IMPACT OF GLOBALIZATION ON PRODUCTIVITY OF U.S. MANUFACTURING LABOR 1988-2003

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ABSTRACT

This paper explores the impact of globalization on some determinants of per worker labor productivity in U.S. manufacturing industries. Information and Communication Technologies (ICTs), and trade liberalization are examined as two main drivers of globalization in this study. The estimation result suggests that globalization has negatively impacted per worker productivity across small, medium, and high skill workers in U.S. manufacturing industries.

JEL Codes: L60, D24, J24
Key Words: Agglomeration, Globalization, Manufacturing, Productivity

I. Introduction

United States manufacturing industries are going through significant changes due to forces globalization driven by technological advancement, and trade liberalization. These changes can be broadly identified as increase in per worker output, decreases in total manufacturing employment, falling of relative contributions of the manufacturing sector to U.S. Gross Domestic Product (GDP), etc.[1] Technological advancement increases labor productivity and thus contributes to increases per worker output and also helps with setting new productivity norms by producing more output with fewer workers. Similarly, trade can enhance productivity via technological spillover. The process of trade liberalization also exposes home industries to increased foreign competition for capturing of market share and procurement of inputs. Increased competition forces U.S. firms to be more cost-effective and innovative in order to thrive or survive. Thus, process of trade liberalization sets firms on continuous quest for cost cuttings to stay competitive via reengineer of plants, importing of inputs at cheaper prices, moving of plants and production processes to offshore locations or else, go out of business. In the backdrop of this fast changing economic landscape it is important and interesting both from academic and policy standpoint to study the impact of globalization on determinants of worker productivity in manufacturing industries in the U.S.

Recent advances in the Internet and other web-based information and communication technologies (ICTs) have reduced the costs and increased the quality of long distance communication, which enables firms to manage supply chains, facilitates knowledge spillover from far away places.[2] The Internet has been officially open for commercial usage following the decommissioning of the National Science Foundation managed NSFNet in 1995. Additionally, recent trade agreements have reduced

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[1] These trends are shown in Figures 1 through 5.
[2] In fact, data show that the growth rate of U.S. labor productivity fell in the 1970s and 1980s but began to rise again in the mid-1990s. The recent increase in U.S. labor productivity is discussed in several books and articles including Krugman and Wells (2006, p. 597) and Jimeno and Saiz (2006) who attribute the observed increase in labor productivity to technological advancements, such as the ICT revolution.

tariff and non-tariff barriers to international trade. Since 1994, tariff rates, and quantitative restrictions on international trade between the U.S., Canada, and Mexico have declined, and nearly all remaining tariff and quantitative restrictions regarding bilateral trades among these countries were gradually phased out under the provisions of the North American Free Trade Agreement (NAFTA).[3] The U.S. further lowered tariff rates on goods imported from a large number of countries in 1995 because of the successful conclusion of the Uruguay round of the General Agreement on Tariffs and Trade (GATT). These events have facilitated the ease of communication and international trade, and thus have increased outsourcing of the production of many intermediate and final goods from U.S. to many foreign locations.

In this paper, I examine the impact of globalization on some determinants of average labor productivity, with special focus on changes in relative contribution of manufacturing labor of different skill levels (proxied by worker's formal education) levels.

Autor, Katz and Kearney (2006) contend that computerization helps with substituting routine jobs, and complementing non-routine jobs, and thereby creating wage polarization and employment polarization in the U.S. labor market. Analyzing U.S. labor force's educational profile and change in occupational employment share data between 1979 and 2007. Ocemoglu and Autor (2010) find evidence that employment growth was negative or zero for medium skill and high skill labors. However, they also find evidence that the growth rate was significantly high for low skill labor during this period, which is a remarkable deviation from the monotonic relationship between employment growth and worker's skill level observed between 1979 and 1989, and from the 'U'-type relationship between these two variables observed between 1989 and 1999[4]. These recent findings hint at a paradigm shift in the labor market fostered jointly by the forces of globalization via its dual channel of ICTs and trade liberalization. These recent studies are quite intriguing and motivate me to analyze the effects of globalization on relative contributions of low skill, medium skill, and high skill labor in the manufacturing industry in the US.

Remainder of this paper is organized as follows: section 2 summarizes the relevant literature on some determinants of labor productivity including ICTs and international trade. section 3 discusses data, model and variable constructions, section 4 presents estimation results and section 5 concludes the paper.

II. Literature Review

Jorgenson and Stiroh (2000) used data for average labor productivity (ALP) [5] across U.S. industries and found that ALP growth was higher for technology intensive industries. Oliner and Sichel (2000) found evidence that use of ICTs and production of computers contributed to the acceleration in productivity in the United States. Autor, Levy and Murnane (2001) used data on job task requirements from 1960 to 1998 and contended that ICTs were influencing job skills demands differentially. The authors argued that ICTs were helping producers to substitute for routine or repetitive manual tasks and complement for activities involving non-routine problem solving and interactive tasks. Gust and Marquez (2004) and Belorgey, Lecat and Maury (2006) studied productivity data from thirteen countries and twenty five countries respectively, and found evidence that increase in spending and usage of ICTs have positive impact on productivity growth.

[3] Reflected in information provided at the website of the Office of the United States Trade Representative, the remaining tariffs and quantitative restrictions were eliminated in January 2008 ((http://www.ustr.gov/trade-agreements/free-trade-agreements/north-american-free-trade-agreement-nafta).
[4] Ocemoglu and Autor (NBER, 2010), Figure 10
[5] defined as real gross output per hour worked

Analyzing U.S. manufacturing data, Moretti (2004), and Morrison and Siegel (1997) found evidence of a positive relationship between workers' educational levels and their productivity. Ilmakunnas, Maliranta, and Vainiomaki (2004), Jones (2001) and others have also found similar evidences for manufacturing industries in other countries.

There are a number of papers that report positive relationships between trade and labor productivity (e.g., Alcalá and Ciccone, 2004; Keller and Yeaple, 2009)[6]. Carbaugh (2009) asserted that trade promotes technological diffusion in the domestic economy via competitive effect and via demonstration effect, which, in turn, increases the pace of economic growth.

Several recent papers find positive relationships between agglomeration and productivity (e.g., Baldwin, Brown and Rigby, 2010; Rigby and Essletzbichler, 2002); however, other empirical papers find otherwise and attribute the negative impact on congestion effect (e.g., Broersma, 2009). Ke (2010) found positive impact of agglomeration on total factor productivity in Chinese manufacturing industry. Lall, Shalizi and Deichmann (2003) explored the relationship between Indian agglomeration and productivity and found that at the firm level, the impact of agglomeration on productivity is positive. They also learned that this benefit comes from improved access to market but benefits of agglomeration may not always outweigh costs associated with locating in dense urban areas.

Rigby and Essletzbichler (2002) examine the impact of three Marshallian micro-determinants of agglomeration (buyer-supplier network, labor matching and technological spillover) and other determinants on productivity using 1992 Census of Manufacturing data. Although they found evidence of all three Marshallian microfoundations contributing to productivity, the study is mainly limited to selected U.S. cities and does not include the time covered in this paper (1988-2003). Wheeler (2006) found firm size effect stronger than agglomeration effect on productivity. However, she also contends that such findings should not necessarily imply that agglomeration economies are less important because industrial clusters may offer an environment conducive for producers to spatially concentrate and optimally operate on a larger scale.

There is a dearth of empirical literature that studies the impact of globalization on manufacturing industries across different skill levels of workers. Furthermore, there are not many recent papers that examine impact of globalization on agglomeration indices representing U.S. manufacturing industries. Furthermore, to the best of my knowledge, there is a dearth of literature in empirical studies that consider Marshallian micro-determinants and plant size as determinants of average labor productivity in the context of U.S. manufacturing industry for the period from 1988 to 2003. This paper is an attempt to fill these voids.

III. Data and variable construction

In this paper, I calculate average per worker labor productivity by taking financial value added in each manufacturing industry as the productivity proxy.
The baseline model I use in this study is as follows:

[6] Alcalá and Ciccone (2004) find statistically significant positive impact of ratio of international trade volume to GDP (*PPP*-adjusted) to average labor productivity. Keller and Yeaple (2009) find firm level evidence of positive relationship between U.S. manufacturing productivity and foreign direct investment.

$$\text{Value Added Per Worker}_{ist} = B_0 + B_1(\text{Low skill workers})_{ist} + B_2(\text{Medium skill workers})_{ist}$$
$$+B_3(\text{High skill workers})_{ist} + B_4(\text{Agglomeration Indices})_{ist} + B_5(\text{Plant size})_{ist}$$
$$+B_6(\text{Fiscal and policy variables})_{ist} + B_7(\text{Low skill workers} \times \text{T95})_{ist}$$
$$+B_8(\text{Medium skill workers} \times \text{T95})_{ist} + B_9(\text{High skill workers} \times \text{T95})_{ist}$$
$$+B_{10}(\text{Agglomeration Indices} \times \text{T95})_{ist}\, B_{11}(\text{Plant Size} \times \text{T95})_{ist}$$
$$+ B_{12}(\text{Fiscal and policy variables} \times \text{T95})_{ist} + B_{13}X_{ist} + B_{14}(X \times \text{T95})_{ist} + \eta_i + \mu_s + \varepsilon_{ist}.$$

The i subscripts (= 1, 2, 76) indicate 76 manufacturing industries at the 3-digit U.S. Standard Industrial Classification (SIC) code level; where s (= 1, 2, …, 48) indicates the 48 lower continental states; and t (= 1988, 1990, 1993, 1994, 1996, 1998, 2000, 2003,) indicates the year.[7] To avoid mixing survey and census data, I utilize years for which survey data were available at the time of research.
I construct the dependent variable ‘Value added per worker’ as follows:

$$\frac{(\text{Value of Shipment} - \text{Cost of material})_{ist}}{(\text{All workers})_{ist}}$$

The variable ‘low skill workers’ is ratio of worker with less than four year college degree to all workers. The variables ‘medium skill worker’ and ‘high skill worker’ are constructed as ratio of workers with bachelor degree to all workers, and ratio of workers with post graduate degree to all workers respectively. These variables are constructed using data from the Current Population Survey. I expect the sign of the estimated coefficient for the low skill labor (LSL) to be negative and medium skill labor (MSL) and high skill labor (HSL) to be positive.

Agglomeration indices used: EGI_{ist} denotes the Ellison-Glaeser index of agglomeration, and EGG_{ist} denotes the Ellison-Glaeser Gini index. The Herfindahl index is used to measure plant size or scale economies. Besides the three labor pooling proxies (three labor groups with three different skill levels as indicated by their varied lengths of academic training across groups), I use proxy for goods pooling (ratio of cost of materials to value of shipment), idea pooling (patent count), average duty rate (ADR) and other economic and fiscal variables.[8] T95 is a time dummy variable set equal to “1” for the years in the sample after 1995 and zero otherwise. $\vec{X}_{ist}$ is a vector of control variables for natural cost advantages, transportation costs, state minimum wage, and maximum state corporate income tax rate, state maximum personal income tax, research and development expenditure ; μ_s and τ_t are unobserved state and year fixed effects, respectively; and ε_{ist} is an identically and independently distributed idiosyncratic error term.

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[7] The subscript i represents U.S. manufacturing industries that are bridgeable over the Standard Industrial
Classification (SIC) codes and subsequent North American Industrial Classification System (NAICS) codes that have replaced SIC since 1997 (see www.census.gov/eos/www/naics for more information on this transition from SIC to NAICS). Alaska and Hawaii are excluded from the analysis due to idiosyncratic nature of these two island-states relative to their 48 continental counterparts.

[8] The average import duty rate (ADR) for industry ‘i’ and year “t” is calculated for 3-digit SIC industries as follows: [ADR_{it} = (total import duty collected_{it}) / (total dutiable value of import_{it})].

I contend that the decline in U.S. manufacturing employment beginning in 1995 is due to increased foreign outsourcing of the production of intermediate and final goods due in large part to trade liberalization and the ICT revolution. I hypothesize that the resulting increase in foreign outsourcing of manufacturing employment may have led to a change in the relative contribution of labor with different skill levels. I also contend that ICTs act as substitute for routine tasks and a complement to non-routine tasks (for both manual and cognitive tasks). Both routine and non-routine tasks can be performed by workers from all skills-based categories (i.e., low skilled, medium skilled and high skilled), however, it is plausible to contend that the share of routine tasks (which are repetitive and requires less cognition and improvisation) is relatively higher for low skill workers (or 'blue collar' workers) than for medium and high skill workers (or 'white collar' workers). Thus, ICTs are expected to increase labor productivity more for those industries that uses LSL proportionately greater compared to total employees on the payroll because ICTs can replace some workers employed in routine and repetitive production processes and thus can potentially allow fewer workers to produce as much or even more than pre-ICT era Output level. However, industries where most employees represent MSL and HSL productivity increase can be moderate because ICTs in these industries play a complementary role not a labor-substituting role. Therefore, I contend that the magnitude of increase in per worker productivity will be different across different skill levels of the workers (i.e., LSL, MSL, and HSL) depending on whether ICTs play a labor substituting role ro a labor-complementing role in a given industry. On the other hand, impact of trade on productivity is also expected to be different across industries that use workers of different skill levels in different intensity relative to their total employment. Generally, free global trade influences worker productivity positively due to competitive effect, demonstrative effect and knowledge spillover (Carbaugh, 2009; Keller and Yeaple, 2009). However, free trade will also force producers from different countries to price their products competitively so that they can capture, retain, or/and expand their stake in the home market, as well as, world market. I contend that this downward pressure on prices (and therefore on productivity measured by monetary value of shipment per worker) due to free trade will be more intense in industries where ICTs play a labor substituting role than in industries where ICTs play a complementary role to labor. Therefore, I argue that the net effect of globalization on labor productivity in a given industry would depend on the relative share of workers of different skill levels in that industry, and on forces of ITCs (or, 'technology effect'), and trade liberalization ('trade effect') on that industry given its relative shares of routine and non-routine (high cognitive) tasks for workers of each skill groups within the industry. Thus, the net impact of globalization in LSL, MSL, and HSL needs to be examining using empirical data. Now, I turn to explaining of the construction of these independent variables and associated control variables.

Following Ellison and Glaeser (1997), I use EGI as a measure of employment agglomeration by industry because of its ability to isolate the influence of external economies of scale (namely the micro-determinants), from the influence of internal economies of scale.[9] EGI is a function of the Gini coefficient, which is also known as the Ellison-Glaeser index of raw geographic concentration (EGG_i) and the Herfindahl index (HI_i) of industry i.[10] Ellison and Glaeser's Gini index (EGG_i) is another well-known measure of employment agglomeration by industry and is defined as

[9] As noted by Ellison and Glaeser (1997), many industries consist of a few large firms producing the bulk of the output in few large plants to tap the benefits of increasing returns to scale; examples of this include the vacuum cleaner industry (SIC 3635). About 75 percent of the workers in this industry are concentrated in only few large plants located across four states. But as Ellison and Glaeser explain, the observed concentration of the vacuum cleaner industry is not due to external economies of scale or the micro-determinants of agglomeration; rather, it is due to internal economies of scale resulting in a heavily skewed plant-size distribution.
[10] This Gini index is also known as Ellison-Glaeser's index of raw geographical concentration.

$EGG_i \equiv \sum_{m=1}^{M} \left(X_m - S_{im}\right)^2$, where 0 < EGG_i < 1, and employment agglomeration in industry i is increasing in EGG_i.

The Herfindahl index is given by $H_{ist} \equiv \sum_{k=1}^{K} Z_{istk}^2$ for the K plants of industry i in state s and year t. Finally, Z_{iskt} represents the employment share of the *k*th plant of industry i in state s and year t.[11] The EGI for a particular time point (t) takes the form as follows : $EGI_{is} = \dfrac{EGG_{is} - (1 - \sum X_{is}^2) H_{is}}{(1 - \sum X_{ix}^2)(1 - H_{is})}$.

I use EGI because this measure of industrial agglomeration controls for industry-specific agglomeration due to internal economies of scale and allows us to measure employment agglomeration resulting exclusively from external economies of scale related to the micro-determinants, natural advantage, transportation costs, and other external factors promoting average labor productivity.[12] We use Herfindahl index to examine the impact of scale economies on labor productivity. I expect the sign of the estimated coefficients associated with these three variables (EGI, Gini and Herfindahl indices) to be positive as theory contends that agglomeration and plant size has productivity enhancing influence via positive spillover of knowledge.

Now I describe the construction of other control variables used in this analysis. The 'cost of material to value of shipment' variable is constructed using data from the Annual Survey of Manufacturers (various years). The expected sign of this variable is negative because by definition higher cost of materials would mean low value added.

Following Rosenthal and Strange (2001), I use the ratio of inventory to the value of shipments as an inverse proxy for transportation cost. The intuition is that perishable goods (such as dairy products, newspapers, and so on) have a lower inventory-to-shipment ratio and relatively non-perishable goods will have a relatively higher inventory-to value-of shipment ratio. It is logical to contend that average storage cost and transportation cost of perishable goods are greater than those of non-perishable goods (perishable goods often required special warehouse and climate controlled transportation facilities which are relatively expensive). Therefore, higher inventory to value of shipment ratio would be associated with lower transportation costs and lower value of this ratio will indicate the perishability of the good and will indicate a higher transportation cost per unit of distance. This variable is constructed from the year-end-inventory data reported in the Annual Survey of Manufacturers (geographic area series). These data are available through 1997. For subsequent years in the sample, I impute the year-end inventory data using the mean values of the previous years.

I use "energy costs per dollar of shipments" as a proxy variable for the importance of proximity to natural resources, such as coal, crude oil, natural gas, and so on in firms' location decisions. The intuition is that firms facing relatively high-energy costs per dollar of shipments would have a lower

[11] Rosenthal and Strange (2001), Bertinelli and Decrop (2005), and many other researchers have used the Ellison Glaeser Index (EGI) as a measure of agglomeration. The Herfindahl index is calculated for the plant size distribution of each industry in a particular year in a particular state using the county business pattern data.

[12] One drawback of the Ellison-Glaeser index is the difficulty in interpreting the values. For example, an agglomeration index of 0.20 does not have an obvious meaning, except for comparison purposes. However, the advantages of this measure seem to outweigh its drawbacks, particularly in the current context. I also use a Gini index as a measure of agglomeration as this traditional measure is easier to interpret with values between zero and one. In contrast, the EGI can be either positive or negative indicating agglomeration or deagglomeration respectively.

per worker value added and vice versa. This variable is constructed using data from the Annual Survey of Manufacturers (geographic area series). Consistent with the findings in Rosenthal and Strange (2001) and Linn (2009), I expect this variable to have negative effect on average productivity. We also include other control variables such as the state minimum wage and maximum state corporate income tax rate, state maximum personal income tax rate, and research and development expenditures by state, year and industry codes. The minimum wage data are from the Bureau of Labor Statistics and maximum state corporate income tax rates are from various volumes of the Book of the States.

The minimum wage should have a negative effect on productivity in industries that rely heavily on unskilled labor.[13] Theoretical and empirical evidence regarding the effect of corporate income taxes (CIT) on productivity is found in tax incidence literature and industrial location decision literature. Corporate tax is focused on corporate profit; therefore, it does not affect relative factor prices and does not influence optimal resource allocation decisions. This viewpoint leads us to predict that corporate income tax would not have any statistically significant impact on labor productivity. Baldwin and Krugman (2003) developed a theoretical model showing that higher tax rates may not cause declines in agglomeration if spatial concentration creates “agglomeration rents,” allowing fiscal authorities to charge higher CIT rates without triggering capital flight. Bartik (1985) used plant location data across manufacturing industries for the years 1972 and 1978. He found that a 10 percent increase in a state-level CIT rate caused a 3 percent decrease in the number of new plants. In contrast, Gius and Frese (2000) found that the influence of the CIT on industrial agglomeration is statistically indistinguishable from zero. I predict that CIT and personal income tax (PIT) both would have a statistically insignificant effect on average productivity. I predict patent count and research and development expenses (both are commonly used as proxy for idea pooling in the agglomeration literature) would have positive effects on productivity.

In order to construct the panel data for the period 1988 to 2003, I had to bridge the data across two industrial classification system regimes. In 1997, the U.S. began using an industrial classification system known as the North American Industrial Classification System (NAICS), which replaced its predecessor classification system known as -the Standard Industrial Classification (SIC) system. The Bureau of Census provides a bridge table between 4-digit SIC and 6-digit NAICS industries. There is a legend that indicates the comparability of the SIC industries and the corresponding NAICS industries. The legends refer to three levels of bridges, viz. i) a complete drawbridge. (i.e., open to through traffic) ii) a partially open drawbridge, and iii) a completely open drawbridge (i.e., bridge is closed for through traffic). A complete drawbridge indicates that the corresponding SIC and NAICS industries are completely bridgeable. For these industries, I am able to construct a complete time series. A partially open drawbridge indicates that the corresponding SIC and NAICS industries do not deviate by more than 3 percent based on sales. A completely open drawbridge indicates that the corresponding data, if bridged, would contain a deviation of more than 3 percent based on sales across SIC and NAICS regimes. Due to this feature of the data, I focus on the series constructed from a strong bridge (completely open drawbridge) between SIC and NAICS.

At the 3-digit SIC code level, there are 140 industries. Due to the change in the industrial classification regimes from SIC to NAICS, constraints of data availability, and issues related to missing values for some explanatory variables, there are 76 industries in our sample. As previously noted, I also exclude Alaska and Hawaii from the sample. The resulting sample consists of 29,184 observations from 48 continental U.S States. Furthermore, I exclude 24,500 observations due to missing information

[13] See, for example, Rohlin (2007) and Thompson (2009) for evidence of the negative effect of the minimum wage on employment. However, Card and Krueger (2000) among others find otherwise.

generally due to the non-disclosure obligations of the reporting agencies. Generally, the Census Bureau withheld data for those for counties that have only one or very few establishments in an industry in a given county in a given year. This withholding of data may have several implications for this study. First, county level disaggregated manufacturing employment count by industry may actually be greater than what is reported in the 'county business pattern' data series. Second, as this data withholding occurs mainly for the counties with one or very few establishments in a given industry, it may lead to an over estimation of employment agglomeration. Third, arguably the absence of such data withholdings would have increased the statistical significance and robustness of our estimation results due to the potential increase in the degrees of freedom. In addition, patent data for some SIC codes were not available for some States for some years. As a result, the sample used in this study consists of 4,684 observations.

Table 1 reports descriptive statistics for our sample of 4,684 observations. The sample mean of EGI is 0.210, sample mean of Gini is 0.496 and the sample mean of the Herfindahl index is 0.454. The sample mean of low skill labor is 0.852 meaning that 85.2 percent of the employees in our sample are without a bachelor degree. The sample mean of medium skill labor is 0.113, meaning that 11.3 percent of the employees of the firms in our sample have bachelor's degrees. The sample mean of high skill labor is 0.035; in other words, 3.5 percent of the employees of the firms in our sample have post-graduate degrees. The sample mean of cost of materials to value of shipment is 0.491, which means that the average cost of materials is 49.1 percent of the value of shipments. The mean value for transportation costs (inventory-to-shipments) is 0.14. The mean for energy cost-to-value-of-shipments is 0.025, and the mean for the maximum state corporate income tax rate is 6.73. Finally, the mean value of the state minimum wage is $4.00. Now I discuss our empirical results.

IV. Regression Results

Results from four specifications are reported in Table 2 all are using average labor productivity as dependent variable. Second and third columns of Table 2 are presenting the estimation results from the OLS model and fixed effect (FE) model respectively. Our baseline result is presented in column 2 labeled as'T95-fixed effects', Fourth and fifth columns present estimation of the similar OLS and FE specifications but they use an interaction variable AD95 instead of T95. In the FE specification (results in third and fifth column from left), I use state and year fixed effects.

I begin by discussing the results in the third and fifth columns (labeled as 'T95-Fixed effect' and 'AD95-Fixed effects' respectively). The estimated coefficients of LSL are negative and estimated coefficients of MSL and HSL are positive and statistically significant at conventional levels.[14] This is consistent with economic theory and the results reported in the existing literature. According to the regression results in column 3 of Table 2, an one percent increase in LSL in manufacturing industries would lead to a 0.1 percent decrease in per worker productivity. Similarly, a one percent increase in the values of MSL and HSL variables will lead to a 0.04 percent increase and a 0.141 percent increase in productivity respectively. The estimated coefficient for the interaction variable LSL×T95 is negative but statistically not significant at conventional levels. This suggests that there were no changes in relative contribution of blue-collar workers on the average manufacturing productivity between the two periods (pre-1995 and post- 1995). In contrast, the estimated coefficient of MSL×T95 and HSL×T95 are

[14] Following Wooldridge (2002), and Cameron and Trivedi (2005), I report clustered standard error. Observations within a cluster may be correlated as the result of unobserved clustering effects. I estimate both robust and clustered standard errors but report only clustered standard errors as it turns out that differences in statistical significance using these alternative measures of standard errors are negligible.

negative and statistically significant at conventional levels, suggesting that the marginal effect of medium skill and high skill workers are negative in the post-1995 period relative to the marginal effect of medium skill and high skill workers on average labor productivity in the pre-1995 period. This is a substantial finding that globalization has attenuated the contribution of medium and high skill labor to per capita value added. The estimated coefficients of the agglomeration variables are positive but statistically insignificant. Estimated coefficient of Herfindahl index is positive and statistically significant indicating positive effect of scale economies on per worker value added. Coefficient for Herfindhal×T95 is negative and statistically significant implying that due to globalization contribution of bigger plants on productivity has decreased.

Turning to the estimates of the other control variables reported in column 2 of table 2, the only ones that are statistically significant at conventional levels are cost of material to value of shipment and patent count in the pre- and post-1995 periods. As predicted, cost of materials has a negative effect and patent has a positive effect on the per worker value added in the pre-1995 period. In the post-1995 period. the signs changed. Interestingly, the R-squared of the model is 12.4 percent, which is rather small. This is more consistent with agglomeration literature than labor productivity literature. In order to enrich the study, I attempt to decompose the total effects of globalization on productivity into its dual channels of technological advancement and trade liberalization.

To decompose the total change in the effect of globalization on the micro-determinants into that part due to trade liberalization and that part due to the ICT revolution, I estimate another specification of our model in which I include the average duty rate (ADR) at the 3-digit SIC code level. By controlling for the decline in the average duty rate due to trade liberalization, I am able to isolate 'trade effect' from total effect of globalization that is composed of both 'tech effect' and 'trade effect' as discussed earlier. I construct the average duty rate (ADR) at the 3-digit SIC code level as follows:

$$ADR_{it} = \left[\frac{\text{Duty collected}}{\text{Dutiable value of import}}\right]_{it}.$$

Data for this variable are from the U.S. International Trade Commission (USITC) database. I expect trade liberalization to make the domestic market more competitive. Increase in ADR would mean higher prices of manufacturing goods in domestic market as it would provide insulation to producers of manufacturing goods from onslaught of cheap imports. Rising price levels will increase per worker value added. Moreover, trade increases productivity via competitive effect, demonstration effect and technological spillover. As a result, I expect the average duty rate to have a positive effect on per worker value added. I also employed an interaction variable in which I let ADR interact with our time dummy variable T95 to account for the two trade acts that went into effect in 1995[15]. I refer to this interaction variable as AD95 (= ADR×T95).

The estimated results for these specifications of the model are reported in the fifth column labeled 'AD95-fixed effect' in Table 2. The estimates obtained using T95 to control for globalization and the estimates obtained using the average duty rate to control for the effect of trade liberalization are very similar. As before, the estimated coefficients of LSL, MSL, and HSL are positive and statistically significant at conventional levels. As before, LSL×AD95, MSL×AD95 and HSL×AD95 all are negative but only HSL×AD95 is statistically significant at conventional levels. The remaining control variables generally have the same signs and significance as before. It should be noted here that the estimated coefficients of interaction variable T95 reflect the effect of globalization due to both ICT ('tech effect') and free trade ('trade effect') where as estimated coefficient of interaction variable D95 implies the impact of only 'trade effect'. The difference between the values of estimated coefficients of these

[15] i.e., North American Free Trade Area (NAFTA) and World Trade Organization(WTO)

interaction variables should help us in isolating magnitude and direction of both 'tech effect' and 'trade effect'.

We observe that the impact of 'tech effect' and 'trade effect' both has negative effect on workers across the three skill levels. We see that in the post-1995 period, globalization played a negative effect on manufacturing worker productivity across all three skill levels although it was statistically significant for MSL (-0.048) and for HSL (-0.169), but not for the LSL. The 'trade effect' was also negative on worker productivity of all skill levels although for only HSL the negative impact of trade was statistically significant. The globalization effect (i.e., combined effects of 'tech' and 'trade) was found to be of greater magnitude relative to 'trade effect' which was plausible. Although from theoretical perspectives one can expect dual 'trade effects' of opposite forces: one that would enhance productivity via competition effect, demonstration effect, and knowledge spill over effect as predicted by Carbaugh, (2009), and another due to fierce global competition for market share that may force sellers to sell products at very competitive price which may decrease the monetary value of value of shipment and thus may lower per worker productivity. This study results suggest that the force of productivity decreasing 'trade effect' due to fierce global competition is stronger that productivity enhancing 'trade effect' due to competition effect, demonstration effect, and knowledge spillover effect. In this study results we also find that plant size has a greater positive influence on worker productivity than agglomeration has because the estimated coefficient of EGI was statistically not significant where as estimated coefficient of Herfindahl index was positive and significant. The interaction variable for EGI was also statistically not significant where as interaction variable for Herfindahl index was negative and statistically significant suggesting that importance of plant size has attenuated in the post-1995 period as a determinant of worker productivity. This result is perhaps suggesting that with the creative use of ICT revolution and global trade, small and medium sized firms (in terms of number of workers employed) can be as productive and as capable of harvesting the benefits of economies of scale as large firms often are.

V. Conclusion

The evidence that relative contribution of low skill manufacturing labor has further dropped in the post-1995 years relative to pre-1995 years may imply that potential productivity gain for LSL by using ICTs as substitute for performers of repetitive tasksis outweighed by productivity declining impact of global trade due to cut throat competition among producers of blue collar intensive manufacturing industries in an environment of ever lowering tariff and non-tariff barriers . The interaction variables LSL×D95, MSL×D95, and HSL×D95 on column 5 (i..e, column titled 'AD95-Fixed Effects') of Table 2 suggest that trade had a statistically significant negative effect only on HSL, but not on MSL or LSL was somewhat counter intuitive, because one would expect blue collar worker (LSL) intensive industries to face more fierce global price competition than industries dominated by MSL and HSL . Future studies using larger dataset are needed to better decompose the impacts of two drivers of globalization 'tech effect' and 'trade effect' on on determinants of labor productivity of U.S. manufacturing workers across various skill groups. Also, cross-country analysis using panel data will generate new knowledge along this strand of studies. .

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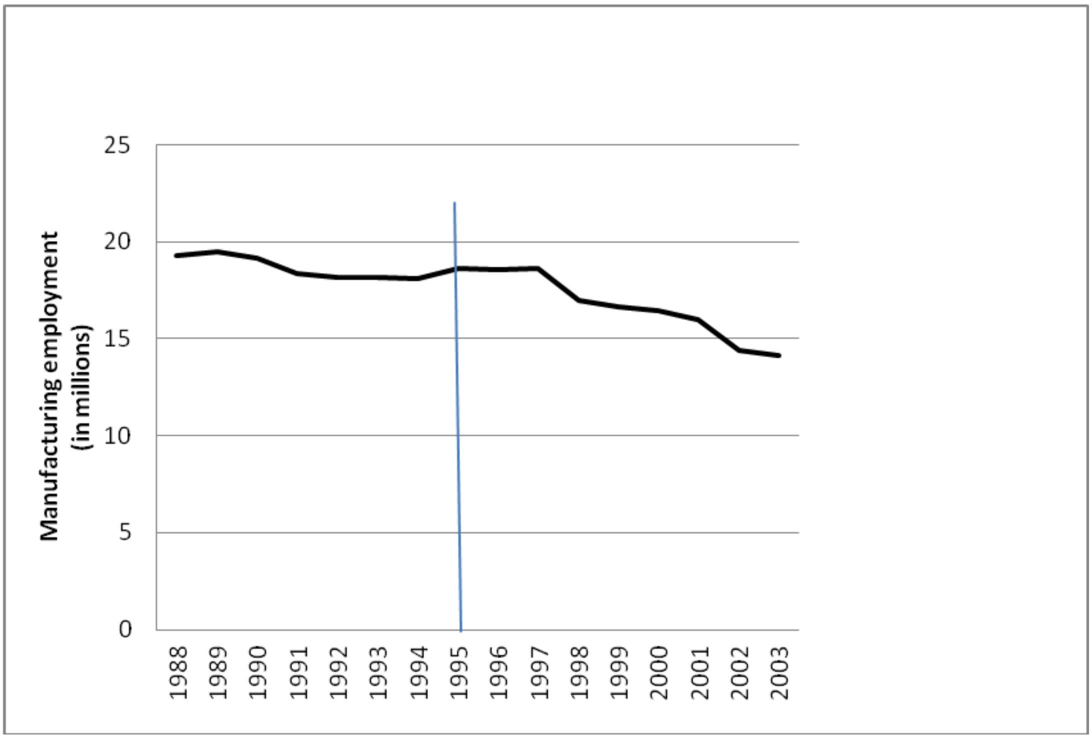
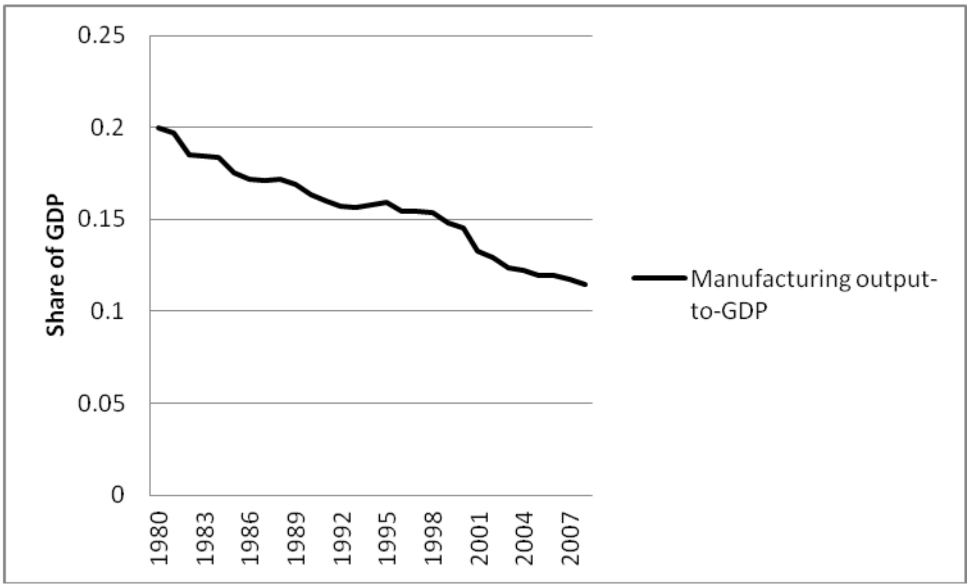
FIGURE 1
TOTAL MANUFACTURING EMPLOYMENT IN THE UNITED STATES (1988-2003)



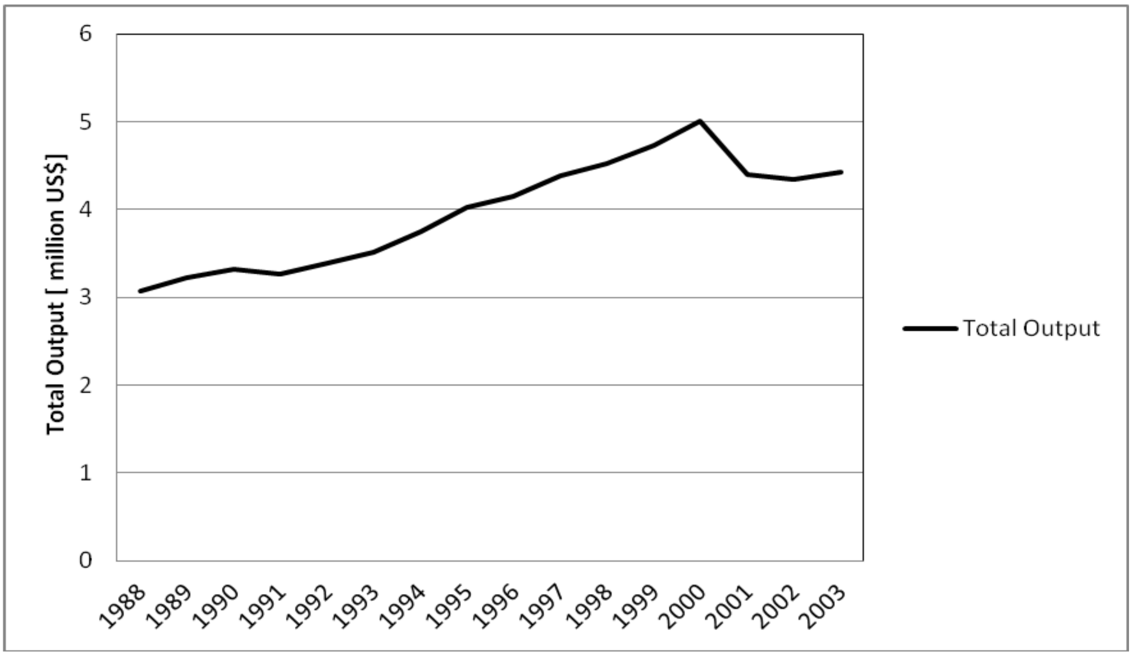
Source: County Business Pattern data, Bureau of Census (1988-2003)

FIGURE 2
MANUFACTURING OUTPUT AS SHARE OF GDP IN THE UNITED STATES (1988-2008)



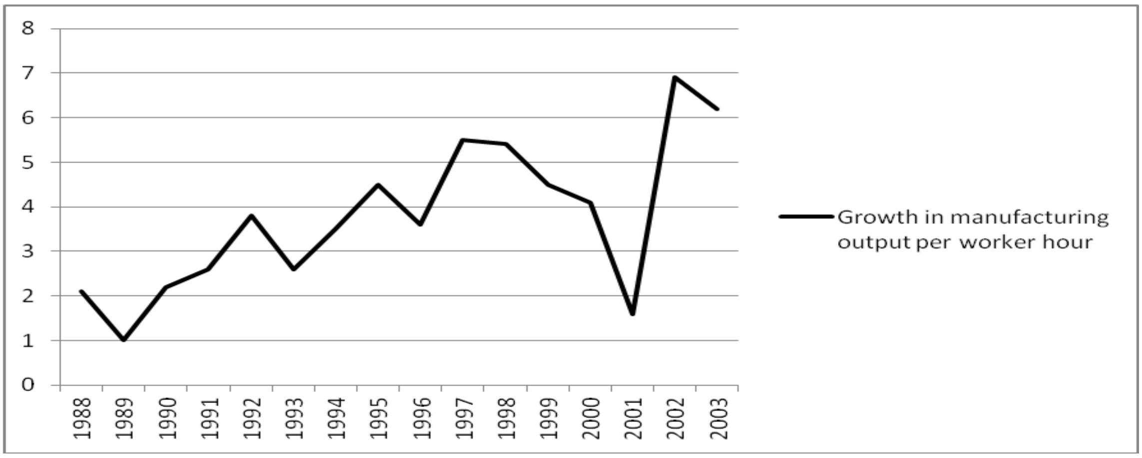
Data Source: Bureau of Economic Analysis, U.S. Bureau of Census

FIGURE 3
HISTORICAL MANUFACTURING OUTPUT IN THE UNITED STATES (1988-2003)



Source: Annual Survey of Manufacturers, U.S. Bureau of Census. *Note:* Total output of manufacturing industries is calculated by adding end-of-year inventory of previous year with the value of shipment in the current year. For example, manufacturing output for the year 1988 is calculated by adding the value of year-end-inventory for year 1987 with value of shipment for year 1988.

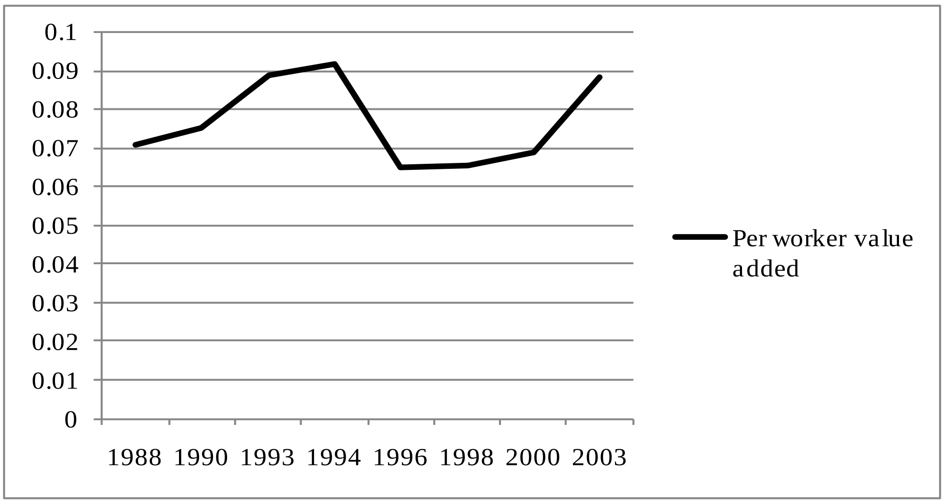
FIGURE 4
GROWTH IN MANUFACTURING OUTPUT PER WORKER HOUR IN THE UNITED STATES, 1988-2003



Data Source: Bureau of Labor Statistics, U.S. Bureau of Census

Note: Output growth rate ismeasured in percent.

FIGURE 5 PER WORKER VALUE ADDED IN MANUFACTURING INDUSTRIES IN UNITED STATES, 1988-2003



Source: Annual Survey of Manufacturers, Geographic Area Series.
Note: Per worker value added is calculated as value of shipment net of cost of materials divided by number of manufacturing workers. For data consistency issues, I construct this graph using only survey data and therefore could not include census data for the years 1992, 1997, 2002

TABLE 2 REGRESSION OF AVERAGE LABOR PRODUCTIVITY

Coefficient	T95		AD95 (= Average duty rate×T95)	
	OLS	FIXED EFFECTS	OLS	FIXED EFFECTS
Constant	0.117***	0.152***	0.117***	0.159***
	(0.023)	(0.031)	(0.023)	(0.031)
Ellison-Glaeser Index (EGI)	0.002	0.003	0.002	0.003
	(0.004)	(0.005)	(0.004)	(0.005)
EGI ×T95 (or EGI×AD95)	-0.010	0.003	-0.003	-0.001
	(0.006)	(0.011)	(0.002)	(0.003)
Gini index (Gini)	0.011	0.007	0.011	0.007
	(0.008)	(0.009)	(0.008)	(0.009)
Gini × T95 (or Gini×AD95)	0.003	0.006	0.002	0.004
	(0.012)	(0.014)	(0.003)	(0.004)
Herfindahl Index (H)	0.085***	0.089***	0.085***	0.089***
	(0.023)	(0.023)	(0.023)	(0.023)
H×T95 (or H×AD95)	-0.087***	-0.097***	-0.024***	-0.029***
	(0.027)	(0.024)	(0.008)	(0.007)
Low skill labor (LSL):	-0.010	-0.010*	-0.010	-0.010*
employees with less than 4	(0.006)	(0.006)	(0.006)	(0.006)
LSL×T95 (or LSL×AD95)	-0.010	-0.011	-0.033	-0.006
	(0.031)	(0.025)	(0.026)	(0.026)
Medium skill labor (MSL):	0.042***	0.044***	0.042***	0.043***
employees with 4 year	(0.012)	(0.012)	(0.012)	(0.012)
MSL×T95 (or MSL×AD95)	-0.028	-0.048*	-0.013*	-0.011
	(0.033)	(0.028)	(0.008)	(0.008)
High Skill Labor(HSL):	0.131***	0.141***	0.131***	0.140***
employees with post	(0.022)	(0.022)	(0.022)	(0.022)
HSL×T95 (or HSL×AD95)	-0.108**	-0.169***	-0.035***	-0.043***
	(0.040)	(0.036)	(0.010)	(0.010)
Ratio of cost of materials	-0.103***	-0.099***	-0.103***	-0.098***
to value of shipment	(0.029)	(0.029)	(0.029)	(0.029)
COSTMAT×T95 (or	0.048	0.049	0.013	0.013
COSTMAT×D95)	(0.034)	(0.035)	(0.009)	(0.008)
Patent count (PATENT)	0.003**	0.002**	0.003**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
PATENT×T95 (or	-0.003**	-0.003***	-0.001**	-0.001***
PATENT×D95)	(0.001)	(0.001)	(0.001)	(0.001)
T95 (or AD95)	0.016	0.001	0.011	0.003
	(0.041)	(0.001)	(0.010)	(0.010)
State minimum wage	0.005**	-0.010	0.005**	-0.010
(MW)	(0.002)	(0.008)	(0.002)	(0.007)
MW×T95(or MW×AD95)	-0.009**	0.004	-0.002**	0.001
	(0.004)	(0.006)	(0.001)	(0.001)
Minimum state corporate	-0.001	-0.001	-0.001	-0.000
income tax rate (CIT)	(0.001)	(0.001)	(0.001)	(0.001)
CIT×T95 (or CIT×AD95)	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Number of observations	4,684	4,684	4,684	4,684
R-squared	0.112	0.124	0.112	0.124

Notes: Clustered standard errors are reported in the square-brackets. Statistical significance of the estimated coefficients is indicated by asterisks at the conventional 10 percent (*), 5 percent (**), and 1 percent (***) levels. Columns labeled T95 control for the time dummy variable for globalization which assumes a value of one (1.0) if year≥ 1995, and a value of zero (0.0) otherwise. Estimates reported in column AD95 control for the average duty rate (AD), and the interaction term AD95 = AD×T95.