The Impacts of Technology and Offshoring on Labor Demand: An Analysis Using Microlevel Data

Deniz Çivril*
International Business School, Brandeis University
dcivril@brandeis.edu

April, 2011

Abstract

Over the 1980s, there was a shift in demand away from production labor to non production labor in manufacturing even though the relative wage of non production labor increased. In 1990s, this shift ceased. While labor economists usually emphasized on skilled biased technological changes to explain the shift, trade economists took the attention to the trade, especially offshoring. Both literature usually used industry level data and divided labor market into two, non production and production labors. I verify these labor shifts using occupational data from Integrated Public Use Microdata Series (IPUMS) for the United States. Additionally, I observe that middle wage jobs continued to decrease in 1990s. Educational level analysis suggests that technology and offshoring are substitutes to high school drop outs and high school graduates but complements to some college and college graduates. However, the results are dependable to including time dummies. In order to see the effects of occupational characteristics, I divide the occupations into 4 groups: routine-offshorable, routine-nonoffshorable, nonroutine-offshorable and nonroutine-nonoffshorable. I carry out the same educational analysis under these four groups. Results suggest that routine task intensive occupations have been negatively affected by technology but non-routine intensive occupations ones are affected positively, regardless of educational level. Offshoring is mostly not significant and when it is significant it has a positive effects on the relatively offshorable occupations contrary to general expectation.

*I would like to thank Prof. Catherine L. Mann for invaluable comments and suggestions.

1 Introduction

Technology and globalization have tremendous effect on the allocation of resources across industries, firms and occupations. The traditional models based on two-inputs (capital-labor, skilled-unskilled labor) predict that losers are the labor-intensive manufacturing sectors and low skilled labors in developed countries. However, recent developments such as job losses in skill-intensive service sectors lead economists to reevaluate the effect of technology and globalization, which becomes unpredictable from the perspective of sectors and skill-groups.

The ongoing debate was about the reasons of the outward shift in relative demand of skilled labor. While Skilled-Biased-Technological-Changes (SBTC) is general agreed upon explanation, other economists also take the attention to trade in intermediate inputs, especially offshoring. The reallocation of unskilled part of production in less developed countries increases the relative demand for skilled labor, shifts the demand curve outward. The winners are high-skilled (non-production) labors.

The course of the debate has changed with the trade in services such as call center service, software design, x-ray diagnostics, basic R&D and hence the discussion in offshoribility of occupations regardless of their skill level. Blinder (2006) asserts that 24 to 36 million jobs are under threat in the US. Jensen and Kletzer (2007) reduce this number to 15-20 million jobs by taking the comparative advantage of the US into consideration. The question has evolved to explore the mechanism to understand what properties of an occupation expose it to the benefits or harms of both technology and globalization effects. Autor, Levy and Murnane (2003) divide an occupation into routine and non-routine tasks and shows how technology can be substitute to routine tasks and complements to non-routine tasks in their model. On the trade side, Grossman and Rossi-Hansberg (2006) build a model of trade in task. As long as tasks are codifiable, they can be easily offshored.

Inspired by these developments, I aim to detect the effects of technology and offshoring at the level of task intensity of occupations. Broad categorization of labor market hides the characteristics of occupations. For example, we know that non-production (high skilled) labor share has been increasing while production has been declining. However, there are also some patterns within these categories and we do not know what kind of occupations increase their share and what kind of others decrease within each category. Therefore, this study documents these patterns and tries to understand the reasons of them from the perspective of technology and offshoring.

Differently from the literature, which uses survey data and usually two types of labors (non-production/production), detailed occupational data at the individual level is used from Integrated Public Use Microdata series for 76 manufacturing industries and the years 1980, 1990 and 2000. Labor market is disaggregated into groups not only by individuals' education level but also by their occupation characteristics to see the mechanism of pass through from technology and offshoring. These occupation characteristic are offshoribility and routineness. Offshorability of a job, which is determined by using Blinder(2009)'s (and Kletzer(2009)'s) index, is defined as the easiness to offshore the work either physically or electronically. Routineness determines if an occupation has tasks that can be described by simple rules and substituted by technology. Non-routine tasks need some reasoning so an occupation that has relatively more non-routine tasks is complemented by technology. I utilize from Autor et al (2003) which has task information of occupations, calculated from Dictionary of Occupational Title (DOT). By using this information, I categorize occupations into two: those which have relatively more non-routine task and those which do not have. Thus I suggest a method to categorize occupations according to their routineness and offshoribility.

Educational level analysis suggest that technology and offshoring are substitute to high school drop outs and high school graduates but complements to some college and college graduates. However, the results are dependable to including time dummies. Task level analysis suggests that routine task intensive occupations have been negatively affected by technology but non-routine intensive occupations ones are affected positively, regardless of educational level. Offshoring is mostly not significant and when it is significant it has a positive effects on the relatively offshorable occupations contrary to general expectation.

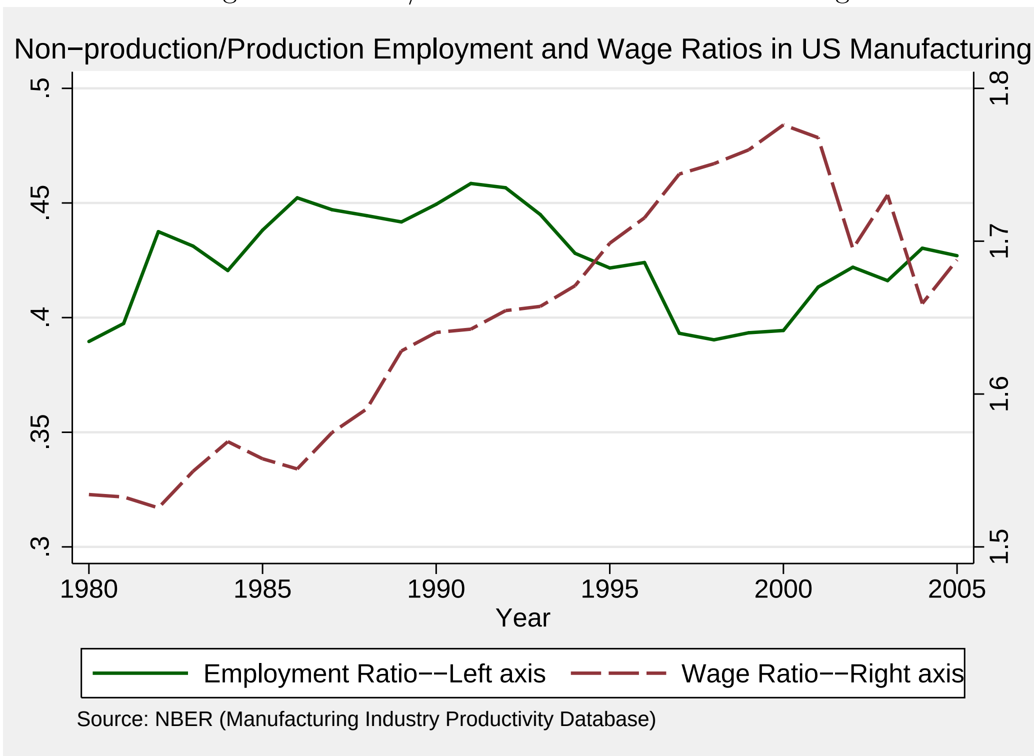
The rest of the paper is organized as follows: Section 2 gives the analysis of IPUMs for the US manufacturing industries and discusses the shortcomings of using two types of labors. Section 3 sets the model and the estimation strategy. Section 4 explains data. Section 5 presents the results and Section 6 concludes.

2 Literature Review and IPUMS Data

Since the beginning of 1980s, we observe almost steady increase in relative wages of skilled and unskilled labors in manufacturing. The same steady increase was also observed in relative employment of these two types of workers until the end of 1980s and then started to decline (Figure 1). The rising relative wages should have taken the employment away from skilled workers in 1980s like in 1990s. However, despite the relative wage increase, relative employment also increased. The general consensus to explain this behavior is the outward shift in relative demand of skilled labor. The problem arises, though, from the reasons of this outward shift. While labor economists usually explain it with Skilled-Biased-Technological-Changes (SBTC) (Berman et al 1994), other economists also emphasize on trade effect (Feenstra, 1996, 1999).

The opposition to trade explanation has two main points. According to neo classical theorems, trade occurs between industries. So some unskilled labor intensive industries must vanish and some

Figure 1: Skilled/Unskilled Ratio in Manufacturing



other high skilled intensive industries must grow or come into existence. However, the shift between labor types is not between industries but within each industry (Berman et al 1994). The other point is that increased use of skilled workers is strongly correlated with investment in computers and in R&D. By looking at four data sets for different time periods between 1940 and 1996, Autor et al (1998) indicate that the rate of skill upgrading has been greater in more computer-intensive industries. Crino (2009) asserts two other reasons at the time which are against trade explanations. The relative price of skilled intensive goods has been declining since 1980 and the skill intensity of production has been increasing.

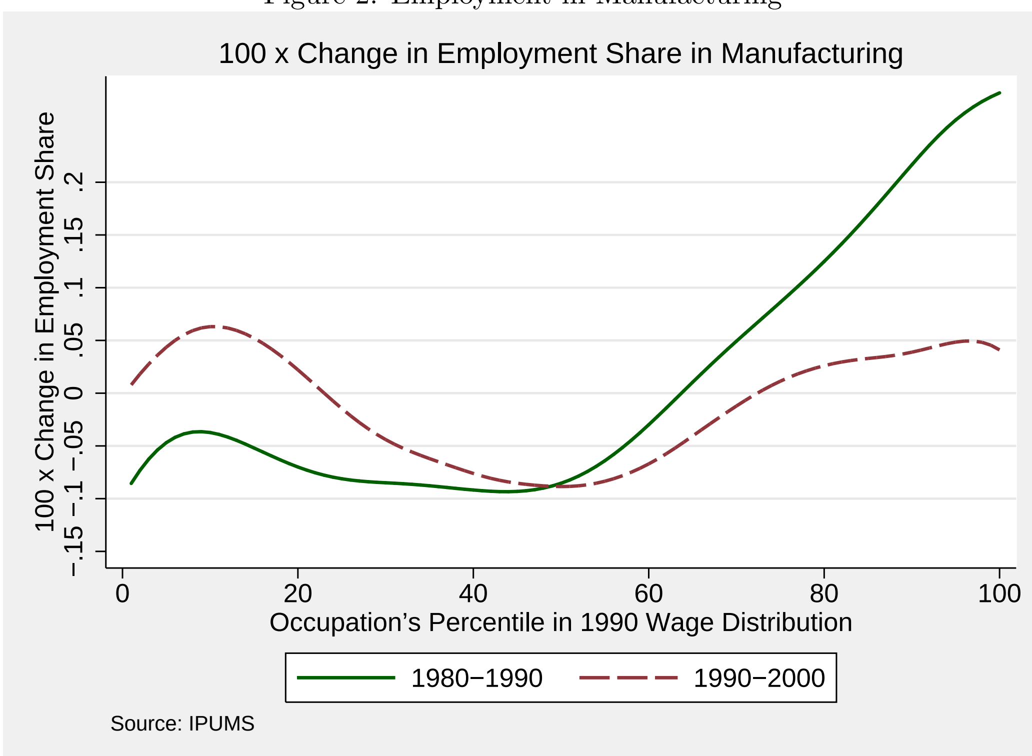
Trade theorists, on the other hand, take the attention to trade in intermediate inputs (Feenstra, Hanson, 1996, 1999). The relocation of unskilled part of production in less developed countries increases the relative demand for skilled labor, shifts the demand curve outward. This is the most direct effect of trade. It has also indirectly contributed to advances in skill biased technology by increasing productivity.

The more disaggregate analysis of labor market in manufacturing reveals more information than

Figure 1. Autor, Levy, Kearney (2006) look at the occupational level distribution of labor market in the last two decades for US labor market overall by using 1980, 1990 and 2000 IPUMS data and comparing change in each occupation share for 1980-1990 and 1990-2000 against 1980 occupational wage percentile.[1] Inspired by their graph, I use the same data but for only those who are employed in manufacturing industries. The reason is that all studies related to trade are in manufacturing because of data availability.

Similarly, change in each occupation share is calculated for 1980-1990 and 1990-2000. Instead of 1980 occupational wage percentile I use 1990 occupational wage percentile.[2] The reason is that some occupations do not exist in 1980 census at all but in 1990 and 2000 census. If 1980 wage distribution was used, one would not have these occupations to compare in the sample. By using locally weighted smoothing regression (bandwidth 0.8) and fitting the relationship between occupational employment share change and occupations wage percentile, I get the Figure 2 for US labor market in manufacturing.

Figure 2: Employment in Manufacturing



[1]See Appendix for their graph.
[2]See Appendix for 1980 occupational wage percentile

Figure 2 shows the change in each occupation given the share of year 1990. Mathematically,

$$\Delta\text{Employment Share}_{1990-1980} = \frac{\text{Share}_{1990} - \text{Share}_{1980}}{\text{Share}_{1990}}$$
$$\Delta\text{Employment Share}_{2000-1990} = \frac{\text{Share}_{2000} - \text{Share}_{1990}}{\text{Share}_{1990}}$$

Assuming that wage level reflects the skill level of labors, the monotonic increase in high skilled occupation from 1980-1990 in Figure 2 coincides with an increase in non-production labor share in Figure 1. However, IPUMS graph gives some more information about second half of the period. In Figure 1, non-production (skilled) labor share of the industry has been decreasing from 1990 to 2000. According to Figure 2 though, the very high skilled labor share continues to grow but with a slower rate. The lost comes from the occupations in the middle, which we cannot see from the aggregate data. This trend is hidden under the broad categorization of skilled and unskilled labors.

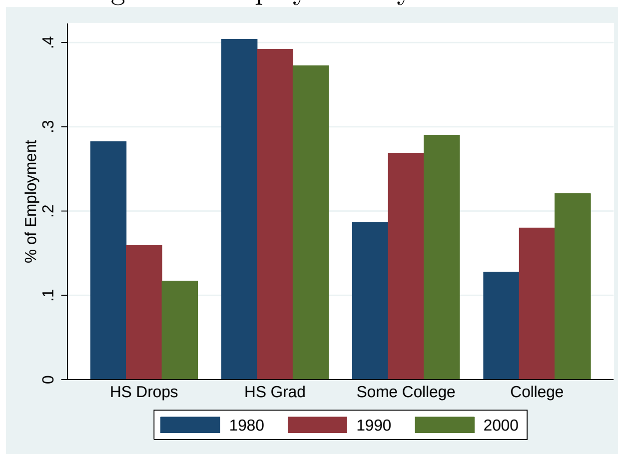
Up to now, both trade and labor literature focus on the shift of 1980-1990 period (Feenstra and Hanson (1996,1999), Slaughter(2001), Morrison and Siegel(2001)). Consider that technology and/or offshoring created the skilled biased demand in the first half. In case this biased stopped, we would expect a line close to zero for 1990-2000 in the Figure 2. In case the biased continued but with a slower rate, we would expect similar line with smaller slope for 1990-2000. However, the share of the middle wage job continued to decrease, low end occupations kept their level or increased their level so that their share relatively rose. The question is that what makes occupations differ so that some jobs still continue to survive and increase their relative share and some others get hurt regardless of their wage level. IPUMS provides individuals' education level and occupation in order to disaggregate the labor market as much as possible. Analysis is carried out by using two approaches to the labor types:

2.1 Approach 1: Educational Analysis

Using education level of individuals, I divide employment into 4 education group: 1. High school drop outs, 2. High school graduates, 3. Some college education, 4. College degree and above.

Figure 3 indicates the percentage of employment by education across years. The known secular trend is clear. The ratios of the high school drop outs and graduates in the employment decrease and some college and college graduates ratios increase by time. The changes are more in 1980s than 1990s. The people who lost their jobs as a middle wage job in Figure 2 must be the ones that were high school drop outs and high school graduates. But it does not give any information why the low paid jobs that are assumed to be low skill labors do not lose their shares. Therefore, I try to explain it with task level categorization of occupation.

Figure 3: Employment by Education



2.2 Approach 2: Task Level Analysis

Although Approach 1 gives some suggestive information, it does not have a strong explanation for middle wage job lost except that people who are employed in these occupations have probably below college education. So I look at the occupation characteristic to find an explanation. Autor et al (2003) identify tasks as routine tasks and non-routine tasks. Routine tasks can be described by simple rules but non-routine tasks need some reasoning. By using the information in this paper, I categorize occupation into two: those which have relatively more non-routine task and those which do not have. Non-routine jobs are supposed to be affected positively by technology. But non-routine does not mean that it is not offshorable. I benefit from both Blinder (2009)'s and Kletzer (2009)'s index to tag the occupation when it is offshorable.[3] With these occupational characteristics, I create 4 groups:

1. Routine-Offshorable occupations: Expected to be most vulnerable ones

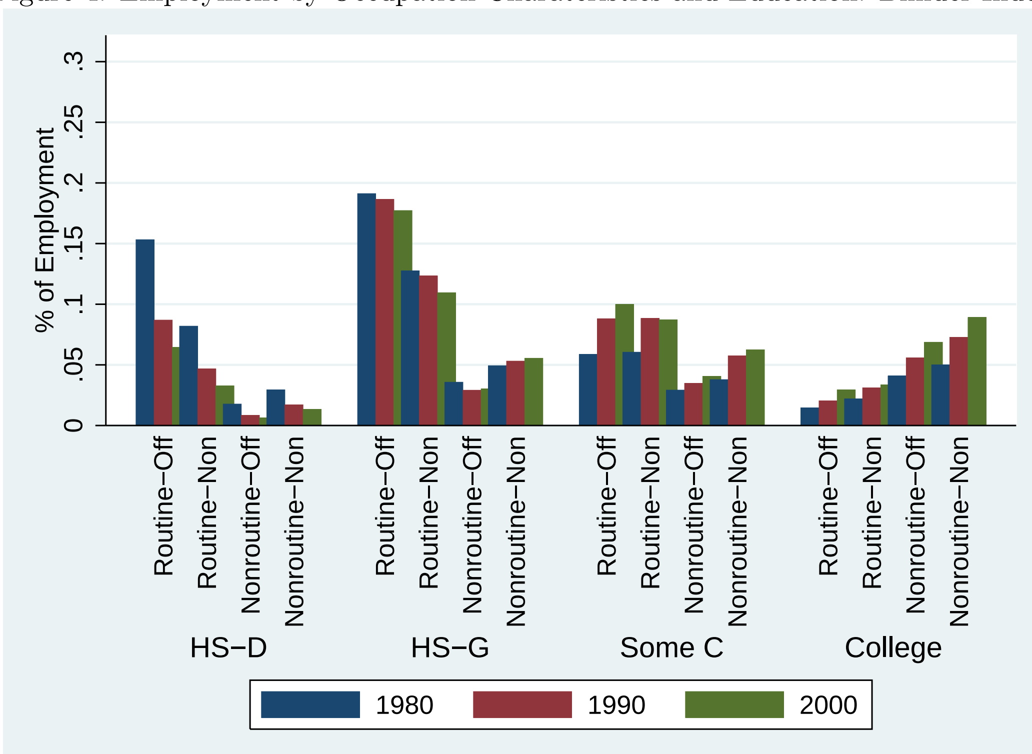
[3]Data Appendix discusses the threshold choices to divide occupations in these categories. I have changed these thresholds. Changes did not affect the significant level of the results in regressions. See Data Appendix for more information.

2. Routine-Non Offshorable occupations: Expected to be affected by technology only and negatively

3. Non Routine-Offshorable occupations: Expected to be affected by technology positively and by offshoring negatively

4. Non Routine-Non Offshorable occupations: Expected to be affected by technology and offshoring positively

Figure 4: Employment by Occupation Charateristics and Education: Blinder Index



The problem with this classification though, I pool all occupations into one category regardless of the education level and lose a lot of information. It disregards the secular trend in education. Negative and positive share changes cancel out each other in each group. Therefore, I look at the distribution of each category under educational categories. As a result, there are 16 categories for each industry.

Figure 4 is based on Blinder's index. We can detect the general secular trend in education within each education category again. The share of the high-school drop outs decreases for each category.

Changes are more dramatic in 1980s then 1990s. For some college and college graduates, there is increase in each task level categorization. However, there are some intriguing informations. Routine task intensive occupations are concentrated in High School Drop Outs and High School Graduate categories. On the other hand, the ratio of non-routine task intensive occupations is higher under Some College and College categories. Assuming that we eliminate the secular trend, if we continue to analyze labor market in 4 education categories, it is expected to get positive effects of both technology and offshoring on high educated categories since these are the ones that have mostly non-routine intensive occupations. They surpass the routine intensive occupations within education category. But we want to know if routine intensive occupations have been affected negatively within each group. Similarly, for High School Drop Outs are employed mostly in routine occupations. If they are employed in non-routine intensive occupation although they are low skilled, they might not be the ones that are affected negatively from technology.

For High School Graduates, the shares of non-routine task intensive occupation have been increasing from 1990 to 2000 and in fact, the share of non-routine and non-offshorable part have been increasing since 1980. We cannot see this trend from the aggregate data. Therefore, an increase in low skilled share in Figure 2 might come from these categories. The loss in the middle jobs on the other hand most probably might come from routine occupations. Some college category stops growing in routine and non-offshorable occupations from 1990 to 2000. [4]

Disaggregation of labor market reveals one very important problem. The effect of secular trend in education is an obstacle that has to be solved to see the real effect of technology and offshoring on different task intensive occupations, which is solved with time dummies in the regressions

For Educational Analysis, there are four types of labors. For Task Level Analysis, there are 16 types of labors; four categories for each education category. Estimations are conducted based on the wage share of each of these labor types for 76 industries, and 3 years (1980, 1990, 2000).

3 Methodology

Following Berman et al. (1994), Feenstra and Hanson (1996), Autor et al (1998), I use trans-log cost function. Firms are the price takers in the factor markets. Each industry produces an output using different types of input. Berman et al (1994) derives the share equation of a quasi-fixed cost

[4] Figure 5 shows the distribution according to Kletzer's index. The share of offshorable occupations is less than the ones in Blinder's index. The reason is that Kletzer's index is more about offshoribility of occupations electronically. On the other hand, Blinder index has also considered occupations that are potentially offshorable when the industry that employs them is offshorable. Since we look at the material offshoring, Blinder's index is more relevant but Appendix has a section that does same analysis for Kletzer's index as well.

function, following Brown and Christensen (1981). Quasi-fixed form is the choice because capital which does not have reliable price deflator can be treated as a fixed factor. The share function is derived by differentiating the cost function of an industry with respect to each input prices and applying Shephard's Lemma. The brief derivation is in the Appendix. The level of offshoring and technology are treated as control factors like in several studies (Feenstra and Hanson (1996), Gieshecker (2002), Hijzen (2005), Ekholm and Hakkala (2005)). The share function is:

$$Share^{j}_{it} = \delta^{j}_{0} + \delta^{j}_{1}\ln\mathrm{Y}_{it} + \delta^{j}_{2}\ln(\mathrm{K/Y})_{it} + \delta^{j}_{3}\mathrm{Off}_{it} + \delta^{j}_{4}\mathrm{Tech}_{it} + \alpha\mathrm{Year}_{t} + \epsilon^{j}_{it} \tag{1}$$

where i denotes industry, t denotes time, Y is output, K is capital. j denotes labor category. Share is wage share of category$j$ in industry i at time t. I estimate the above equation for each category j one by one using fixed effect estimator[5] for 72 industries and 3 years which are 1980, 1990, 2000. Figure 2 shows employment shares instead of cost shares. So as a robustness check I perform the analysis using employment shares as well.

Equation 1 needs some explanations and modifications for estimation procedure. Following the literature, instead of value added, shipment is used for Y. The general reasoning is not having good price deflators for materials and so not having real value added measures (Berman et al 1994).

According to the derivation of wage shares from trans-log cost function, relative wages should appear in the equation 1. There are a lot of discussions about this in the literature. One can assume that industry-level labor supplies are perfectly elastic. Slaughter(2001), for example, discusses referring Hamermesh that at the firm level, firms choose employment given wages. But economy wide wages are endogenous. Since he has data at 4 digit industry level, he justifies his regression without wages by saying they are close to firm level. On the other hand, Berman et al (1994), Feenstra and Hanson (1999) assume that price changes are the result of quality changes so the difference in non-production and production labor does not vary across industries.

There are four types of labors according to education level in this study and average hourly wages can be calculated from IPUMS data for each educational category by industry. Ekholm and Hakkala (2005) assume that wages are set economy-wide so including time dummies will capture the wage effects. Given that I have education categories, I also assume that wage differences reflect the quality differences and they are set on economy wide so do not vary across industries. Furthermore, the data is for the years 1980, 1990 and 2000. Ten year gaps allow economy wide changes which are assumed same for each industry in labor and again captures by time dummies. [6]

The other concern is whether offshoring is exogenous in the equation 1. Amiti and Wei (2006)

[5] Based on Hausman test

[6] As a robustness check, estimations are conducted with wages as well. The results do not change except some changes in time trend, which supports the discussion of Ekholm and Hakkala (2005).

and Geishecker (2006), for example, try to solve this problem with general method of moments using lagged values as instruments. Previous studies simply assume it is exogenous. The advantage of these studies is to have longer time periods. Although in this study, the time period covers 20 years, the data points available are only three years so lagged values cannot be used as instruments. On the other hand, assuming that offshoring activities are based on long decision process and contracting relations with other firm in other countries, 10 years difference between these years can be an advantage to think that offshoring is exogenous in this equation and labor allocation between groups of labor types is done given the level of offshoring.

4 Data and Measuring Offshoring

Offshoring is defined differently in the literature. In this study it describes the relocations of some parts of production abroad through affiliates or unaffiliated suppliers. Offshoring can be divided into two types: material offshoring and service offshoring. The former is to define relocation of production activities and the later is for reallocation of service activities like call center operations, accounting.

Service offshoring takes the attention after dot-com explosion of late 1990s. It makes the untradeable tradable and is shown the reason of the job losses in US by mass media. But many studies do not support this view. Because of data limitation service offshoring effects are studied on manufacturing sector. However service offshoring is not specific to manufacturing sectors so the studies are very restricted. There are two reasons of not using service offshoring in this study. Firstly, the time period is until 2000, dot-com bust has just started so the effect on occupations in manufacturing is limited and the studies that look at service offshoring could not find very significant effect (Amiti, Wei, 2006). Secondly, constructing service offshoring data is not possible for earlier years.

In order to construct offshoring data, I follow the standard method of Feensta, Hanson (1996, 1999).

$$\frac{\left[\sum_j \text{Purchases of intermediate inputs}_{ij}\right]\left[\frac{\text{Import}_j}{\text{Total Consumption}_j}\right]}{\text{Total non-energy intermediate purchases}_i}$$

where j refers to an industry that supply the intermediate input to industry i. The summation in the numerator gives the estimate of imported material inputs from other industries. Dividing it with total non-energy intermediate is the broad measure of Feenstra, Hanson (1996, 1999). The narrow measure is obtained by restricting the four-digit industry i and j in the formula to be within the same two-digit SIC industry. They explain the argument with an example. Import of steel by a US automobile producer is not considered as offshoring but import of automobile parts is considered. Estimations are done for both broad and narrow measure of offshoring.

IPUMS data uses 1990 Census Industry Codes. These codes are created based on 1987 3-digit SIC level so the concordance between SIC level data and Census data are made easily. In order to construct offshoring data in 3-digit SIC level, I firstly calculate numerator and denominator of offshoring formula separately. Then at 3-digit level, I sum up the numbers I have for numerator and denominator. By taking the ratio, one can get the offshoring level of the industry at 3-digit.

One can calculate the intermediate input purchases from Input-Output tables of Census of Manufactures. Total consumption is $(shipments + imports - export)$. I use the import export data available from Peter Schott's webpage.

It should be noted that there are critics about these offshoring measures. (Sitchinava, 2007). Economy-wide import share is used to proxy for import of intermediate inputs but total imports share has goods unrelated to intermediate inputs so the result can be over or underestimated offshoring measures according to the variation of the share of unrelated goods. Focusing on only imported intermediate inputs as defined by end-use classification, these measures are modified in some studies. (Sitchinava, 2007, Bergstrand and Egger, 2008) Feenstra and Jensen (2009) have been also working on a paper to develop these measures.

High-technology variable is calculated based on Feenstra and Hanson (1999). Bureau of Labor Statistics (BLS) provides capital by asset type for 1948-2002 in 2000 constant dollars on 2-digit SIC level. High technology capital capitals are includes computers and computer related peripheral equipment, software, communication equipment, office and accounting machinery, scientific and engineering instruments, and photocopy and related equipment. I multiplied capital stock of each asset with their rental prices and sum them up. Then I divide this sum with total equipment capital stock which also multiplied by its rental price. The ratio gives me the high technology capital ratio. In order to focus on only computer related technological changes, another ratio is calculated with computers and computer related peripheral equipment and software for robustness checks.

$$\text{High Tech Share}_i = \frac{\sum_j \text{Rental Price}_j * \text{Capital Stock}_j}{\text{Rental Price} * \text{Total Capital Stock}}$$

where j refers to asset type, i refers to industry.

Table 1:

year	Broad Material Offshoring (%)	High Tech Capital Share (%)(at 2 digit SIC level)
1980	8.76	6.81
1990	15.27	12.63
2000	21.41	14.83

Note: Weighted by the industry share of real shipment, 76 industries at 3 digit Census classification

5 Results

5.1 Approach 1: Educational Analysis

Table 2: Education by Employment

	HS Drop	HS Grad	Some College	College
ln(Y)	0.563*	−0.746*	−0.700*	0.318
ln(K/Y)	0.224*	−0.333*	−0.208	0.116
Technology	0.037	−0.179*	−0.052	0.104
Offshoring	0.036	−0.098	−0.122	0.087
Year 1990	−0.590***	0.001	0.690***	0.167***
Year 2000	−0.866***	−0.038	0.889***	0.326***
Observations	220	220	220	220
Adjusted R^2	0.917	0.394	0.797	0.757

Standardized beta coefficients

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Fixed effect panel regressions

Table 2 and Table 3 have the regression results for 4 types of labor groups. First table has the time dummies and the second one does not. The published coefficients are standardized beta coefficients so that we can see the relative importance of each variable.

The results generally depend on including time dummies separately or not. This problem is very common in the literature. There is not enough cross-sectional variation in regressors over time which is independent of time itself. If we assume that this pass-through occurs via technology and offshoring, we might drop individual time dummies. Based on this assumption, Table 3 has expected positive effects in wage share bill for high skilled workers and negative effects for low skilled workers.

Table 3: Education by Employment

	HS Drop	HS Grad	Some College	College
ln(Y)	-0.461	-0.830^{**}	0.227	0.786^{**}
ln(K/Y)	-0.366	-0.378^{**}	0.336	0.379^{**}
Technology	-0.319^{*}	-0.178^{*}	0.365^{*}	0.204^{**}
Offshoring	-0.465^{**}	-0.122	0.387^{**}	0.280^{***}
Observations	220	220	220	220
Adjusted R^2	0.468	0.396	0.331	0.636

Standardized beta coefficients

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Fixed effect panel regressions. Robust standard errors.

Siegel and Morrison (2001) look at the labor elasticities at education level for US. The methodological framework is Leontief short-run cost function, different from this paper's. Similarly, they find that material offshoring has decreased the demand or workers without any college education. There is no significant effect on workers with some college which is not in line with my results. But the positive effect on college graduates is again similar. Time dummies are also problematic in their study.

What we learn from this basic educational analysis though how hard to distinguish time trend in education from offshoring and technology. Time dummies are really important to get rid of general trend and focus on variation within each industry, which affects different task differently according to the characteristics of occupations. Each educational category has different occupations that have different properties and aggregation of them just cancels out so we cannot get any significant results with time dummies in the equation. Next section try to solve this problem with task level analysis.

5.2 Approach 2: Task Level Analysis

Task level analysis introduces a couple of dummy variable to distinguish various effects. First of all, time dummies are used to get rid of secular educational trend in each educational category as before. Remember that routine task intensive occupations are concentrated in High School Drop Outs and High School Graduate categories; non-routine task intensive occupations are concentrated in Some College and College categories. Therefore, task level group dummies are added to the regression to take the effect of these different concentrations within each education category. (Task variable above where m stands for task categorization: Routine-Offshorable, Routine-Nonoffshorable, NonRoutine-Offshorable, NonRoutine-Nonoffshorable) The aim is to capture the effect of technology when it interacts with routine category (routine dummy if it is Routine-Offshorable or Routine-Nonoffshorable) and the effect of offshoring when it interacts with offshorable category (tradable dummy if it is Routine-Offshorable or NonRoutine-Offshorable). Therefore, 'routine' dummy and 'tradable' dummy are interacted with related variables.

$$Share_{it}^{jm} = \delta_0^j + \delta_1^j \ln \mathrm{Y}_{it} + \delta_2^j \ln(\mathrm{K/Y})_{it} + \delta_3^j \mathrm{Off}_{it} + \delta_4^j \mathrm{Tech}_{it} + \delta_5^j \mathrm{Off}_{it} * Tradable$$
$$+\delta_6^j \mathrm{Tech}_{it} * Routine + \alpha \mathrm{Year}_t + \gamma \mathrm{Task}_m + \epsilon_{it}^j$$

Table 4: Task Level Analysis: Blinder

	HS Drop	HS Grad	Some College	College
ln(Y)	0.282**	−0.235**	−0.372**	0.170
ln(K/Y)	0.112*	−0.105*	−0.110	0.061
Technology	0.211***	0.030	−0.032	0.248***
Technology*Routine	−0.370***	−0.173***	0.009	−0.380***
Off Broad	−0.018	−0.090**	−0.093*	0.064
Off-Broad*Tradable	0.075	0.119*	0.058	−0.033
Routine-NonOff	−0.262**	−0.241**	0.124	0.097***
NonRoutine-Off	−0.867***	−0.958***	−0.496***	0.135***
NonRoutine-NonOff	−0.761***	−0.732***	−0.030	0.520***
Year 1990	−0.321***	0.000	0.366***	0.093***
Year 2000	−0.473***	−0.012	0.472***	0.180***
Observations	876	880	880	877
Adjusted R^2	0.614	0.657	0.453	0.728

Standardized beta coefficients

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Fixed effect panel regressions. Robust standard errors.

Table 4 shows the results for Blinder Index. Time dummies and task level group dummies are as expected. Time dummies are negative for low-skilled labors and positive for high skilled labors. There is no clear time trend in High School Grad category as one expects from Figure 4. This figure also shows why we have negative coefficients for task level group dummies. While low-skilled labor categories have relatively less non-routine intensive occupations, high-skilled labor categories have more of them. These dummies exactly reflect this trend. After eliminating all these trends, we can analyze the effect of technology and offshoring.

The coefficients of technology show the effects on the wage share bill of each category when the category is non-routine. There is no significant result for High School Graduates and Some College categories. Technology is not effective in the change of shares in these categories. However, we have positive effect of technology for High School Drop Outs and College categories. Therefore, technology is complement to non-routine intensive occupation in these categories and is a positive reason to have an increase. Routine dummy with the technology interaction, on the other hand, gives the effect of technology when the category is routine. Except Some College, we have negative coefficients. We need to look at the summation of coefficient to understand the overall effect. In each case, coefficients for these interactions outweigh the coefficients of the technology which indicate that technology is substitute to routine intensive occupation categories. Coefficients are standardized beta coefficient so we cannot compare them between education groups but within each regression.

Table 5: Task Level Analysis with Narrow Offshoring: Blinder

	HS Drop	HS Grad	Some College	College
ln(Y)	0.279**	−0.219**	−0.347**	0.147
ln(K/Y)	0.112*	−0.105**	−0.108	0.061
Technology	0.209***	0.031	−0.032	0.247***
Technology*Routine	−0.368***	−0.173***	0.009	−0.379***
Off Narrow	0.043	−0.038	−0.063	0.116*
Off-Narrow*Tradable	−0.027	−0.030	−0.051	−0.056
Routine-NonOff	−0.320***	−0.327***	0.066	0.093***
NonRoutine-Off	−0.866***	−0.958***	−0.496***	0.135***
NonRoutine-NonOff	−0.818***	−0.818***	−0.087	0.516***
Year 1990	−0.320***	−0.001	0.362***	0.095***
Year 2000	−0.471***	−0.013	0.465***	0.183***
Observations	876	880	880	877
Adjusted R^2	0.613	0.654	0.454	0.730

Standardized beta coefficients

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Fixed effect panel regressions. Robust standard errors.

For High School Grad and Some College Graduates, there are negative effects in non-offshorable occupation, which are against common belief. In fact being offshorable make a positive impact in High School Grad category although its significant level is not as high as others. One reason might be related to the index. The index measures offshoribility according to easiness to offshore both electronically and physically. Electronic offshorability has not started until recently. We do not have such a term back in 1980s and even in 1990s.[7] Therefore, we might mix up negative effect of material offshoring on physically offshorable occupation with electronically offshorable ones.

[7]As a future work, I need to differentiate these two understanding of offshoribility

Besides technology and offshoring, production of industry is also effective in the variation of shares. As the production increase in an industry, the shares of High School and Some College degrees labors decline. On the other hand, High School Drop Outs has been positively related with the production. If we go back to Figure 2, we can say that routine occupation has been losing shares overall when we get rid of secular trend in education but also output elasticity of Some College and High School graduates is negative. If they are employed in middle-wage occupations then one of the reason of polarization in Figure 2 might be also these negative relation.

Following the literature, narrow offshoring is used in Table 5. Differently from broad offshoring, there is not any significant effect of offshoring but College Graduates. It has slightly positive effect on non-offshorable occupation in this category.

One other change is using import penetration [8] instead of offshoring variable. We have now more significant results of trade variable for different categories. Similar to Table 4, Table 6 shows that import penetration has a negative effect on non-offshorable occupations and once they are offshorable, their share is positively affected.

Table 6: Task Level Analysis with Import Penetration: Blinder

	HS Drop	HS Grad	Some College	College
ln(Y)	0.245**	−0.258**	−0.360*	0.220*
ln(K/Y)	0.081	−0.117**	−0.082	0.088
Technology	0.207***	0.022	−0.056	0.238***
Technology*Routine	−0.336***	−0.144**	0.028	−0.379***
Routine-NonOff	−0.190**	−0.176*	0.192**	0.123***
NonRoutine-Off	−0.823***	−0.919***	−0.473***	0.135***
NonRoutine-NonOff	−0.644***	−0.624***	0.064	0.546***
Year 1990	−0.302***	0.004	0.349***	0.086***
Year 2000	−0.431***	−0.000	0.429***	0.159***
M-Pen	−0.157**	−0.197***	−0.085	0.080
M-Pen*Tradable	0.197***	0.246***	0.195**	0.016
Observations	876	880	880	877
Adjusted R^2	0.573	0.629	0.459	0.728

Standardized beta coefficients

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Fixed effect panel regressions. Robust standard errors.

The graph at the beginning is employment shares instead of cost shares. So, I perform the analysis using employment shares as well. The effect of income is now higher in College. Capital

[8] Import/(Import+Output-Export)

intensity is also complement to College graduates.

Table 7: Task Level Analysis with Employment Share: Blinder

	HS Drop	HS Grad	Some College	College
ln(Y)	0.157*	−0.266***	−0.216*	0.444**
ln(K/Y)	0.065	−0.117**	−0.071	0.182**
Technology	0.195***	0.017	−0.045	0.257***
Technology*Routine	−0.352***	−0.124***	0.109*	−0.390***
Off Broad	−0.030	−0.098**	−0.092**	0.061
Off-Broad*Tradable	0.097	0.144*	0.090	0.009
Routine-NonOff	−0.295***	−0.287***	0.033	0.100**
NonRoutine-Off	−0.921***	−0.984***	−0.573***	0.105*
NonRoutine-NonOff	−0.800***	−0.767***	−0.255***	0.334***
Year 1990	−0.260***	0.043***	0.316***	0.068***
Year 2000	−0.377***	0.060***	0.428***	0.126***
Observations	876	880	880	877
Adjusted R^2	0.628	0.714	0.584	0.584

Standardized beta coefficients

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Fixed effect panel regressions. Robust standard errors.

6 Conclusion

Skilled biased technological bias toward non-production labor ceased in 1990s. But the more disaggregate data reveals that this bias continues for some occupations even during 1990s. Surprisingly, not only high-skilled occupations but also some low skilled occupations increase their share of employment as opposed to decrease in some middle skilled occupation. This variation suggests us that it is not the skilled level but some other factors can be effective for the survival of occupations.

In the literature, there are two effects that are under discussion: technology and offshoring. Technology is a complement to non-routine tasks but substitute to routine ones. On the trade side, offshoring must affect offshorable occupations negatively. I utilize two other studies to categorize occupations according to their tasks and offshoribility: Autor et al (2003) and Blinder (2009). First analysis is done on educational basis only. It directs us to more disaggregate analysis since general secular trend in education hides the variation in each category like in the case of production and non-production categories. So the analysis is carried out under both educational and task level analysis to see if the occupation is exposed to technology or offshoring or both of them.

Results suggest that routine task intensive occupations have been negatively affected by technology but non-routine intensive occupations ones are affected positively, regardless of educational level. Offshoring is mostly not significant and when it is significant it has a positive effects on the relatively offshorable occupations contrary to general expectation. Outcome of an industry, on the other hand, has a negative effect on high school and some college degrees while there is a positive effect on the high school drop outs and college degrees when we eliminate the occupational characteristics and secular education trend.

7 References

Amiti, Wei, Shang-Jin Wei, "Service Offshoring, Productivity and Employment: Evidence from the United States", *Discussion Paper 5475, Centre for Economic Policy Research*, London, 2006

Autor, David H., Lawrence F. Katz and Melissa S. Kearney, "The Polarization of the US Labor Market" ,*American Economic Review Papers and Proceedings*, 96(2), May 2006, 189 - 194.

Autor, David H., Lawrence F. Katz and Alan Krueger, "Computing Inequality: Have Computers Changed the Labor Market?",*The Quarterly Journal of Economics*, 113(4), November 1998, 1169-1214

Autor, David H., Frank Levy and Richard J. Murnane, "The Skill Content of Recent Technological Change: An Empirical Exploration", *The Quarterly Journal of Economics*, 118(4), November 2003, 1279-1334

Berman, Eli, John Bound and Zvi Griliches, "Changes in the Demand for Skilled Labor within US Manufacturing: Evidence from the Annual Survey of Manufactures",*The Quarterly Journal of Economics*, CIX, 1994, 367-398

Bernard, Andrew B., J. Bradford Jensen and Peter K. Schott "Survival of the Best Fit: Exposure to Low-wage Countries and the (Uneven) Growth of U.S. Manufacturing Plants", *Journal of International Economics*, 68(1), 2006, 219-237

Chan, Wing H., Daniel P. Rich, "Occupational Labour Demand and the Sources of Non-neutral Technical Change",*Oxford Bulletin of Economics and Satistics*, 68(1), 2006

Crino, Rosario "Offshoring, Multinationals and Labour Market: A review of the Empirical Literature",*Journal of Economic Surveys*, Vol 23 No2, 2009, 197-249

Ekholm, K. and Hakkala, K., "The Effect of Offshoring on Labor Demand: Evidence from Sweden." Working Paper 654,*The Research Institute of Industrial Economics*, 2005

Feenstra, Robert C., and Gordon H. Hanson, "The Impact of Outsourcing and High Technology Capital on Wages: Estimates for the United States, 1979-1990",*Quarterly Journal of Economics*, 114, 1999, 907-940.

Feenstra, Robert C., and J. Bradford Jensen, "Evaluating Estimates of Materials Offshoring from US Manufacturing", 2009

Geishecker, Ingo, "Does Outsourcing to Central and Eastern Europe Really Threaten Manual Workers' Jobs in Germany", *World Economy*, 29(5), 2006, 559-583

Grossman, Gene M., Esteban Rossi-Hansberg, "Trading Tasks: A Simple Theory of Offshoring ",*American Economic Review*, 98:5, 2008, 1978-1997

Kletzer, Lori G., "Understanding the Domestic Labor Market Impact of Offshore Services Outsourcing: Measurement Issues", presented in Measurement Issues Arising from the Growth of Globalization Conference, November 6-7 2009

Morrison, C. and Siegel, D. "The Impacts of Technology, Trade and Outsourcing on Employment and Labor Composition". *Scandinavian Journal of Economics*, 103(2), 2001, 241264.

Sitchinava, Nino, "Trade, Technology, and Wage Inequality: Evidence from US Manufacturing, 1989-2004", University of Oregon, PhD Dissertation

Slaughter, M.J. "International Trade and Labor-Demand Elasticities", *Journal of International Economics* 54(1), 2001, 2756.

8 Appendix Kletzer's Offshoribility Index

Table 8 indicates the same regression using Kletzer's Index. Task level group dummies are different from the previous table since non-offshorable part is different from Blinder's Index. So we have positive results for non-offshorable categories. We keep the same analysis regarding technology. Furthermore, we fail to detect any negative effect of offshoring.

Figure 5: Employment by Occupation Charateristics and Education: Kletzer Index

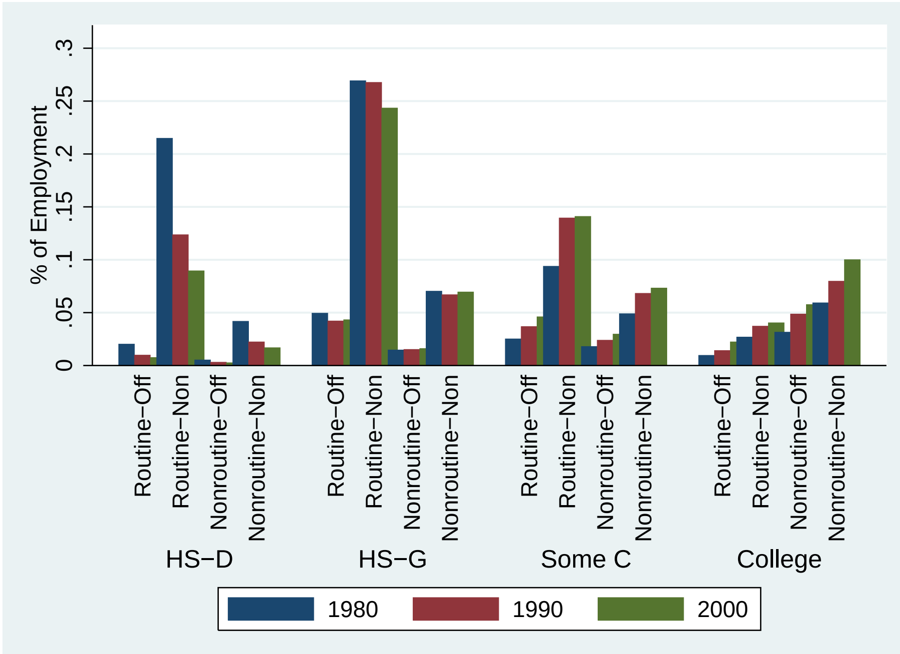


Table 8: Task Level Analysis: Kletzer

	HS Drop	HS Grad	Some College	College
ln(Y)	0.225**	−0.157**	−0.235**	0.160
ln(K/Y)	0.088*	−0.070**	−0.070	0.058
Technology	0.146***	0.019	−0.020	0.232***
Technology*Routine	−0.264***	−0.115***	0.005	−0.359***
Off Broad	−0.112**	−0.085**	−0.034	0.059
Off-Broad*Tradable	0.253***	0.130**	−0.012	−0.027
Routine-NonOff	0.920***	0.996***	0.830***	0.172***
NonRoutine-Off	−0.205***	−0.174***	−0.058*	0.087*
NonRoutine-NonOff	0.131**	0.214***	0.478***	0.610***
Year 1990	−0.236***	0.001	0.231***	0.088***
Year 2000	−0.351***	−0.007	0.297***	0.170***
Observations	859	879	879	876
Adjusted R^2	0.728	0.884	0.809	0.759

Standardized beta coefficients

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Fixed effect panel regressions. Robust standard errors.

9 Appendix Data

Integrated Public Use Microdata Series (IPUMS):

I use the 1% IPUMS sample for the 1980, 1990 and 2000, including workers who are between 18 and 65 years of age. Following Autor, Levy, Murnane (2003) I use full-time equivalent hours of labor supply. The variable "personal weight (perwt)" indicates how many persons in the US population are represented by a person in the sample. Full-time equivalent hours of labor supply is calculated by multiplying this weight with worked hours per week divided by 35 and worked weeks divided by 50. If worked hours and weeks are not reported because of self employment: For the case of occupational analysis, I fill the blank with average hours by occupation and education, if problem still exist average hours by education. For the case of industrial occupation analysis, I use average hours by industry, occupation, education and drop each of them one by one if problem continues.

DOT Task Means:

Task values are taken from the webpage of David Autor. There are 5 tasks for each occupation in the index: MATH (non-routine analytic), DCP (non-routine interactive), STS (routine cognitive), FINGDEX (routine manual), EHF (non-routine manual). Each ranks from 0 to 10. Occupation is Non Routine if MATH, DCP or EHF is more than all other. There are some occupations that have both routine and non-routine task (for example STS is 8 but DCP is 7). As long as DCP or MATH are higher than 7, they are in non-routine categories. I change this threshold to 6 and 8 but get similar results. So there are not a lot of occupations that are affected by this threshold in general such that it changes their category.

NBER Productivity Database:

http://www.nber.org/nberprod/

This database contains annual industry-level data on output, employment, payroll and other input costs, shipment, investment, capital stocks, TFP, and various industry-specific price indexes. The database covers all 4-digit manufacturing industries from 1958-1996 and recently they updated the data until 2005. Two version of data are available: 1987 SIC codes (459 industries) and 1972 SIC codes (448 industries) I use capital stock, shipment and value added in 1987 SIC codes for the years 1980, 1990, 2000.

Technology Variable:

High-technology variable is calculated based on Feenstra and Hanson (1999). Bureau of Labor Statistics (BLS) provides capital by asset type for 1948-2002 in 2000 constant dollars on 2-digit SIC level. High technology capital capitals are includes computers and computer related peripheral equipment, software, communication equipment, office and accounting machinery, scientific and engineering instruments, and photocopy and related equipment. I multiplied capital stock of each asset with their rental prices and sum them up. Then I divide this sum with total equipment capital stock which also multiplied by its rental price. The ratio gives me the high capital ratio.

Import-Export Data:

Robert Feensta's Webpage has import-export data for the years 1972-2001 but they are based on 1987 export-based SIC numbers or import-based SIC numbers. These are not the same as the SIC numbers used to identify U.S. industries because industries in the US are sometimes defined in terms of the processing that occurs in them. Peter Schott did the required crosswalks at 1987 SIC level at country level. I get the industry level data by adding values of each industry from all countries.

Robert Feenstra's Webpage

http://www.internationaldata.org/

Peter Schott's Webpage

http://www.som.yale.edu/faculty/pks4/

Blinder and Kletzer Index:

Blinder Index (2009): There are 817 occupations in his index. He categorizes occupations in 4 categories: Category 1 (75-100) - Highly Offshorable, Category 2 (50-75) - Offshorable, Category 3 (25-50) - Non-Offshorable, Category 4 (0-25) - Highly Non Offshorable.

For the analysis, I chose the occupations in 60% and above (threshold 70% is also tried but it does change the analysis). On the other hand IPUMs has only 351 occupations with broader categories. The matching is done between BLS Occupational Categories (SOC) and Census occupational categories. And fortunately most of the disaggregate occupations that refers to one occupation in Census fall into same category (either offshorable or non-offshorable).

Kletzer Index (2009): There are 799 occupations in her index. Kletzer does not have any categorization but only ranking so in order to be consistent with Blinder's index I Look at the number of occupations and its ratio in Blinder's index and create a threshold for her Index, which is comparable with Blinder's index.

10 Appendix Theory

We follow the translog cost function following literature Berman et al. (1994), Autor et al. (1998), Feenstra and Hanson (1996), Ekholm and Hakkala (2005) . Christensen et al (1972) derives translog cost function as a second order Taylor's series approximation in logarithms. There is no ex ante restrictions like homotheticity, homogeneity, constant returns to scale, etc on the production structure.
The translog function for an industry is:

$$lnC = \alpha_0 + \sum_{i=1} \alpha_i lnP_i + \frac{1}{2} \sum_{i=1} \sum_{j=1} \alpha_{ij} lnP_i lnP_j + \delta_y lnY + \frac{1}{2} \delta_{yy} (lnY)^2 + \sum_{i=1} \delta_{iy} lnP_i lnY \tag{2}$$

where $i, j = 1, , S$ shows the S inputs, C is total cost, Y is output and P_i's are the prices of factor inputs. By differentiating (1) with respect to lnP_i and imposing $\frac{\partial C}{\partial P_i} = D_i$ according to Shephard's lemma, we get cost-share equation for each input i :

$$\frac{\partial lnC}{\partial lnP_i} = \frac{P_i}{C} \frac{\partial C}{\partial P_i} = \theta_i = \frac{P_i D_i}{C} = \alpha_i + \sum_{j=1} \alpha_{ij} lnP_j + \delta_{iy} lnY \tag{3}$$

where $\sum_{i=1} P_i D_i = C$.

11 Appendix Figures

Figure 6: Employment in the Economy

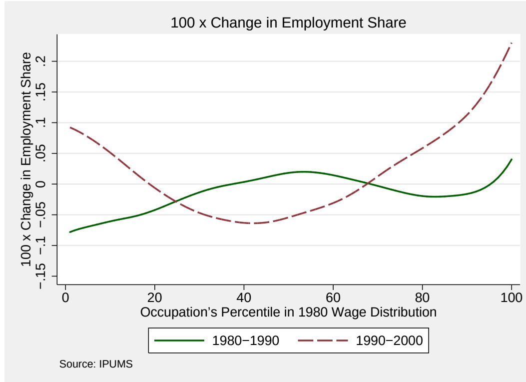


Figure 7: Employment in the Economy

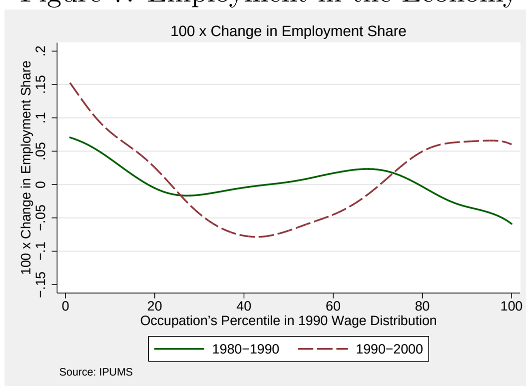


Figure 8: Employment in Manufacturing