridges to convert our data. Table A-4 shows the SIC to NAICS matches for which the percentage share of the SIC group in the NAICS group is given as zero in the 1997 Bridge.

The BEA's SIC to NAICS Bridge also identifies twelve four-digit SIC groups beginning with the 5, 7 or 8 which are matched to NAICS manufacturing groups for 1997. Under the SIC, only four-digit industry groups beginning with the digit '2' are classified as manufacturing industries.

We drop the SIC to NAICS bridge for these twelve non-manufacturing SIC industry groups to limit our analyses to activities which are characterized as taking place in the manufacturing sector under both industry classification systems. Table A-5 lists the twelve SIC to NAICS matches involving non-manufacturing sector SIC groups and indicates whether or not the NAICS group is dropped from our analyses. When the share of these non-manufacturing SIC groups in a NAICS group is greater than five percent, we drop the NAICS group from our analyses. The exception to this rule is when a NAICS group is aggregated with other NAICS groups in our analyses, so that the non-manufacturing SIC group makes up less than five percent of the aggregated NAICS groups. This exception applies to two NAICS groups and is noted in the table by asterisks.

Table A-4
SIC Group Comprises Zero Percent of NAICS Group: SIC/NAICS Bridges Dropped

SIC Group	NAICS Group
2034	311211
2074	311225
2099	311340
2048	311611
2052	311812
2043	311920
2392	314911
2439	321113
2439	321912
2421	321918
2816	325182
3952	325998
2499	332321
3537	332439
3728	332912
3443	333415
3743	333911
3728	333995
3728	333996
3661	334416
3825	334416
3089	335121
3548	335311
3714	336211
3292	336340
3479	339911
3479	339912
3479	339914

Table A-5 SIC Codes Starting with Numbers 5, 7, and 8 (non-manufacturing industry groups)			
SIC Group	NAICS Group	Percent Share of SIC Group in NAICS Group	Solution
5131	313311	19%	Keep NAICS group, drop the SIC/NAICS bridge*
5131	313312	0%	Keep NAICS group, drop the SIC/NAICS bridge
5147	311612	7%	Drop NAICS group
5441	311330	3%	Keep NAICS group, drop the SIC/NAICS bridge
5441	311340	2%	Keep NAICS group, drop the SIC/NAICS bridge
5461	311811	100%	Drop NAICS group
5699	315999	6%	Keep NAICS group, drop the SIC/NAICS bridge*
5712	337110	7%	Drop NAICS group
5712	337121	2%	Keep NAICS group, drop the SIC/NAICS bridge
5712	337122	3%	Keep NAICS group, drop the SIC/NAICS bridge
5714	314121	15%	Drop NAICS group
7379	334611	100%	Drop NAICS group
7534	326212	100%	Drop NAICS group
7694	335312	4%	Keep NAICS group, drop the SIC/NAICS bridge
7819	334612	42%	Drop NAICS group
8072	339116	100%	Drop NAICS group
Notes:*NAICS Group is part of Grouped Code from Table A-5 below.			

<u>Input-Output Industry Codes</u>

Data in the U.S. Input-Output Accounts are reported using industry I-O Classification Codes, which differ from the standard SIC or NAICS industry codes in a relatively small number of cases. This adds another layer of data code conversion in the process of creating our data sets. Because we make use of data from the 1987, 1992, 1997 and 2002 Benchmark Input-Output Accounts in our analyses, we need to match these I-O Classification Codes to SIC and NAICS codes to finally arrive at data with common NAICS codes. The Benchmark Input-Output Accounts for 1987 and 1992 provide the IO Classification code to SIC code match for those years. We use these matches along with the Census Bureau's SIC to NAICS bridge to construct the conversions from 1987 and 1992 IO Classification codes to NAICS code (that is, IO Classification code to SIC code, and then SIC code to NAICS code). The Benchmark Input-Output Accounts for 1997 and 2002 provide the IO Classification code to NAICS code matching for those years.

While most of the IO Classification codes match one-to-one with SIC codes there are some IO Classification codes which represent multiple SIC codes (e.g., the IO code 141900 is matched with the SIC codes 2061-3). In turn, these multiple SIC codes convert into multiple NAICS codes. We consequently need to treat these bundled SIC/NAICS groups as single industry groups in our analysis. In some cases, the suppressed data issues in the Census Bureau's SIC to NAICS Bridge meant that we needed to drop some of the multiple SIC-NAICS bridges that made up a bundled group. Generally, we kept bundled NAICS groups in which about 95 percent or more of shipments could be converted using the SIC to NAICS Bridge. Table A-6 shows the bundled NAICS groups resulting from the conversion from IO Classification codes. The table also presents the SIC groups and NAICS groups that make up the bundled group and the percent of the bundled NAICS group's shipments that were converted using the SIC to NAICS Bridge. Table A-6 also shows the SIC-NAICS bridges that were dropped for each bundled NAICS group, which accounts for the less than 100 percent conversion for some groups. The listed SIC-NAICS bridges were dropped due to data suppression (noted in Tables A-2 and A-3 above), zero percent conversion (noted in Table A-4 above), or because the SIC groups are not from the manufacturing sector (noted in Table A-5 above), or because the bridge constituted a very small (near zero) percent of the bundled group. This last group of dropped SIC-NAICS bridges is presented in Table A-7. [23]

Table A-6 Bundled IO Classification/SIC/NAICS Groups					
IO Classification Group	**SIC Group**	**NAICS Group**	**Percent of NAICS Group Included after Dropping SIC-NAICS Bridges**	**Dropped SIC/NAICS Bridges**	
				SIC	**NAICS**
141900	206A	31131A	100%		
	2061	311311			
	2062	311312			
	2063	311313			
142005	206B	3113AA	95-96%		
142001	2064	311330		2099	311340
142003	2067	311340		5441	311330
				5441	311340
160100	22AA	313AAA	94%		
	2211	313210			
	2221	313311		2299	313210
	2231			5131	313311
	2261				
	2262				
16AA18	22BB	313BBB	~100%		
180300	2257	313241		2259	313249
160300	2258	313249		2299	313312
	2269	313312		2231	313312
	2281	313111		2284	313312
	2282	313112		5131	313312
				2231	313312
18AA34	23AA	315AAA	97%		
180400	2311	315211		2395	315211
340301	2321	315212		2395	315212
	2322	315221		2396	315999

[23] Note that Table A-7 only includes those dropped SIC-NAICS bridges from Table A-6 that aren't already listed in Tables A-3 through A-5.

	2323	315222		2399	315999
	2325	315223		5699	315999
	2326	315224			
	2329	315225			
	2331	315228			
	2335	315231			
	2337	315232			
	2339	315233			
Table A-6, cont.	2341	315234			
	2342	315239			
	2353	315291			
	2361	315292			
	2369	315299			
	2371	315991			
	2381	315992			
	2384	315993			
	2385	315999			
	2386				
	2387				
	2389				
	3151				
200600	243A	32121A	100%		
	2435	321211			
	2436	321212			
20AA21	244A	321920	97%		
210000	2441			2429	321920
200901	2449			2499	321920
	2448				
240701	267A	32AAAA	~100%		
	2671	322221		2679	322222
	2672	322222			
		326112			
240702	267B	32BBBB	100%		
	2673	322223			
	2674	322224			
		326111			
240AAA	26AA	3221AA	~100%		
240800	2621	322121		3842	322121
240500	2631	322122		3842	322291
	2676	322130			
		322291			
250000	2650	3222AA			
	2652	322211			
	2653	322212			

	2655	322213			
	2656	322214			
	2657	322215			
260AAA	27AA	32311A	94%		
260501	2752	323110		2759	323113
260700	2754	323111		2771	323113
	2759	323112		3999	323110
	2771	323114		3999	323111
		323115		3999	323112
Table A-6, cont.		323119		3999	323119
270100	28AA	3AAAAA	~100%		
	2812	325110		2816	325182
	2813	325120		2819	325998
	2816	325131		2899	325199
	2819	325132			
	2865	325181			
	2869	325188			
		325192			
		325193			
		325199			
		331311			
290100	2830	32541A	100%		
	2833	325411			
	2834	325412			
	2835	325413			
	2836	325414			
270201	287A	32531A	100%		
	2873	325311			
	2874	325312			
1A3A6A	AAAA	3BBBBB	100%		
170600	3061	326291			
320300	3069	313320			
640900	2295	326192			
	3996	326299			
320400	3080	32CCCC	~100%		
	3081	325991		3089	335121
	3082	326113		3999	326199
	3083	326121			
	3084	326122			
	3085	326130			
	3086	326140			
	3086	326150			
	3087	326160			
	3088	326191			

	3089	326199			
340201	314A	31621A	100%		
	3143	316213			
	3144	316214			
	3149	316219			
350100	32AA	32721A	100%		
	3211	327211			
	3229	327212			
	3231	327215			
370200	3320	33151A	100%		
Table A-6, cont.	3321	331511			
	3322	331512			
	3324	331513			
	3325				
380800	335A	33131A	~100%		
	3353	331315		3353	332996
	3354	331316		3357	331319
	3355	331319			
381100	336A	33152A	100%		
	3363	331521			
	3365	331524			
381300	336B	33152B	100%		
	3364	331522			
	3369	331528			
410100	3450	33272A	100%		
	3451	332721			
	3452	332722			
37AA42	3AAA	33AAAA	98%		
420500	3495	332612		3495	334518
370103	3496	332618		3399	332618
	3315	331222			
4AAAAA	3BBB	33BBBB	~100%		
470300	3544	332212		3523	332212
420201	3545	333511		3524	332212
	3423	333514		3699	332212
		333515		3799	332212
				3999	332212
420800	349A	3329AA	~100%		
	3491	332911		3494	332999
	3492	332912		3429	332919
	3494	332919		3499	332919
	3498	332996			
490100	356A	33391A	100%		
	3561	333911			

		3563		333912			
490500		356B	33361A		100%		
		3566		333612			
		3568		333613			
500200		359A	33399A		100%		
		3593		333995			
		3594		333996			
51010A		357A	33411A		~100%		
	510102	3572		334112		3578	333313
	510104	3575		334113		3699	334119
		3577		334119			
Table A-6, cont.		3578					
550200		364B	33CCCC		~100%		
		3645		335121		3999	335121
		3646		335122		3699	335129
		3647		335129			
		3648		336321			
550300		364A	33593A		100%		
		3643		335931			
		3644		335932			
5AAAAA		36AA	33DDDD		95%		
	560500	3663		334220		3661	334418
	570300	3669		334290		3714	336322
	580400	3672		334412		3661	334416
		3675		334414		3825	334416
		3676		334415			
		3677		334416			
		3678		334417			
		3679		334418			
		3694		334419			
				336322			
600200		37AA	33641A		100%		
		3724		336412			
		3764		336415			
600400		37BB	33641B		~100%		
		3728		336413		3728	332912
		3769		336419		3728	333995
						3728	333996
620200		382A	33451A		~100%		
		3823		334513		3829	339112
		3824		334514		3699	334519
		3829		334519			
621000		382A	33EEEE		100%		
		3826		333314			

	3827	334516			

Table A-7 SIC/NAICS Bridges Dropped in Creation of Bundled IO Classification/SIC/NAICS Groups		
IO Group	**SIC Group**	**NAICS Group**
16AA18	2231	313312
18AA34	2395	315211
18AA34	2395	315212
18AA34	2396	315999
18AA34	2399	315999
20AA21	2429	321920
240701	2679	322222
260AAA	2759	323113
260AAA	2771	323113
380800	3357	331319
37AA42	3399	332618
420800	3494	332999
51010A	3578	333313
620200	3829	339112

As shown in Tables A-2 to A-7 above, the SIC to NAICS conversions along with the creation of the bundled IO Classification/SIC/NAICS groups led to some industry groups being dropped from our sample during those years in which SIC to NAICS conversions were necessary. Our calculation of imported inputs ratios for the manufacturing sector (presented in section III in the text) and our counterfactual analysis (presented in section IV in the text) required us to carry out SIC to NAICS data conversions for the years 1987 and 1992. Table A-8 below gives an indication of the extent to which the data sample we used for these analyses is affected by dropping industry groups during the data conversion process. The conversion to NAICS data resulted in dropping industry groups from our sample that made up 8 percent of employment for the whole US manufacturing sector in 1987 and 10 percent of manufacturing sector employment in 1992. The table also shows the values of imported and total inputs used in US manufacturing production found in the original SIC coded data and in our sample of converted NAICS data. As noted in the text, because the SIC to NAICS conversion leads to a smaller decrease in the value of imported inputs than total inputs, the analysis using our sample produces an imported inputs ratio for the whole manufacturing sector in 1987 and 1992 that is larger than would be found in the original SIC coded data. As a result, the growth in the imported inputs ratio over the 1987 to 2002 period for the industry groups presented in Tables 1 and 2 in the text are likely to be somewhat understated.

Table A-8: Loss in samples due to conversion from SIC and IO Classification codes to NAICS codes
Employment (thousands) and Inputs (millions of current dollars) used in US manufacturing production, 1987 and 1992

	1987			1992		
	Employment	Imported Inputs	Total Inputs	Employment	Imported Inputs	Total Inputs
Original SIC Benchmark Data	17,716	93,614	841,929	16,967	127,775	1,011,619
Converted NAICS Data	16,346	89,306	790,659	15,318	123,088	950,509
Loss from Conversion	-7.7%	-4.6%	-6.1%	-9.7%	-3.7%	-6.0%

<u>Code Matching for Regression Analyses</u>

The regression analyses presented in section V of the text required additional code matching as we drew upon various data sources for employment, shipment, trade, productivity, and capital stock variables in our regression equations. Table A-1 above shows how our data differed by industry group coverage, industry groupings, and sources for different years. Because of these differences we found that for some industry groups matching or converting data proved impossible. As a result, a large number of industry groups needed to be dropped from our

Table A-9: NAICS Industry Groups in Regression Analyses Sample
Names of bundled industry groups in bold

311100	311111	**3152A9**	315211	**322210**	322211	**32721A**	327215	**333920**	333921	**335910**	335911
	311119		315212		322212	**327213**	327213		333922		335912
3112AA	311211		315221		322213	**327320**	327320		333923	**335920**	335921
	311212		315222		322214	**331100**	331111		333924		335929
	311213		315223		322215		331112	**333990**	333991	**335930**	335931
	311221		315224	**324110**	324110	**325A31**	331311		333992		335932
	311222		315225	**325A31**	325110		331312		333993	**336110**	336111
	311223		315228		325120		331314		333994		336112
	311225		315231		325131		331315		333995	**336120**	336120
311230	311230		315232		325132		331316		333996	**334A63**	336311
311310	311311		315233		325181		331319		333997		336312
	311312		315234		325182	**331490**	331491		333999		336321
	311313		315239		325188		331492	**334111**	334111		336322
311420	311411		315291		325191	**331510**	331511	**33411B**	334112		336330
	311412		315292		325192		331512		334113		336340
311510	311511		315299		325193		331513		334119		336350
	311512		315991		325199	**332235**	332211	**334A63**	334220		336360
	311513		315992	**325211**	325211		332212		334290		336370
	311514		315993	**325212**	325212		332213		334310		336391
311520	311520		315999	**325400**	325411		332214		334411		336399
311615	311615	**3161A9**	316110		325412	**332320**	332321		334412	**336411**	336411
311810	311811		316991		325413		332322		334414	**336500**	336510
	311812		316992		325414		332323		334415	**336611**	336611
	311813		316993	**325510**	325510	**332400**	332410		334416	**336612**	336612
312110	312111		316999	**325520**	325520		332420		334417	**337215**	337215
	312112	**316200**	316212		325611		332431		334418	**337900**	337910
	321212		316213	**325610**	325612		332439		334419		337920
	312113		316214		325613	**332500**	332510	**334413**	334413	**339112**	339112
312200	312210		316219	**325620**	325620	**333111**	333111	**334510**	334510	**339113**	339113
	312221	**321100**	321113	**326210**	326211	**333130**	333131	**334511**	334511	**339910**	339911

	312229		321114		326212		333132	**334515**	334515		339912
	314110	**32121A**	321211	**326220**	326220	**333415**	333415	**334517**	334517		339913
314110	314121		321212		327111	**332235**	333511	**335110**	335110		339914
314120	314129	**32121B**	321213		327112		333512	**335210**	335211	**339920**	339920
	314911		321214	**327110**	327113		333513		335212	**339930**	339931
314910	314912	**321219**	321219	**327120**	327121		333514	**33522A**	335221		339932
		321920	321920		327122		333515	**335222**	335222	**339950**	339950
		321991	321991		327123		333516	**33522A**	335224	**339990**	339991
					327124		333518		335228		339992
					327125	**333611**	333611	**335311**	335311		339993
				32721A	327211	**333910**	333911	**335312**	335312		339994
					327212		333912	**335313**	335313		339995
							333913	**335314**	335314		339999

sample and further industry group bundling was required. In the end, we were left with ninety-one bundled manufacturing industry groups in our data set which together comprised about 56 percent of total employment in the manufacturing sector in 2005. Table A-9 lists the bundled groups in our regression sample and the 6-digit NAICS industry groups comprising each one.

In Table A-10, we present a picture of the distribution of these 91 bundled industry groups across the 21 three-digit NAICS industry groups in the manufacturing sector in 2005. Only two three-digit groups in the manufacturing sector are not represented at all in our sample – the Textile Mills group and the Printing and Related Support Activities group. The 91 bundled industry groups in our regression sample vary widely in employment size. In 2005, the average employment size of an industry group in our sample was about 87 thousand workers, with a minimum industry size of about 11 thousand and a maximum size of about 1 million workers. Chart A-1 shows the distribution of industry group employment sizes in 2005.

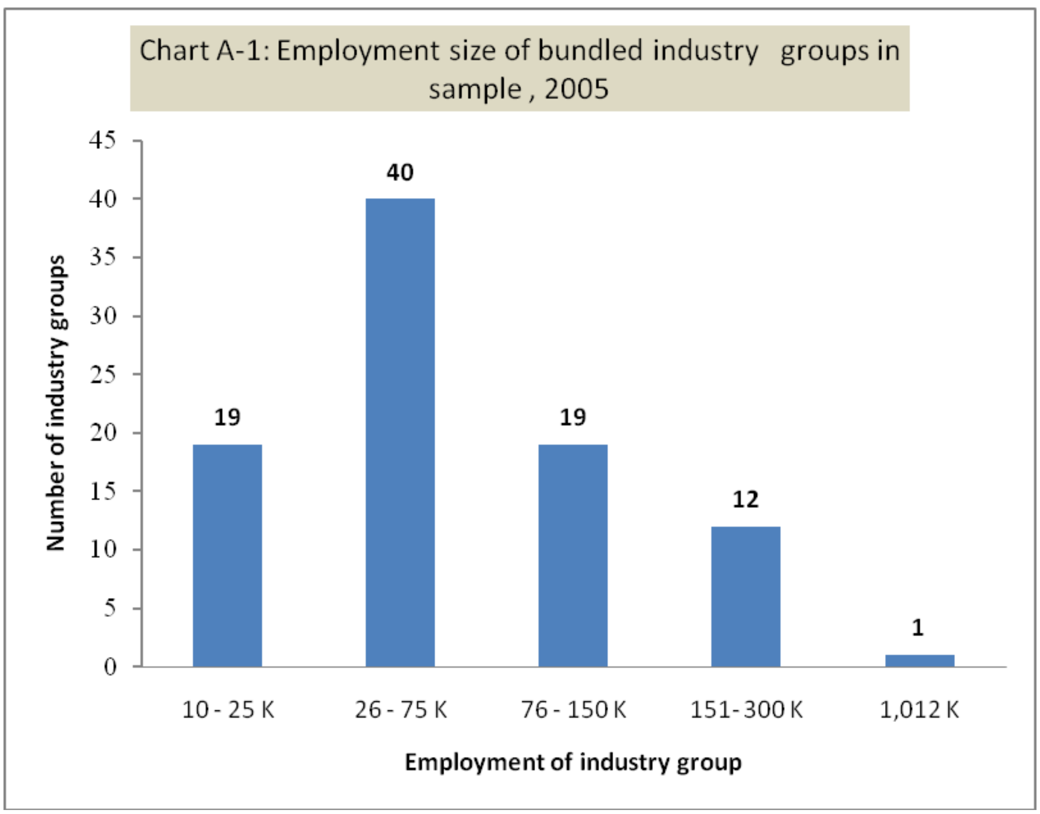

Table A-10: Regression analyses sample, 2005					
NAICS	**Three-digit Industry Group**	**Industry Groups in Sample**	**Sample Employment (thousands), 2005**	**Industry Employment (thousands), 2005**	**Sample Share of Total Employment, 2005**
	Total Manufacturing Sector	91	7,952.8	14,226.2	56%
311	Food mfg	9	786.9	1,477.6	53%
312	Beverage & tobacco product mfg	2	125.6	191.9	65%
313	Textile mills	0	-	217.6	0%
314	Textile product mills	3	128.5	176.4	73%
315	Apparel mfg	1	220.7	250.5	88%
316	Leather & allied product mfg	2	39.7	39.6	100%
321	Wood product mfg	6	347.4	559.2	62%
322	Paper mfg	1	182.4	484.2	38%
323	Printing & related support activities	0	-	646.3	0%
324	Petroleum & coal products mfg	1	68.0	112.1	61%
325	Chemical mfg	8	693.9	872.1	80%
326	Plastics & rubber products mfg	2	95.6	802.3	12%
327	Nonmetallic mineral product mfg	5	292.9	505.3	58%
331	Primary metal mfg	3	285.1	466.0	61%
332	Fabricated metal product mfg	5	682.0	1,522.0	45%
333	Machinery mfg	8	577.0	1,165.5	50%
334	Computer & electronic product mfg	7	1,031.4	1,316.4	78%
335	Electrical equip., appliance, & component	11	351.4	433.5	81%
336	Transportation equipment mfg	8	1,383.5	1,772.3	78%
337	Furniture & related product mfg	2	116.0	568.2	20%
339	Miscellaneous mfg	7	544.8	647.2	84%
Note: Industry employment data from U.S. Bureau of Labor Statistics					

Intermediate goods data

Intermediate goods data is used in the calculation of our industry outsourcing variable - the industry imported inputs ratio. We attain industry intermediate goods data from the Benchmark Input-Output Accounts provided by the US Bureau of Economic Analysis (BEA) for the years 1987, 1992, 1997, and 2002. As discussed above, the industry data in the 1987 and 1992 Benchmark IO Accounts are reported using IO Classification codes. The Benchmark Input-Output Accounts for 1987 and 1992 provide the IO Classification code to SIC code match for those years. We use these matches along with the Census Bureau's SIC to NAICS bridge to construct the conversions from 1987 and 1992 IO Classification codes to NAICS code. We convert the data in the 1997 and 2002 Benchmark Input-Output Accounts to NAICS code using the IO Classification to NAICS code matching for those years provided by the BEA. We discuss in section 2 below how we calculate the imported inputs ratio using the intermediate goods data from the Benchmark IO Accounts. In section 2, we also describe how we create the imported inputs ratio for each year in the years 1990 to 2005 period using intermediate goods data from the four benchmark years.

Trade data

Trade data plays a role in constructing multiple variables in our analyses; we use trade data in the calculation of industry imported input ratios, domestic demand, and import penetration. For the years 1987 and 1988, we attain our import and export data from the National Bureau of Economic Research's NBER Trade Database, while we compile our trade data for years after 1988 from the United States International Trade Commission (USTIC) Tariff and Trade Dataweb. In compiling our trade data, several issues arise involving the conversion across industry classification codes. Both US import and export data is initially collected at the border using the harmonized system (HS), which is an international classification system for commodities. When we compile this data it has been converted from HS to SIC or NAICS codes (depending on the year) for use with other industry data. The conversion of HS to SIC/NAICS industry codes, however, results in some industry groups being missing. This is because when trade data is collected the process of production for a commodity is often not known for certain, and it is the production process that is often used to assign a commodity to an industry code. Consequently, some groups of commodities are bundled into common SIC/NAICS codes while other SIC/NAICS codes have no trade assigned to them at all. In some cases the missing trade data for an industry group means that we need to drop that group from our sample. In about half of the cases, however, we were able to impute the trade values for missing industry groups by finding the trade (import or export) share of the bundled group and then applying that share to each group separately to find the trade values for the missing groups.[24]

An additional industry code conversion had to be carried out for trade data from 1987 and 1988 which is reported in an earlier version of the SIC code, SIC 1972, rather than the SIC 1987 version of the rest of our SIC data. We made use of an SIC 1972 to SIC 1987 concordance made available at the National Bureau of Economic Research (NBER) website.[25] In the small number of cases in which the converted SIC 1972 trade data didn't include industry groups created in the SIC 1987 system, we set the values for 1987 and 1988 at the industry group's 1989 level so as not to have to drop the group for our sample.

We converted our SIC trade data from years prior to 1997 to NAICS code using the SIC-NAICS conversion from the Census Bureau's "1997 Economic Census: Bridge Between NAICS and SIC" as described above. Trade data was deflated using the Consumer Price Index (CPI-U) provided by the BLS with a base year of 2000.

Employment and wages

We compiled US total employment, production worker employment, and wage data in NAICS code from 1990-2005 from the US Bureau of Labor Statistics (BLS). We drew on the National Bureau of Economic Research's NBER-CES Manufacturing Industry Database for employment data in SIC code for the years 1987 to 1989. We converted the employment data from these years into NAICS code using the SIC-NAICS bridge provided by the Census Bureau. Because the BLS's employment data is in many cases reported at a level higher than the six-digit industry group, we often had to bundle data for other variables in our regression analyses to correspond to the aggregation level of the BLS employment data. Wage data was deflated and matched for regression code using the Consumer Price Index (CPI-U) provided by the BLS with a base year of 2000.

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[24] See Feenstra (1996), for a discussion of the conversion of industry trade data into SIC codes and this method of imputing trade values for missing SIC groups.
[25] The concordance is provided by Bartelsman, Becker and Gray (2000) at the NBER-CES Manufacturing Industry Database (the http://www.nber.org/nberces/).

Shipments

We use shipments data to construct several variables used in our analyses, including industry domestic demand, capital share, and import penetration. Industry shipments data was compiled from the US Bureau of Economic Analysis (BEA) in SIC code prior to 1998 and in NAICS code for 1998 and later years. We converted the SIC data to NAICS using the SIC-NAICS bridge provided by the Census Bureau. We used the industry price indices provided along with the shipments data by the BEA to deflate shipment values using a base year of 2000.

Productivity

Productivity data is available from the US Bureau of Labor Statistics (BLS) for the years 1987 to 2005 in NAICS code at the 4-digit industry level. We assigned the six-digit NAICS industry groups in our sample its corresponding four-digit NAICS productivity value when all of its industry groups fell under one four-digit NAICS code. If our bundled industry group combined six-digit NAICS codes from more than one four-digit NAICS group, we weighted the industry productivity values by the individual six-digit industry group shipment values to arrive at the productivity value for the bundled group.

Capital stock

We used industry capital stock data for 1990-2005 found in 1997 NAICS version of the National Bureau of Economic Research's NBER-CES Manufacturing Industry Database (1958-2005). We used the capital stock and shipments data found in the database to create the Capital Stock/Shipments ratio we use in our regression analyses.

2. Calculating the imported inputs ratio

In section III of the text, we present in Table 1 the share of imported inputs in total inputs used for manufacturing industry groups at the 3-digit NAICS level. To calculate these ratios we look first to the Use Tables of the Input-Output Accounts from the U.S. Bureau of Economic Analysis (BEA) to find the value of the manufacturing commodities used as inputs by each industry. For each industry, we then multiply the value of each manufacturing good used in production by the import penetration ratio of that good to arrive at the value of imports of that commodity used as inputs by the industry. A basic assumption of this method of calculating the value of imported inputs is that the import share of the commodity when it is used as an intermediate good in each particular industry is the same as the import share of the commodity in the economy as a whole. We then sum up the value of the manufactured goods imported and used as inputs by the industry to find the industry's total imported manufactured inputs used in production. The industry's share of imported inputs in total inputs used (the imported inputs ratio) is found by dividing the calculated value for industry imported inputs by the value of all manufactured inputs used in production by the industry. The share of imported inputs in total inputs used is calculated at the 6-digit NAICS industry level before being summed up to the 3-digit level for presentation in Table 1 of the text.

To determine the import penetration ratio used in our calculation we draw on shipments data from the BEA and trade data from, depending on the year, either the US International Trade Commission or the National Bureau of Economic Research (see Table A-1 above). The formula for a good's import penetration ratio is given by: imports of good / (shipments + imports – exports).

As presented in the text, the steps in calculating imported inputs as a share of total inputs used in production (the imported input ratio) can be presented in the following equations:

$$\text{Imported Inputs}_i = \Sigma_J[\text{inputs of good j by industry i*imports of good j/(shipments}_j + \text{imports}_j - \text{exports}_j)],$$

where j denotes individual manufactured goods used in production by industry i, and

$$\text{Imported Input Ratio}_i = \text{Imported Inputs}_i/\text{Total Inputs}_i.$$

We also calculate what we call "the share of imported inputs in total inputs produced" for manufacturing industries and present these results at the 3-digit NAICS level in Table 2 of the text. This imported inputs ratio represents the imports share of those intermediate goods which an industry produces. In creating this ratio we make use of the Make Tables of the Input-Output Accounts; these tables assign commodities produced in an economy to the industry groups that produce them. To arrive at the import share of total inputs produced, we use the values of imported and total intermediate goods we found using the Use Table of the Input-Output Accounts and, referring to the Make Tables of the Input-Output Accounts, we allocate those values to the industries that produce the intermediate goods. Summing across all the intermediate goods produced by an industry we find all the imported and total inputs allocated to that industry and so calculate its share of imported inputs in total inputs produced.

We require the full Benchmark Input-Output Accounts to calculate imported inputs ratios for industries at the six-digit level. Thus, we produce imported inputs ratios for only the benchmark years of 1987, 1992, 1997 and 2002 (the last year for which a Benchmark IO Account has been published). We present these ratios for industries at the 3-digit NAICS level in Tables 1 and 2, and use the 1987 and 2002 benchmark results in our counterfactual analysis (as discussed below). However, for our regression analyses, we require yearly values for industry imported inputs from 1990 to 2005. For each industry, we use a linear trend between the benchmark year values to create this yearly variable. For the years 2003 through 2005, we extend the 1997 to 2002 trend line to generate imported input ratios for those years.

3. Counterfactual Analysis of Employment Loss from Foreign Outsourcing

To carry out the counterfactual analysis of the effects of foreign outsourcing on employment in US manufacturing industries presented in section IV of the text, we use industry data grouped at the 4-digit NAICS level.[26] Along with the calculated values of imported inputs produced by industry groups we make use of 1987 and 2005 industry values for shipments, employment, and total inputs from sources described in Table A1. Since the latest benchmark I/O accounts provided by the BEA were for 2002, we calculated imported inputs for 2005 using the 2002 I/O accounts. In doing this we assumed that the technology of production of industry groups in regards to the use of intermediate goods did not change between 2002 and 2005.[27] Given this assumption, we could calculate input use for 2005 by multiplying the inputs/shipment ratio of 2002 by 2005 shipment values. As discussed in the text, due to the inability to completely match some industries from SIC to NAICS in the conversion process, we needed to drop some industry groups in 1987 that together made up 7.7% of total employment that year (the conversion loss is detailed in Table 5 of the text). Examination of the data indicated that the conversion loss doesn't greatly alter the proportions of imported to total inputs in the aggregated four digit

[26] There are 79 four-digit NAICS level industry groups in the manufacturing sector.
[27] Setting the industry imported inputs ratios in 2005 to 2002 levels likely leads to some underestimation of the employment loss over the 1987 to 2005 period. Our calculated industry imported input ratios show a consistent upward trend over the 1987 to 2002 period which could be expected to extend to 2005.

NAICS industry groups or the manufacturing sector as a whole in 1987. For the manufacturing sector as a whole, the imported inputs ratio for the unconverted SIC data in 1987 is 11.4% while for the converted NAICS data in that year the imported inputs ratio is 11. 2%. The results of the analysis are presented at the 3-digit NAICS level in Table 4 in the text.