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THE IMPACT OF GLOBALIZATION ON AGGLOMERATION:

THE CASE OF U.S. MANUFACTURING EMPLOYMENT FROM 1988 TO 2003

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Abstract

This paper explores the impact of globalization on the micro-determinants of agglomeration, namely labor pooling (LP), goods pooling (GP), and idea pooling (IP). According to our estimates, LP now has a negative effect on employment agglomeration in U.S. manufacturing.

More specifically, we find that trade liberalization is increasing the marginal effect of LP on employment agglomeration in U.S. manufacturing, but this positive effect is overwhelmed by the large negative effect of the ICT revolution. We also find that the ICT revolution is having substantial positive effect on the marginal effect of GP on employment agglomeration in U.S. manufacturing; whereas, trade liberalization has a negligible effect on the marginal effect of GP on employment agglomeration. Finally, we report evidence that internal economies of scale have a substantial effect on employment agglomeration in U.S. manufacturing.

JEL classification: L60, R12

Key Words: Agglomeration, Globalization

1. Introduction

According to Marshall (1890) and others, the spatial concentration of economic activity or agglomeration is due to external economies of scale. Prominent examples of industrial agglomeration include the concentration of automobile manufacturing in the state of Michigan and the concentration of the computer and software industries in Silicon Valley. Marshall (1890), Fujita (2000), Rosenthal and Strange (2001), Duranton and Puga (2004), among others contend that such patterns of industrial location occur because of three types of external economies, namely those from labor pooling (LP), from goods pooling (GP), and from idea pooling (IP).

Economies of LP are the cost savings available to agglomerated firms from efficient matching of the demand and supply sides of the labor market. For example, when firms locate nearby an abundant supply of labor with skills matching their requirements, there are cost savings as a result of lower hiring costs and/or productivity increases. Furthermore, Helsley and Strange (1990) and Overman and Puga (2009) contend that large labor markets improve the chances of matching the skill requirements of firms with the particular skills of workers. Increasing the average quality of matches increases the productivity of labor and thus lowers the costs of producing a unit of output.

Economies of GP are the cost savings that agglomerated 'input-heavy' firms acquire from sharing expensive and indivisible inputs and facilities. Duranton and Puga (2004) contend that 'input-heavy' agglomerated firms can save costs by sharing many indivisible public goods, production facilities, and market places which would be prohibitively expensive for a geographically isolated firm to provide itself. For example, it may be prohibitively expensive to arrange for electric power production for a geographically isolated firm. But agglomerated firms

can achieve cost savings from economies of scale in producing electricity by co-locating near an electric utility. Thus, proximity to one another reduces the costs of production to each agglomerated firm relative to the case of dispersed firms. Cost savings from such input sharing is an important motivation for agglomeration by input-heavy firms.

Economies of IP are the cost savings that accrue to agglomerated firms from sharing knowledge about industrial best practices and about research and development (R&D) activities. For example, when firms are agglomerated, industrial workers and researchers of similar interests and abilities have greater opportunities to share knowledge and exchange ideas critical for successful innovation. Such innovations reduce the costs of production and allow firms to differentiate their products and thereby increase their market shares.

Although there is an extensive theoretical and empirical literature on the economic determinants of industrial agglomeration, there is little or no analysis of recent trends in agglomeration. An important exception is Kim (1995), who examines trends in industrial location in the U.S. from 1870 to 1987. However, the period since 1995 is particularly interesting because trade liberalization and the internet revolution have accelerated the outsourcing of U.S. manufacturing employment; a process that is often referred to as globalization. The resulting decline in manufacturing employment due to the forces of globalization over the past ten or fifteen years is well documented. For example, Burke et al. (2004) report the loss of 3.3 million manufacturing jobs between 1997 and 2003. During the period from 1995 to 2003, total U.S. manufacturing employment decreased by 22 percent, a loss of 4 million manufacturing jobs. This trend is also evident in figure 1 which shows a steady decline in U.S. manufacturing employment since 1995.

Despite these important economic trends, there is very little analysis of the impact of this loss in manufacturing employment on employment agglomeration in the U.S. Furthermore, it is not clear on an a priori basis what effect the decline in U.S. manufacturing due to globalization is having on employment agglomeration among U.S. manufacturing firms For example, if the attrition in manufacturing employment occurs primarily among firms that are spatially dispersed (not agglomerated), the resulting decline in U.S. manufacturing employment would increase employment agglomeration. The remaining firms would retain the cost advantage of agglomeration and thereby remain competitive with foreign firms. This could lead to a self-limiting process which would stop the outsourcing of U.S. manufacturing employment over time. Conversely, if the attrition in U.S. manufacturing employment is occurring among agglomerated firms or industries, incumbent firms would continuously lose cost competitiveness as employment agglomeration decreases over time. As a result, the competitive advantage of U.S. manufacturing firms would steadily erode over time, and this would lead to still further losses in U.S. manufacturing employment. Therefore, understanding the impact of the loss in manufacturing jobs due to globalization on employment agglomeration in the U.S. is important not only from an academic point of view but also from a policy perspective.

The focus of this paper is on the effect that globalization may be having on the marginal effects of the micro-determinants of industrial agglomeration among U.S. manufacturing firms. There is a general perception that manufacturing jobs are disappearing in the U.S. due to globalization. Arguably, industrialized countries, like the U.S., are entering a new phase of globalization fostered by recent technological advances and trade liberalization.[1] Recent

[1] In a meeting at the Bank of Mexico in November 2005 Allan Greenspan, a former chairperson of the Federal Reserve Bank commented: "The rise of the deficit and the ability to finance it appears to coincide with a pronounced new phase of globalization that has emerged in the past decade. This phase is characterized by a major acceleration

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. This allows firms to manage supply chains over long distances which may affect the advantages of agglomeration because of GP. ICTs may also allow firms to share information and access advances in R&D over long distances which may affect the advantages of agglomeration because of IP.

The internet officially opened for commercial usage since the decommissioning of the National Science Foundation–managed NSFNet in 1995. Recent trade agreements have reduced tariff and non-tariff barriers to international trade. Since 1994, tariffs and quantitative restrictions on trade between the U.S., Canada, and Mexico have declined due to the North American Free Trade Agreement (NAFTA). The U.S. further lowered tariffs on goods imported from a large number of countries in 1995 as a result of the successful conclusion of the Uruguay round of the General Agreement on Tariffs and Trade (GATT). These two events – the ICT revolution and trade liberalization -- have arguably facilitated the ease of communication and international trade thus increasing the outsourcing of the production of many intermediate and final goods by U.S. based multi-national firms. The fact that these three events (NAFTA, GATT, and commercial access to the internet) all occurred in or about 1995 provides us with an opportunity to identify the effect of these two channels of globalization on the marginal effects of the micro-determinants of employment agglomeration among U.S. manufacturing firms.

To test this hypothesis, we estimate a model of employment agglomeration and test whether there was a structural change in the marginal effects of the micro-determinants of

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in U.S. productivity growth and the decline in what economists call home bias, the parochial tendency to invest domestic savings in one's home country." (http://www.federalreserve.gov/boarddocs/speeches/2005/20051114/default.htm).

agglomeration after 1995. We estimate a number of fixed effects (FE) regression models that include a time dummy variable for the period after 1995. This time dummy variable is interacted with the proxy variables for GP, LP, and IP. The dependent variable in these regressions is the Ellison-Glaeser index of agglomeration (EGI). The independent variables in these regressions include proxies widely used in the literature for GP, LP, IP, and, as discussed in greater detail below, a set of control variables for natural cost advantages, transportation costs, state minimum wages, and state corporate income tax rates.

This study analyzes data spanning the period from 1988 to 2003, covering 76 industrial sectors, and the lower 48 continental states.[2] The data used in this study are from a variety of sources, including the County Business Pattern (CBP) data series, U.S. International Trade Commission (USITC) database, the Current Population Survey (annual demographic series), the Annual Survey of Manufacturers, and the U.S. Patent and Trademark Organization (USPTO) database. Our findings are consistent with the hypothesis that a structural change occurred in 1995 due to globalization. This structural change is impacting the marginal effects of the micro-determinants of employment agglomeration among U.S. manufacturing firms. According to our estimates, LP now has a negative effect on employment agglomeration in U.S. manufacturing. More specifically, we find that trade liberalization is increasing the marginal effect of LP on employment agglomeration, but this positive effect is overwhelmed by the large negative impact of the ICT revolution. We also find that the ICT revolution is having a substantial positive effect on the marginal effect of GP on employment agglomeration among U.S. manufacturing firms. In

[2] In calculating the agglomeration index, we use data from the Annual Survey of Manufacturers and skip the data from the economic census years, which occur twice in every ten years (e.g., 1992 and 1997 are economic census years for the decade 1991–2000). The years in the sample are 1988, 1990, 1993, 1994, 1996, 1998, 2000, and 2003. We aggregate the data at the 3-digits Standard Industrial Classification (SIC) level, for which there is a bridge between SIC and NAICS (North American Industrial Classification System). As the economic structures of Alaska and Hawaii are arguably different from those of the lower forty-eight continental states, we exclude Alaska and Hawaii from this study.

contrast, trade liberalization has a negligible impact on the marginal effect of GP on employment agglomeration among U.S. manufacturing firms. Finally, we report evidence that internal economies of scale have a substantial effect on employment agglomeration in U.S. manufacturing.

The remainder of the paper is organized as follows. In the next section, we briefly review the literature on the impact of globalization on U.S. manufacturing employment; then we review the literature on the micro-determinants of agglomeration. Section III describes the empirical model, variable construction, and data used in this study. Section IV discusses the empirical results, and Section V concludes.

2. Literature Review

We begin this section by briefly summarizing the evidence supporting our contention that recent declines in U.S. manufacturing employment are largely due to the foreign outsourcing of manufacturing as a result of the ICT revolution and trade liberalization. We conclude this section by briefly summarizing the literature on the micro-determinants of employment agglomeration.

Burke et al. (2004) link U.S. manufacturing job losses to the concurrent increase in the foreign outsourcing of intermediate goods production. Using national input-output data, they examine the sources of inputs of 19 major manufacturing industries for the period between 1987 and 2002. They find that the share of foreign-sourced inputs in total manufactured inputs almost doubled between 1987 and 2002, from 12.4 percent to 22.1 percent. Similarly, Vogiatzoglou (2006) reports evidence that U.S. manufacturing is increasingly relocating to Mexico during this period. Finally, Deitz (2004) and Deitz and Orr (2006) attribute the decline in U.S. manufacturing employment to labor productivity growth as a result of recent ICT advances and

the increase in global competition as a result of trade liberalization. Recent empirical work by Atrostic and Nguyen (2002), Autor et al. (2003), and Matteucci et al. (2005) also document the productivity enhancing impact of recent ICT advances. In short, a substantial empirical literature finds that the combined effects of the ICT revolution and trade liberalization are contributing to the decline in U.S. manufacturing employment.[3] Furthermore, these studies find that the increase in global competitiveness forces less competitive U.S. manufacturing firms to cut back on their domestic operations, move their operations overseas, or go out of business. As discussed below, these forces are likely to have an impact on the marginal effects of the micro-determinants of employment agglomeration among U.S. manufacturing firms which is the focus of this study.

Turning to the literature on the micro-determinants of agglomeration, Duranton and Puga (2004) provide an excellent review of the theoretical literature on the determinants of agglomeration. Rosenthal and Strange (2004) provide a comprehensive summary of the growing empirical literature on the determinants, and Audretsch and Feldman (2004) summarize the theoretical and empirical literatures on idea pooling as a micro-determinant of agglomeration.

Helsley and Strange (1990) develop a theoretical model with two kinds of positive externalities associated with a firm moving into a city. The first is the traditional productivity externality; the second positive externality is the result of spatial competition and the heterogeneity of workers. The authors derive an equilibrium condition for an agglomeration economy with a matching process between workers and firms, contending that equilibrium-sized agglomeration can be likened to a local public good. Francis's (2009) theoretical paper uses

[3] Henceforth, outsourcing as a result of trade liberalization and technological advancement will be referred to as globalization. However, these two mechanisms (i.e., trade liberalization and technological advancement) may affect the micro-determinants of agglomeration differently.

simulation to derive a spatial equilibrium. This paper shows that in-migration of labor as a result of agglomeration increases the quality of matching and labor productivity.

Overman and Puga (2009) analyze plant-level data for the United Kingdom and find evidence of labor-market pooling as a micro-determinant of agglomeration. They estimate and compare both plant-level and industry-level idiosyncratic fluctuations in employment. They show that industries with a greater frequency of idiosyncratic employment fluctuations tend to be more agglomerated than other industries. The authors contend that establishments using workers with similar skills find it beneficial to locate in agglomerated areas where a supply of workers with comparable skills is relatively abundant.

A number of papers examine the effectiveness of GP as a micro-determinant of agglomeration. Bartelsman, Ricardo, and Caballero (1994) analyze the effects of input supplies and linkages of intermediate goods on industrial productivity and find that long-run growth in industrial productivity is related to linkages to intermediate goods. Using plant-level, census data on U.S. manufacturing, Homes (1999) finds that most agglomerated industries display a relationship that is consistent with input sharing. He reports that the pantyhose industry is concentrated in North Carolina, with 62 percent of the national employment in this sector. This industry in North Carolina displays a purchased input intensity of 53 percent, while the national average for purchased input intensity is only 40 percent. Homes and Stevens (2002) find that plant size is larger when an industry is concentrated, implying that agglomeration increases access to intermediate inputs, which facilitates plant-size expansion. Duranton and Puga (2004) develop a theoretical model of aggregate increasing returns due to input sharing, despite constant returns to scale and a perfectly competitive output market. Ellison, Glaeser, and Karr (2010) analyze U.S. plant level manufacturing data from 1987 and 1997 Census of Manufacturing to

examine the impact of three micro-determinants of industrial co-agglomeration. They report natural advantage to be the most important factor followed by input-dependency (GP).

Idea pooling also is a potentially important source of agglomeration due to knowledge spillovers. Marshall (1890), Arrow (1962), and Romer (1986) contend that an agglomeration of similar firms facilitates the exchange of ideas among workers, which in turn leads to innovation and growth. Porter (1990) describes similar spillovers but emphasizes inter-firm competition rather than inter-firm cooperation, contending that positive externalities in the form of innovations and growth are maximized when firms compete for market share. Jacobs (1969) contends that the coagglomeration of diverse industries creates a fusion of knowledge and thus promotes innovation and growth. She describes the transition of Detroit from a shipbuilding city to an automobile manufacturing city. The agglomeration of these diverse industries facilitated innovations affecting gasoline engines for automobiles due to the knowledge of and experience with making gasoline engines for use in ships.

Feldman and Audretsch (1999) report evidence that per-capita product innovation is generally higher in larger metropolitan statistical areas, suggesting that the propensity of knowledge spillovers is positively related to the diversity of economic activities. Jaffe, Trajtenberg, and Henderson (1993) analyze patent citation data and find evidence of a strong localization of knowledge spillover that attenuates with geographical distance. Greenstone, Hornebeck, and Moretti (2008) study productivity and agglomeration data for large manufacturing plants. They find evidence that total factor productivity increases when a large manufacturing plant moves into an existing area of agglomeration.

The literature on agglomeration economies can be broadly classified into localization economies and urbanization economies. Localization economies are external to firms but internal

to an industry in a geographic region. According to Glaeser et al. (1992), localization economies are often referred to as the micro-foundations of agglomeration. Following Feldman (2000), urbanization economies refer to scale effects that depend on city size or density. This paper focuses on localization economies that are external to the firms but internal to an industry.

In a seminal paper, Ellison and Glaeser (1997) construct a measure of industrial agglomeration that enables them to distinguish between spatial concentrations resulting from industrial organization due to internal increasing returns to scale versus spatial concentrations resulting from the micro-determinants of agglomeration. Using their measure of agglomeration along with manufacturing employment data from the Census of Manufactures, they analyze patterns of U.S. manufacturing agglomeration in 1987. They find that most manufacturing industries are only slightly concentrated relative to more highly agglomerated industries, such as ICT firms in Silicon Valley and the automobile industry in Michigan. Ellison and Glaeser (1999) examine U.S. manufacturing agglomeration. They find that natural advantage is the single most important micro-determinant of agglomeration.

In a highly influential paper, Rosenthal and Strange (2001) examine the micro-determinants of agglomeration using manufacturing employment data for the year 2000. They use EGI as a measure of employment agglomeration and regress it on proxies for GP, LP, and IP, along with control variables for transportation costs and natural cost advantages. They find a positive and statistically significant relationship between agglomeration and the micro-determinants, but their influence appears to differ with distance. They point out that GP and transportation costs influence agglomeration positively at the state level but display little impact on agglomeration at the county or zip-code level. In contrast, IP positively influences agglomeration at the zip-code level only; a finding which they attribute to the rapid attenuation

of knowledge spillovers across space. They find the influence of LP to be positive and statistically significant across all levels of space, i.e., zip code, county, and state.

Both Ellison and Glaeser (1997) and Rosenthal and Strange (2001) examine agglomeration at a single point in time. We contribute to this literature by using panel data to examine the changing influence of the micro-determinants of employment agglomeration due to the effect of globalization on U.S. manufacturing employment.

O'Brien (1992) and Cairncross (1997) contend that increased globalization is eroding the importance of location on economic activity, meaning that industrial agglomeration may be declining. In contrast, Ohmae (1995), Porter (1998), and Fujita et al. (2000) contend that globalization is in fact increasing the importance of location, meaning that the importance of agglomeration in firm location decision making may be increasing. In short, the effect of increased foreign outsourcing and the resulting decline in U.S. manufacturing employment on industrial agglomeration in the U.S. is ambiguous. Now, we turn to a description of our empirical strategy.

III. Empirical Model, Variable Construction, and Data

We estimate the impact of globalization on the micro-determinants of agglomeration using the following model:

$$\begin{aligned} EGI_{ist} &= B_0 + B_1(LP)_{ist} + B_2(GP)_{ist} + B_3(IP)_{ist} + B_4(T95)_{ist} + B_5(LP \times T95)_{ist} \\ &+ B_6(GP \times T95)_{ist} + B_7(IP \times T95)_{ist} + \vec{B}_8 \vec{X}_{ist} + \vec{B}_9(\vec{X}_{ist} \cdot T95_t)' + \mu_s + \tau_t + \varepsilon_{ist}. \end{aligned}$$

The i subscripts (= 1, 2, …, 76) indicate 76 manufacturing industries at the 3-digit Standard Industrial Classification (SIC) code level; s (= 1, 2, …, 48) indicates the 48 lower continental

states; and t (= 1988, 1990, 1993, 1994, 1996, 1998, 2000, and 2003) indicates the year.[4] To avoid mixing survey and census data, we utilize years for which survey data are available. EGI_{ist} denotes the Ellison-Glaeser index of agglomeration, and, as discussed in greater detail below, EGG_{ist} denotes the Ellison-Glaeser Gini index. LP, GP, and IP are proxy variables for labor pooling, goods pooling, and idea pooling, respectively.[5] 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; 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.

As previously discussed, we contend that the decline in U.S. manufacturing employment beginning in 1995 is due to the increased foreign outsourcing of the production on intermediate and final goods due in large part to trade liberalization and the ICT revolution which begin in 1995. We hypothesize that the resulting increase in foreign outsourcing of manufacturing employment may have led to a change in the effects of the micro-determinants of agglomeration. As previously discussed, the effect of globalization on employment agglomeration in the U.S. is ambiguous. If globalization indeed is influencing the effect of the micro-determinants of agglomeration, then we should expect to find that the marginal effects of the micro-determinants are different in the post-1995 period relative to their values in pre-1995 period. More precisely,

[4] 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). We exclude Alaska and Hawaii from the analysis.

[5] 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 $import_{it}$)].

our null hypothesis is that $B_5 = B_6 = B_7 = 0$ in the model described above. Now, we turn to a detailed explanation of the construction of these variables.

Following Ellison and Glaeser (1997), we 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.[6] 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.[7] To better appreciate the construction of EGI, we briefly describe Hoover's (1936) locational Gini quotient (LQ_{im}), the locational Gini coefficient (G_i), and Ellison and Glaeser's index of raw geographic concentration (EGG_{im}), where the subscripts refer to industry i and region m.

To illustrate the construction of LQ_{im}, consider an economy with M regions (m = 1, …, M), S_{im} represents industry i's share of total manufacturing employment in region m, and X_m represents total manufacturing employment in region m. We define industry i's location quotient in region m to be $LQ_{im} = S_{im}/X_m$.[8] Spatial concentration also can be measured using a locational Gini coefficient. A locational Gini coefficient varies between 0 and 1.0, and agglomeration is increasing in the value of G_i. Ellison and Glaeser's Gini index (EGG_i) is another well-known measure of employment agglomeration by industry and is defined as $EGG_i \equiv \sum_{m=1}^{M} (X_m - S_{im})^2$, where $0 < EGG_i < 1.0$, and employment agglomeration in industry i is increasing in EGG_i.

[6] As noted by Ellison and Glaeser (1997), many industries consist of a few large firms producing the bulk of the output in a particular industry because 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 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.

[7] This Gini index is also known as Ellison-Glaeser's index of raw geographical concentration.

[8] See Gallagher (2007) for a clear description of the construction of locational quotient (LQ_{im}) and a brief discussion of other measures of agglomeration and co-agglomeration.

The problem with this approach to measuring agglomeration is that a value of $EGG_i > 0$ does not necessarily mean that industry i is agglomerated because of external economies of scale. For example, suppose an industry is made up of a small number of large plants and that this industrial structure is the result of internal economies of scale. In this case, EGG_i takes on a large value, but this is because of internal economies of scale and not external economies of scale, namely the micro-determinants of agglomeration.[9] To overcome this issue, Ellison and Glaeser (1997) propose the following measure: $EGI_{ist} \equiv \frac{EGG_{ist} - \left(1 - \sum_c X_{ct}^2\right) H_{ist}}{\left(1 - \sum_c X_{ct}^2\right)\left(1 - H_{ist}\right)}$ where X_{ct} is the manufacturing share in county c in year t and state s, and the summation is over all the counties in state s. 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.[10]

In the case of a perfectly competitive industry with a large number of small plants, H_{is} approaches zero, and EGI_{is} approaches $EGG_{is}/(1-\sum X_{is}^2)$.[11] In this case, EGI measures spatial concentration and, unlike the Gini coefficient (EGG_{is}), is independent of agglomeration as a

[9] As an example, Ellison and Glaeser (1997) referred to the situation of the U.S. vacuum cleaner industry (SIC code 3635). Roughly 75 percent of the total employment in this sector is contained in one of the four largest plants, but this concentration is driven by the inherent organization of the industry and not necessarily the agglomeration forces. The EGI was developed "to facilitate comparisons across industries, across countries or over time. When plants' location decisions are made as in the model, differences in the size of the industry, the size and distribution of plants, or the fineness of the geographic data that are available should not affect the index"(Ellison and Glaeser, 1997, p. 890).

[10] 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.

[11] We calculate the Herfindahl index using the median employment for different plant-size levels for each industry and year covered in this study.

result of internal economies of scale. According to this measure, EGI_{is} takes on a value of zero when industry i is not concentrated in some region(s) but is spread evenly, as would result from a random location process. EGI_{is} takes on a positive value when industry i is concentrated in some region(s). In short, we use EGI because this measure of industrial agglomeration controls for industry-specific agglomeration due to internal economies of scale and thus 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 employment agglomeration.[12]

Now we describe the construction of the proxy variables for the micro-determinants of agglomeration and the other control variables used in this analysis. The proxy for labor pooling (LP) is the ratio of employees with bachelor's degree to all employees. The reason for using an educational-profile-based measure of LP is that specialization of a worker often increases with the length of their academic training, and agglomeration enables firms to hire specialized workers. Some industries that rank high in terms of LP include electronic computers, storage devices, and terminals (SIC 357), fertilizers, pesticides and agro-chemicals (SIC 287), medicinal chemicals (SIC 283), and so on. These industries clearly require specialized engineering skills. Now we proceed by describing the construction of the remaining variables in the baseline model.

The goods-pooling (GP) variable is constructed using data from the Annual Survey of Manufacturers (various years). The commonly used proxy for GP is the ratio of the cost of materials–to-value of shipments. Since the cost of materials is likely to be positively correlated

[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. We also use a Gini index as a measure of agglomeration as this traditional measure is easier to interpret with values between zero and 1.0. In contrast, the EGI can be either positive or negative indicating agglomeration or deagglomeration respectively.

with the weight of the inputs, industries in which the cost of materials is high also employ materials that weigh a lot. Understandably, such industries have incentives to save on transportation costs by locating in close proximity to the sources of their inputs. For example, the main input of the meat-packing industry (SIC 201) is butchered cows, goats, hogs, and lambs. These live animals constitute a major source of input costs and also weigh a lot. Therefore, the meat-packing industry can save on transportation costs by locating in proximity to the source of livestock. Similar reasoning accounts for the high GP ranking of the rubber, plastic hose, and belting industry (SIC 305).

Our proxy for IP is the ratio of employees with post-graduate degrees to all employees. Industries with higher shares of employees with highly specialized training are likely to be more innovative and hence more sensitive to IP driven agglomeration. This variable is constructed using data from the Current Population Survey.

Consistent with the findings of Rosenthal and Strange (2001), we expect GP, LP, and IP to have a positive effect on industrial agglomeration. However, we hypothesize that the ICT revolution and trade liberation may influence the marginal effects of these three factors on employment agglomeration in the U.S. Therefore, the algebraic signs of the interaction variables GP×T95, LP×T95, and IP×T95 cannot be predicted by economic theory alone.

Following Rosenthal and Strange (2001), we use the ratio of inventory to the value of shipments as a proxy for transportation costs, the idea being that highly perishable goods (such as dairy products, newspapers, and so on) have a lower inventory-to-shipment ratio. Therefore, industries producing perishable goods should locate in proximity to their consumers to reduce transportation costs. Assuming that the consumers of such products are widely dispersed, industries with high transportation costs due to the perishability of their output also will be

widely dispersed. This variable is constructed from the year-end-inventory data reported in the Annual Survey of Manufactures (geographic area series). These data are available through 1997. For subsequent years in the sample, we impute the year-end inventory data using the mean values of the previous years. This inverse proxy for transportation costs (i.e., inventory-to-shipment) should have a positive effect on agglomeration. Industries with relatively few perishable products incur lower transportation costs, everything else held constant, and would therefore be more agglomerated. On the other hand, industries with highly perishable products would incur higher average transportation costs per unit of distance, everything else held constant, and therefore would locate close to their output markets resulting in less agglomeration.

We 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 save on energy costs by locating near places with an abundant supply of such natural resources. This variable is constructed using data from the Annual Survey of Manufactures (geographic area series). Consistent with the findings in Rosenthal and Strange (2001) and Linn (2009), we expect this variable to have negative effect on employment agglomeration. We also include other control variables, including the state minimum wage and maximum state corporate income tax rate. 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 agglomeration in industries that rely heavily on unskilled labor.[13] Theoretical and empirical evidence regarding the effect of corporate income taxes (CIT) on firm location decisions is mixed. For example, Baldwin and Krugman (2003) develop 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) uses plant location data across manufacturing industries for the years 1972 and 1978. He finds that a 10 percent increase in a state-level CIT rate causes a 3 percent decrease in the number of new plants. In contrast, Gius and Frese (2000) find that the influence of the CIT on industrial agglomeration is statistically indistinguishable from zero at conventional levels of significance.

In constructing the panel data for the period 1988 to 2003, we have to bridge the data across two industrial classification regimes. In 1997 the U.S. began using a new industrial classification system known as the North American Industrial Classification System (NAICS), which replaces the earlier 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 are a completely open drawbridge (open that is to automobile traffic), a partially raised drawbridge, and a completely raised drawbridge. A completely open drawbridge indicates that the corresponding SIC and NAICS industries are perfectly bridgeable. For these industries, we are able to construct a complete time series. A partially raised drawbridge indicates that the

[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.

corresponding SIC and NAICS industries do not deviate by more than 3 percent based on sales. A completely raised 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, we 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 missing values for some explanatory variables, there are 76 industries in our sample. As previously noted, we also exclude Alaska and Hawaii from the sample. The resulting sample consists of 29,184 observations. Furthermore, we exclude 21,450 observations due to missing information generally due to the non-disclosure obligations of the reporting agencies. Generally data are withheld by the Bureau of Census for counties when there are only one or very few establishments in an industry in a given county. This withholding of data may have several implications. First, county level disaggregated manufacturing employment data 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, the absence of such data withholding may have increased the statistical significance and robustness of our estimation results due to the increase in the available degree of freedom. In any event, the resulting sample consists of 7,734 observations.

Table 1 reports descriptive statistics for our sample of 7,734 observations. The sample mean of EGI is 0.210, and the sample mean of the Herfindahl index is 0.454. The sample mean of LP 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 GP is 0.491, which means that the cost of materials is 49.1 percent of the value of shipments. The sample mean of IP is 0.035; in other words, 3.5 percent of the employees of the firms in our sample have post-graduate degrees. 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 we discuss our empirical results.

IV. Empirical Results

Four specifications are reported in table 2. In the columns labeled EGI, we report the results of two specifications results using EGI as the dependent variable. Despite the advantages of using EGI as measure of employment agglomeration by industry, we also report the results obtained by using the Gini index of spatial concentration as the dependent variable. In these regressions, we control for plant size by including the Herfindahl index as a regressor. These results are reported in the columns labeled Gini index. We estimate both specifications using state and year fixed effects.

We begin by discussing the results in the columns labeled T95, starting with the estimates obtained by using EGI as the dependent variable. The estimated coefficients of LP, GP, and IP are positive and statistically significant at conventional levels.[14] This is consistent with economic

[14] Following Wooldridge (2002), and Cameron and Trivedi (2005), we report clustered standard error. Observations within a cluster may be correlated as the result of unobserved clustering effects. We 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.

theory and the results reported in the existing literature. The estimated coefficient for the interaction variable LP×T95 is negative and statistically significant at conventional levels. In fact, the absolute value of the estimated coefficient of LP×T95 is nearly twice that of the estimated coefficient of LP. This suggests that LP has a positive effect on employment agglomeration in the pre-1995 period, but, in the post-1995 period, it has a negative effect. In contrast, the estimated coefficient of GP×T95 is positive and statistically significant at conventional levels, suggesting that the marginal effect of GP on employment agglomeration has more than doubled in the post-1995 period relative to the marginal effect of GP on agglomeration in the pre-1995 period. Finally, the estimated coefficient of IP×T95 is negative but statistically indistinguishable from zero at conventional levels. This finding suggests that there has been no change in the marginal effect of IP on employment agglomeration between the two periods under investigation.

As previously noted, it is difficult to interpret the meaning of a unit change in EGI. However, people may have a sense of the meaning of a one standard deviation change in the value of a random variable relative to its sampling distribution. Therefore, we measure the "marginal" effect of LP, GP, and IP in the pre- and post-1995 periods by computing the effect of a one standard deviation change of a micro-determinant as a proportion of a one standard deviation change in EGI. Table 3A reports the marginal effects of LP, GP, and IP, using the estimated coefficients reported in columns 1 and 2 of table 2.

In the pre-1995 period, as reported in table 3A, the marginal effect of LP is 5.5, meaning that a one standard deviation increase in LP results in a 5.5 percent of one standard deviation increase of EGI. In the post-1995 period, the marginal effect of LP is -5.9, meaning that a one standard deviation increase in LP results in a 5.9 percent of one standard deviation decrease in

EGI. This suggests that globalization has changed LP from a force for globalization into a force for de-agglomeration. In this an interesting finding that merits further investigation. The marginal effect of GP in the pre-1995 period is 10.3, meaning that a one standard deviation increase in the value of GP results in a 10.3 percent of one standard deviation increase in EGI. However, the marginal effect of GP is 24.1 in the post-1995 period. In other words, a one standard deviation increase in the value of GP results in a 24.1 percent of one standard deviation increase in EGI. This is a substantial effect. Finally, the marginal effect of IP is 3.9 in the pre-1995 period, meaning that a one standard deviation increase in IP results in a 3.9 percent of one standard deviation increase in IP. Since the estimated coefficient of IP×T95 is statistically insignificant at conventional levels, the marginal effect in the post-1995 period is essentially the same as in the pre-1995 period.

Turning to the estimates of the other control variables reported in column 1 of table 2, the only ones that are statistically significant at conventional levels are the state minimum wage and transportation costs in the pre- and post-1995 periods. The state minimum wage has a negative effect on agglomeration in the pre-1995 period, suggesting that a higher state minimum wages causes a decrease in employment agglomeration. The marginal effect of the state minimum wage is -12.6, meaning that a one standard deviation increase in the state minimum wage results in a 12.6 percent of one standard deviation decrease in EGI. The marginal effect of the minimum wage (MW) in the post-1995 period is approximately zero because the estimated coefficient of MW×T95 is approximately equal (in absolute value) to the estimated coefficient of the state minimum wage in the pre-1995 period but has the opposite sign. In the pre-1995 period, the estimated coefficient of transportation costs (TC) is positive and statistically significant. Recall that our proxy for transportation costs is an inverse measure, so a positive coefficient is

consistent with transportation costs having a negative effect on employment agglomeration. A finding that transportation costs have a negative effect (positive coefficient) is consistent with the theory and existing empirical findings. In the pre-1995 period, the marginal effect of transportation costs is 7.9, meaning that a one standard deviation increase in transportation costs results in a 7.9 percent of one standard deviation decrease in EGI. Finally, in the post-1995 period, the marginal effect of transportation costs is 24.5, meaning that a one standard deviation increase in transportation costs results in a 24.5 percent of one standard deviation decrease in EGI. This is a substantial effect.

Interestingly, the R^2 of the EGI specification of the model is about 8 percent, which is rather small. This is consistent with the findings of Rosenthal and Strange (2001). To explore the effect of internal economies of scale on employment agglomeration, we estimate our model using the Gini index of spatial concentration as the measure of employment agglomeration and control for plant size by including the Herfindahl index as a regressor. This specification is reported in the column of table 2 which is labeled Gini index. Interestingly, there is a fivefold increase in the R^2 for the specification estimated using the Gini index as the dependent variable relative to the R^2 obtained using EGI as the dependent variable. In other words, large plant size due to internal economies of scale appears to explain substantially more variation in employment agglomeration than the proxy variables for the micro-determinants of agglomeration. The estimated marginal effect of the Herfindahl index (HI) is 27.8, meaning that a one standard deviation increase in the Herfindahl index results in a 27.8 percent of one standard deviation increase in EGI. This is a substantial effect. The marginal effect of the Herfindahl index in the post-1995 period is 23.0, which is slightly attenuated relative to the marginal effect in the pre-1995 period. The marginal effect of the Herfindahl index in the post-1995 period is still substantial.

There are three possible explanations for our finding that the explanatory power of the regression increases when the Herfindahl index is used as a regressor. First, despite the theory, internal economies of scale as measured by the Herfindahl index are an important explanation of employment agglomeration in U.S. manufacturing. Second, perhaps the operational measures of the micro-determinants of agglomeration used in this and other studies are not particularly good measures of internal economies of scale. This would suggest that future research should focus on developing better measures of the micro-determinants of agglomeration. Third, as a recent study by Ellison, Glaeser, and Kerr (2010) suggests, perhaps coagglomeration is an important determinant of employment agglomeration in manufacturing.

Having said this, the signs and statistical significance of the estimated coefficients are more or less the same in the two specifications of the model. More specifically, in the Gini index specification of our model, as with the EGI specification, the estimated coefficients of LP, GP, and IP are positive and statistically significant. Furthermore, the estimated coefficients of LP×T95, GP×T95, and IP×T95 have the same signs and statistical significance as before. The estimated coefficient of the state minimum wage is negative and statistically significant at conventional levels, and that of transportation costs is positive and statistically significant. These are the same results that we obtained with the EGI specification of the model. However, the interaction terms MW×T95 and TC×T95 are not statistically significant at conventional levels in the Gini index specification of the model. In another departure from the findings with the EGI specification, the maximum state corporate income tax rate is negative and statistically significant at conventional levels. With these three relatively minor exceptions, the signs and significance of the estimates are the same in the two specifications of the model.

Thus far, we have reported the total change in the effect of the two channels of globalization under investigation on the micro-determinants of agglomeration. However, we have identified to channels of change due to globalization, namely trade liberalization and advances in internet communication technologies. 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, we estimate another specification of our model in which we 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, we are able to decompose the effect of globalization on the marginal effect of a given micro-determinant on agglomeration into the change due to trade liberation and the change due to the ICT revolution.

We 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. We expect trade liberalization to make the domestic market more competitive. This should lead domestic manufactures to strive to reduce by further exploiting the advantages of agglomeration and for marginal producers to be eliminated from the market. As a result, we expect the average duty rate to have a positive effect on agglomeration. We also interact ADR with our time dummy variable T95 to account for the two trade acts that went into effect in 1995. For convenience, we refer to this interaction variable as D95 (= ADR×T95).

The estimated results for these specifications of the model are reported in the columns labeled D95 in table 2. As before, we estimate two specifications of this model, one with EGI as the dependent variable and one with the Gini index as the dependent. As in the case of the

specifications using T95 to account for the impact of globalization, the estimates obtained using the average duty rate to control for the effect of globalization are very similar whether we use EGI as the dependent variable or the Gini index. Therefore, we focus on the estimates obtained with the EGI specification of the model. As expected, the average duty rate (ADR) has a positive and statistically significant effect at conventional levels on EGI. As before, the estimated coefficients of LP, GP, and IP are positive and statistically significant at conventional levels. However, using D95 to control for the effect of globalization rather than simply T95, has an interesting effect on the interaction terms. As before, LP×D95 is negative and statistically significant at conventional levels, and the estimated coefficient of IP×D95 is negative but indistinguishable from zero. In contrast to our previous finding, the estimated coefficient GP×D95 is small and statistically indistinguishable from zero. This finding suggests that the doubling of the marginal effect of GP in the post-1995 period is working through the ICT channel rather than the trade liberalization channel of globalization. The remaining control variables generally have the same signs and significance as before.

By controlling for the effect of trade liberalization, we are able to decompose the total change in the effect of the micro-determinants into the part due to trade liberalization and the part due to widespread adoption of ICTs. These decompositions are reported in Table 3B. For ease of interpretation, the decompositions are based on standard deviations, as in the case of Table 3A. For example, the total change in the marginal effect of LP in the pre- and post-1995 periods is -11.3 percentage points (= -5.9 – 5.5). Using the estimated coefficients of LP and LP×D95 reported in table 2, we estimate trade liberalization increases the marginal effect of LP on agglomeration by 5.8 percentage points. In contrast, the ICT revolution decreases the marginal effect of LP by 17.1 percentage points. Apparently, the ICT revolution attenuates the

cost savings from agglomeration due to LP. Since the internet facilitates long-distance communication thus enabling firms to manage supply chains over long distances, firms can better exploit lower labor costs abroad and manage the supply chain over long distances due to the ICT revolution.

Following this methodology for the other micro-determinants, we estimate that trade liberalization increases the marginal effect of GP on agglomeration by 1.8 percentage points; thus, trade liberation accounts for very little of the increase in the marginal effect of GP on globalization. In contrast, the ICT revolution increases the marginal effect of GP on agglomeration by 12.0 percentage points or approximately 87 percent of the total increase in the marginal effect of GP on agglomeration due to globalization. Prior to the ICT revolution, effective management of supply chains may have required co-agglomeration of suppliers of intermediate goods with the firms using their outputs as inputs. With the advent of the ICT revolution, the advantage of such co-agglomeration disappears, and firms outsource production of intermediate goods to take advantage of lower costs from production abroad.

Finally, we decompose the total change in the marginal effect of IP on agglomeration. According to our estimates, trade liberalization increases the marginal effect of IP on agglomeration by 3.9 percentage points, and the ICT revolution decreases the marginal effect of IP by 5.6 percentage points. Thus the total effect of globalization on IP is negative (1.7 percentage points). The opposite effects of trade liberalization and the ICT revolution on the marginal effect of IP on agglomeration cancel one another; the result being no change in the marginal effect of IP on agglomeration in the post-1995 period relative to the pre-1995 period. In

In table 3B, we report a similar decomposition of the total change in the marginal effects of the micro-determinants of agglomeration due to the two channels of globalization, based on

the estimates using the Gini index as the dependent variable. The results are very similar to those described above for the estimates obtained using EGI as the dependent variable.

V. Conclusion

Figure 1 shows that the decline in U.S. manufacturing employment gained momentum after the mid-1990s. According to a substantial body of empirical research, this trend reflects the major sources of globalization, particularly trade liberalization and the ICT revolution. We investigate what if any impact these two channels of globalization are having on the marginal effects of the micro-determinants of agglomeration. Theoretically the impact of globalization on agglomeration is ambiguous. According to our estimates, the marginal effect of LP on agglomeration is now negative, and the marginal effect of GP on agglomeration is now larger. Based on our estimates, trade liberalization increases the marginal effect of LP on agglomeration but this positive effect is overwhelmed by the large negative effect of the ICT revolution on the marginal effect of LP on agglomeration. We find that trade liberalization has a negligible impact on the marginal effect of GP, but the ICT revolution is having a substantial effect. Finally, we report evidence that internal economies of scale have a substantial effect on agglomeration; a finding that deserves further study.

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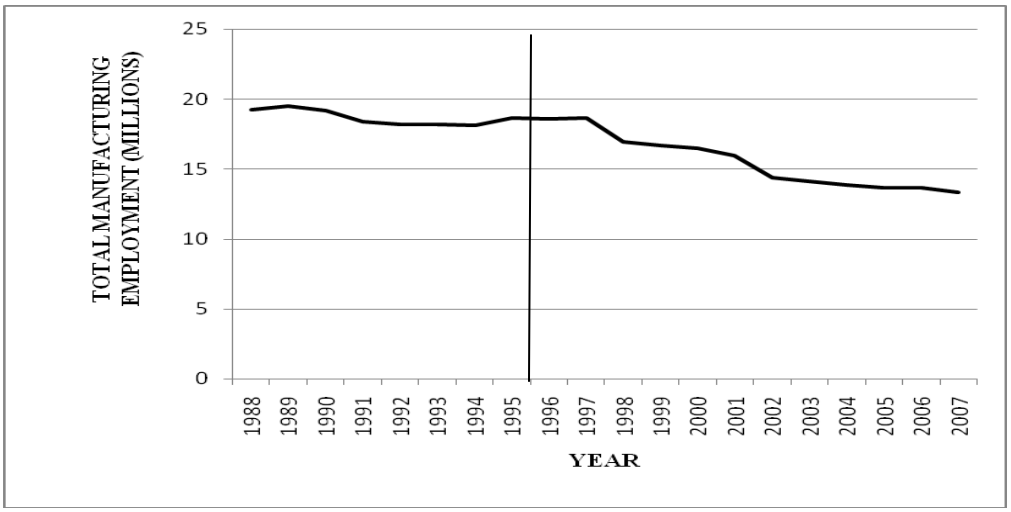
FIGURE 1
TOTAL MANUFACTURING EMPLOYMENT IN THE UNITED STATES, 1988-2007



Source: County Business Pattern data, Bureau of Census (1988-2007)

TABLE 1
DESCRIPTIVE STATISTICS

Variable name	Variable description	Mean value [standard deviation]
Ellison-Glaeser index	Ellison-Glaeser index of agglomeration	0.210 [0.373]
Gini index	Gini index of agglomeration	0.496 [0.189]
Herfindahl index	Herfindahl index of industrial organization	0.454 [0.121]
Labor pooling 1	Share of employees with bachelor's degree	0.113 [0.131]
Labor pooling 2	Share of employees with less than bachelor's degree	0.853 [0.154]
Labor pooling 3	Share of managerial workers	0.168 [0.161]
Labor pooling 4	Per worker value added net of cost of materials (in millions of US $'s)	0.082 [0.060]
Labor pooling 5	Wages per dollar of value of shipments	0.123 [0.167]
Goods pooling	Ratio of the cost materials to value of shipments	0.491 [0.116]
Idea pooling 1	Share of employees with post-graduate degrees	0.035 [0.074]
Idea pooling 2	Patent count	102.652 [237.194]
Average duty rate	Average duty rate	5.654 [3.604]
Minimum wage	State minimum wage	4.001 [0.587]
Corporate income tax	Maximum state corporate income tax rate	6.727 [2.021]
Transportation costs	Ratio of value of inventory to value of shipments	0.140 [0.066]
Energy costs	Cost of energy per dollar of shipments	0.025 [0.017]
Number of observations		7,734

TABLE 2
EGI AND GINI INDEX[1]

Coefficient	T95[2]		AD95 (= Average duty rate×T95)[3]	
	EGI	Gini index	EGI	Gini index
Constant	0.173*** [0.122]	0.118*** [0.050]	0.059 [0.110]	0.074** [0.046]
Labor pooling (LP)	0.156*** [0.041]	0.044*** [0.011]	0.200*** [0.041]	0.059*** [0.012]
LP ×T95[2] (or LP×AD95)[3]	-0.323*** [0.069]	-0.133*** [0.041]	-0.035*** [0.009]	-0.013*** [0.006]
Goods pooling (GP)	0.332*** [0.054]	0.047*** [0.017]	0.374*** [0.055]	0.068*** [0.017]
GP ×T95 (or GP×AD95)[3]	0.444*** [0.165]	0.586*** [0.109]	0.013 [0.016]	0.044*** [0.011]
Idea pooling (IP)	0.197*** [0.053]	0.102*** [0.022]	0.210*** [0.053]	0.110*** [0.022]
IP ×T95(or IP×AD95)[3]	-0.085 [0.118]	0.009 [0.073]	-0.012 [0.017]	-0.005 [0.010]
Average duty rate (ADR)[3]	-	-	0.013*** [0.001]	0.005*** [0.000]
T95[2] (or AD95)[3]	-0.489*** [0.152]	-0.289*** [0.102]	-0.016 [0.013]	-0.006 [0.008]
Herfindahl index (HI)	-	0.858*** [0.027]	-	0.848 [0.028]
HI ×T95[2] (or HI×AD95)[3]	-	-0.183*** [0.045]	-	-0.021*** [0.004]
State minimum wage (MW)	-0.080*** [0.036]	-0.016** [0.012]	-0.068*** [0.032]	-0.011 [0.010]
MW×T95[2] (or MW×AD95)[3]	0.080*** [0.031]	0.017 [0.016]	0.001 [0.002]	-0.002 [0.001]
Maximum state corporate income tax rate (CIT)	0.010 [0.006]	-0.003** [0.003]	0.002 [0.006]	-0.004*** [0.003]
CIT ×T95[2] (or CIT ×AD95)[3]	-0.001 [0.005]	0.002 [0.002]	-0.001 [0.001]	-0.001 [0.001]
Energy costs (EC)	-0.252 [0.360]	0.189 [0.244]	-0.379 [0.314]	0.158 [0.226]
EC×T95[2] (or EC×AD95)[3]	0.286 [0.694]	0.177 [0.507]	-0.078 [0.085]	-0.032 [0.054]
Transportation costs (TC)	0.445*** [0.158]	0.169** [0.065]	0.443*** [0.154]	0.166** [0.033]
TC×T95[2] (or TC×AD95)[3]	0.939* [0.520]	0.420 [0.312]	0.098* [0.058]	0.067** [0.033]
Number of observations	7,734	7,734	7,734	7,734
R-squared	0.079	0.438	0.090	0.443

Notes:
[1] Clustered standard errors are reported in the square-brackets. Statistical significance of the estimated coefficients is indicated by asterisks next to the estimated coefficients, at the conventional 10 percent (*), 5 percent (**), and 1 percent (***) levels.
[2] The estimates reported in the columns labeled T95 control for the time dummy variable for globalization (T95) which assumes a value of one (1.0) if year $\geq$ 1995, and a value of zero (0.0) otherwise.
[3] The specification reported in the columns labeled AD95 control for the average duty rate (AD), and the interaction term AD95 = AD×T95.

Table 3A
Pre- and Post-1995 marginal effects of the Marshallian determinants of agglomeration (percent)

Marshallian determinants of agglomeration	Dependent variable = EGI		Dependent variable = Gini index	
	pre-1995	post-1995	pre-1995	post-1995
Labor pooling	5.5	-5.9	3.0	-6.2
Goods pooling	10.3	24.1	2.9	38.9
Idea pooling	3.9	2.2	4.0	4.3

Table 3B
Decomposition of the change in the marginal effects (percent)

Marshallian determinants of agglomeration	Dependent variable = EGI			Dependent variable = EGG		
	Δ in total effect	Δ due to trade agreements	Δ due to ITC	Δ in total effect	Δ due to trade agreements	Δ due to ITC
Labor pooling	-11.3	5.8	-17.1	-9.2	3.2	-12.4
Goods pooling	13.8	12.0	1.8	36	6.9	29.1
Idea pooling	-1.7	3.9	-5.6	0.3	4.1	-3.8