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IMPACTS OF TRADE ON WAGE INEQUALITY IN LOS ANGELES:

ANALYSIS USING MATCHED EMPLOYER-EMPLOYEE DATA[1]

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ABSTRACT

Over the past twenty-five years, earnings inequality has risen dramatically in the US, reversing trends of the preceding half-century. Growing inequality is closely tied to globalization and trade through the arguments of Heckscher-Ohlin. However, with few exceptions, empirical studies fail to show that trade is the primary determinant of shifts in relative wages. We argue that lack of empirical support for the trade-inequality connection results from the use of poor proxies for worker skill and the failure to control for other worker characteristics and plant characteristics that impact wages. We remedy these problems by developing a matched employee-employer database linking the Decennial Household Census (individual worker records) and the Longitudinal Research Database (individual manufacturing establishment records) for the Los Angeles CMSA in 1990 and 2000. Our results show that trade has a significant impact on wage inequality, pushing down the wages of the less-skilled while allowing more highly skilled workers to benefit from exports. That impact has increased through the 1990s, swamping the influence of skill-biased technical change in 2000. Further, the negative effect of trade on the wages of the less-skilled has moved up the skill distribution over time. This suggests that over the long-run, increasing levels of education may not insulate more skilled workers within developed economies from the impacts of trade.

IMPACTS OF TRADE ON WAGE INEQUALITY IN LOS ANGELES: ANALYSIS USING MATCHED EMPLOYER-EMPLOYEE DATA

"Many of us have memories of the postwar era, when the benefits of prosperity were broadly shared and millions of Americans climbed out of poverty into a middle class that was the envy of the world. Sometime in the late 1970s, our economy began to go a different way, sending most of its rewards to those who already had the most. The result is a concentration of income and wealth that is not only higher than it has been since the 1920s, but higher than that of any of the world's other developed nations."

James Lardner (2005)

1. INTRODUCTION

Since the late 1970s, the wages of less-skilled workers in the US have fallen dramatically relative to more highly skilled workers. Over much the same period, merchandise imports as a proportion of US GDP have more than doubled, and imports from low-wage developing economies have risen even more sharply (Bernard et al. 2006). This correlation has led many to invoke the arguments of Heckscher-Ohlin and suggest that globalization is responsible for depressing the relative wages of the less-skilled as these workers face increased competition, in the form of trade, from low-wage developing economies (Collins 1998; Choi and Greenaway 2001; Wood 1995). While this claim tends to garner considerable attention in policy-debate, recall presidential candidate Ross

Perot's "giant sucking sound", and while public anxiety about the outsourcing of US jobs grows (see special issue of *Time Magazine*, 1 March 2004), empirical analyses, using factor-content models or the relative price movements suggested by Stolper-Samuelson, have repeatedly failed to provide compelling evidence that trade is the primary determinant of rising inequality (Lawrence and Slaughter 1993; Freeman 1995; Richardson 1995). Consequently, attention has moved from trade-based explanations of the shifts in relative wages toward the role of skill-biased technological change (Haskell and Slaughter 1998).

This paper is motivated by a number of significant problems in existing empirical studies of the trade-inequality link. In large part, these problems result from the use of aggregate, industry level, data. Three problems are identified here:

1. The inability to accurately measure worker skills and the use of unreliable proxies for skill such as production and non-production worker status
2. The search for trade impacts in inter-industry price movements and thus the assumption of homogeneity in terms of products produced and technologies employed within industries
3. The failure to control for individual worker and establishment characteristics that impact wages.

We propose to remedy these failings by linking longitudinal micro-datasets from the US Census Bureau to create a matched employer-employee dataset for the Los Angeles CMSA for 1990 and 2000. Individual worker characteristics (including detailed educational attributes) from the one-in-six long from of the Decennial Household Census are matched to manufacturing establishment-level records from the Longitudinal Research Database to re-examine the trade-inequality connection.

Our analysis focuses on two key research questions. First, how has increased foreign competition affected the wage levels of workers in different educational classes across the Los Angeles economy? Second, what is the influence of foreign competition on the relative wages of low-skilled workers versus high-skilled workers (i.e. wage inequality)? In relation to these questions, we also explore how the influence of trade on wages has moved through the 1990s, and we examine the relative impacts on wages of trade and skill-biased technological change.

By answering these questions we seek to re-engage the trade and wage inequality literature and present direct evidence of the impacts of global processes on local labor markets. There is at this time broad agreement that the varied processes we commonly label "globalization" have wrought significant change upon much of the world's population. Yet, we remain quite ignorant of the specific ways in which key aspects of the global manifest themselves in social, economic and political activities across different spatial scales. Within economic geography, Bridge (2002, pp362) argues that this ignorance reflects "…only a residual interest in evaluating the *outcomes* of globalization". He chides economic geographers for failing to confront the ways in which processes of globalization actually produce economic geographies. Dicken (2004) too laments this state of affairs, linking it to the absence/irrelevance of economic geographers in key debates on globalization. He follows Taylor (2000) in calling for the mapping and analysis of the geographically uneven outcomes of globalization.

The paper is organized as follows. The following section reviews the literature on wage inequality paying particular attention to the advocates of trade-based accounts and those who favor the skill-biased technological change argument. This review ends with a discussion of the flaws in most empirical accounts of the trade-inequality relationship. Section 3 deals with the research design, where consideration is given to our methodology for constructing a matched employer-employee database and to the econometric models used to interrogate those data. In section 4 we present our results for the Los Angeles CMSA. The paper concludes with a summary of key findings and a discussion of important extensions to this work.

2. TRADE AND WAGE INEQUALITY: THE LITERATURE

From the onset of the Great Depression through 1950 income inequality in the US declined steadily. Through two-decades of postwar growth, the relative wages of high-income workers versus low-income workers climbed very slowly. This abruptly changed in the late-1970s when the relative wages of high-income workers increased sharply. Levy and Murnane (1992) and Katz and Murphy (1992) trace the broad dimensions of the rise in income inequality, noting the rapid climb of the college (education/skill) premium through the 1980s, a similar marked increase in the returns to experience and steady growth in inequality within education-experience categories. While variations in the supply of workers of different quality were shown to have been significant between the 1970s and 1980s, for example, the spike in young well-educated workers associated with the baby boom, most agree that the dramatic shifts in relative wages during the 1980s hinge on demand (Katz and Murphy 1992).

Rising unemployment in the deep recession of the early 1980s was attributed by many to the inability of US firms to compete within an increasingly integrated global economy. Bluestone and Harrison (1982) and Thurow (1987) described the “hollowing out” of the American middle-class as a result of deindustrialization. Thus, as US manufacturers collapsed in the face of burgeoning foreign competition, they saw displaced workers left to compete for a handful of high paying jobs and many low paying jobs in the service sector. While these claims generated much public attention, they remained mostly conjectural and they failed to recognize that growing volumes of imports were not shedding labor wholesale across manufacturing industries, but rather that particular types of jobs within those industries were being lost (Levy and Murnane 1992). Clearly, more nuanced arguments about the effect of trade and technology on the demand for different types of workers were required.

Standard Trade Theory

One such argument is readily supplied by the neoclassical trade model of Heckscher-Ohlin. In very general terms, consider a world comprising developed and developing countries defined by their relative shares of skilled and unskilled workers. In this world, producers of a particular commodity use the same technology and prices of commodities are set in international markets as a result of trade. It seems reasonable to assume further that developed economies are characterized by a relative abundance of skilled workers and developing economies are characterized by a relative abundance of unskilled workers. (For a more detailed list of assumptions underpinning the Heckscher-Ohlin model see Bhagwati and Dehejia 1994.) The basic model then establishes that developed countries will specialize in the production of skilled-labor intensive goods and developing economies will specialize in the production of goods that use less-skilled workers intensively.

Trade between developed and developing countries will shift relative prices within each country as goods produced by less (more) skilled labor become more abundant in developed (developing) economies. According to the Stolper-Samuelson theorem, as relative goods prices shift through trade, factor prices will equalize. Thus, in the simple model just outlined, as the relative price of commodities produced by less-skilled labor in developed countries falls, as a result of trade, then the relative returns to less-skilled labor in developed countries will also fall. The Stolper-Samuelson theory also predicts that as the relative price of less-skilled labor falls in developed countries, then the ratio of less-skilled to more-skilled workers should increase across industries.

There has been much recent discussion of these trade arguments, particularly concerning the exogeneity of prices. Haskell and Slaughter (1998) and Slaughter (2000) provide an overview. Linkages between technology change, trade and price shifts are prominent in these discussions and significantly complicate empirical examination of the relationships between trade and relative wage movements. In a general sense, there is growing recognition that trade and technological change are closely connected. The simple model outlined above, is perhaps only useful for analysis of trade between economies with different relative factor endowments (see Balassa 1979). Of course much trade today is between countries with similar endowments. However, it is relatively easy to extend these arguments, incorporating scale effects for example, to model trade in this situation (see Helpman and Krugman 1985).

Empirical Investigation of the Impacts of Trade

Empirical analysis of the influence of trade on the labor markets of developed and developing economies tends to fall into one of two categories. Work in the first category focuses on the "factor-content" of imports and exports and rests largely on the volume of trade. Research in the second category comprises more direct tests of the Stolper-Samuelson argument and focuses on shifts in the relative prices of commodities produced with different bundles of skilled and less-skilled labor. It is fair to say that most empirical analysis in the US has focused on tests involving price shifts, whereas factor-content studies tend to be somewhat more popular in Europe.

[Table 1 about here]

Factor-Content Studies

In factor-content studies, the amounts of labor of different skill varieties that are embodied in a country's imports and exports are calculated. For the US, which is a net importer of goods produced with less-skilled labor, trade increases the supply of less-skilled workers and thus decreases the demand for such workers in the US. At the same time, exports from the US, that tend to be skilled-labor intensive, reduce the relative supply of skilled labor. The factor-content model is operationalized by estimating the demand for labor of different quality within different sectors of the economy and then combining that data with estimates of imports and exports by industry. The second step in the use of the factor-content model is to examine how trade induced movements in the relative supply of labor drive wage changes. This step requires a measure of wage elasticity (Deardorff and Staiger 1988).

Most factor-content studies do not find trade to be the primary determinant of earnings inequality, at least in the US. Borjas et al. (1992) argue that trade explains about 15% of the increase in US wage inequality through the 1980s. Sachs and Shatz (1994) also conclude that trade caused a decline in the relative wages of the less-skilled, but they note that the weight of this impact is unclear. In his use of the factor-content approach, Wood (1994) shows that trade is largely responsible for the rise in wage inequality. He claims that trade shifts relative wages by an order of magnitude more than found in most other studies. He argues that even within an industry, the commodities produced in developed and developing countries differ, with variable impacts on different kinds of labor. He thus advocates use of labor input coefficients for less skilled workers from developing countries to estimate the displacement of such workers by imports in the developed world. Sachs and Schatz (1994) are highly critical of this assumption. Collins (1992) criticizes both Wood (1994) and Sachs and Schatz (1994) for assuming the elasticity of substitution between less-skilled and more-skilled workers is too low, thus exaggerating the trade impact on the inequality. However, with these methods, Wood (1994) can explain about half of the rise in wage inequality experienced through the 1980s, perhaps more if the trade effect spills-over to non-traded sectors (Freeman 1995). Leamer (1996) condemns the factor-content approach wholesale, for focusing on trade volumes and not the price effects that more clearly emanate from Stolper-Samuelson, though Krugman (1995) disagrees.

Tests of Stolper-Samuelson

Stolper-Samuelson arguments account for rising wage inequality in developed economies through a trade-induced increase in the price of skilled-labor-intensive commodities relative to unskilled-labor-intensive commodities (Slaughter 1998). Thus, tests for trade-based explanations of inequality rest on the movement of prices for goods embodying different amounts of skilled and unskilled labor. Bhagwati (1991), Lawrence and Slaughter (1993), Leamer (1996) and Baldwin and Cain (2000) all examine the movement of commodity prices and find, in general, that there is no evidence that the price of low-skill labor-intensive commodities fell relative to the price of high-skill labor-intensive commodities during the 1980s, when inequality rose fastest. A subsidiary test of Stolper-Samuelson could focus on the substitution of less-skilled for high-skilled labor across sectors in developed economies. However, there is agreement that through the 1980s and 90s, the ratio of skilled-workers to less-skilled workers has been rising across the US economy. Extending the traditional trade model Feenstra and Hanson (1996) suggest that this is the result of outsourcing less-skilled work by US companies. Thus, the rise in the skill-ratio might be consistent with an expanded vision of trade in a world economy that is becoming increasingly integrated.

In summary, whether using factor-content models or the price-based tests advocated in a Stolper-Samuelson model, there is little support that trade is the primary determinant of rising earnings inequality in the 1980s in the US and elsewhere. It is this result that has led many to argue that the main driver of inequality is skill-biased technological change. That is, the new technologies introduced during the 1980s, raised the productivity and wages of workers with high levels of human capital and had little impact on the wages of less-skilled workers (Freeman 1995; Haskell and Slaughter 2001, 2002). Note that in parts of Europe, wage-inequality did not increase after 1980, rather there has been a significant increase in the rate of unemployment of the less-skilled. This difference between the US and Europe is typically explained by institutional differences in labor markets between these regions, wages being much stickier downwards in Europe (Brenton and Pelkmans 1999; Choi and Greenaway 2001).

Sub-National Impacts of Trade

With very few exceptions, we know remarkably little about the sub-national influence of trade in the US economy. There are an increasingly large number of studies on income variation across space, most looking at questions of convergence, (see Rey 2005 for a review), but relatively few that focus on explaining income inequality in US regions (though see Nielsen and Alderson 1997), and fewer still that explicitly engage trade. Aggregate state trade data are available, but links between trade and inequality are rare. Silva and Leichenko (2004) develop a series of exchange-rate price measures to capture the effects of changes in the prices of international imports and exports on local labor markets and report significant differences in terms of how globalization affects income inequality across US states. While this work is important, it does not say what kinds of workers bear the brunt of the impacts of trade.

Weaknesses of Existing Empirical Work

Most studies of the relationship between trade and earnings inequality rest on standard neoclassical trade models. This is perhaps surprising given the amount of attention over the last 50 years or so to supplant those models (Krugman and Helpman 1985; Markusen and Venables 1996; Brenton 1999). A concern to evaluate the trade-inequality relationship using other techniques also follows from unease with many of the assumptions of existing trade arguments (Bhagwati and Dehejia 1994; Slaughter 1998):

1. Heterogeneity within industries, in terms of commodities produced and technologies used, means that relative (industry-level) prices can shift for reasons other than trade. Thus simple tests of the Stolper-Samuelson argument are compromised.
2. It is assumed in almost all of the studies discussed above that product prices for open economies are determined at the global level and are not influenced by domestic forces. Leamer (1996) and Feenstra and Hanson (1997) relax this assumption and allow technological progress within the US to influence the prices of products in the US. However, it remains unclear what really influences product prices (Slaughter 1998).
3. Factor prices are clearly not determined solely by factor-price equalization operating at the same global level. The impact of the baby-boom generation and the declining education premium in the 1970s make this clear.

These problems suggest that alternative ways of examining the trade-inequality-technology relationship may be useful. In the methodology section below, a simple empirical model of wage inequality is offered that focuses on the characteristics of workers and plants that impact wages, and then explicitly adds variables to capture trade and technology arguments. That empirical model does not rely on the movements of product prices and the associated assumptions noted above.

On top of the problems of operationalizing the standard trade model, there are long-standing problems of identifying measures for many of the key arguments in the debate. Perhaps most important in this respect is the failure, in many studies to adequately identify worker skills. In both empirical tests of factor-content models (Borjas et al. 1993; Sachs and Schatz 1994) and Stolper-Samuelson arguments (Leamer 1993; Lawrence and Slaughter 1993; Haskell and Slaughter 2002) the non-production and production worker categories found in industry accounts are frequently employed as proxies for skilled and unskilled workers, respectively. Leamer (1994) and Lawrence (1995) have long been critical of this. Slaughter (1998a) in recent reviews acknowledges the problem but assumes that it does not bias results. Forbes (2000) shows that skill classification really does matter.

A second empirical problem results from analysis as the industry level. Aggregate studies of this type, even those working at the 4-digit level of the Standard Industrial Classification, fail to capture heterogeneity within industries. With firms producing different mixes of output, with different technologies and workers of varying skill, focusing on industry-level price shifts captures a lot more than factor-price equalization. All of the studies discussed above suffer from this problem.

Finally, it is well-known that wages vary across workers and firms with quite different characteristics. Failing to control for those characteristics can further compromise analysis of the trade-inequality linkage.

We remedy these empirical problems by developing a matched employer-employee database to examine how trade and technological change impact the wages of less-skilled and more-skilled manufacturing workers across the Los Angeles CMSA in 1990 and 2000. Data development and estimation strategies are outlined in the next section.

3. RESEARCH DESIGN

Data and Matching Procedures

As noted above, weaknesses in the analysis of the impacts of trade on wage inequality have long been recognized. Many of these weaknesses stem from the use of aggregate, industry-level, data. The growing availability of micro-data (see Bartelsman and Doms 2000) offer solutions to some of these problems. With wages dependent on both worker characteristics (age, sex, education/skill) and establishment characteristics (plant-size, multi-establishment status, capital investment/technology), matched employer-employee data would be ideal for analysis of the trade-inequality link.

Unfortunately, the lack of matched employer-employee data has severely limited such efforts. The only existing large-scale data set combining individual worker information and plant data in the US is the Worker-Establishment Characteristics Database (WECD) developed by Troske (1998). Use of the WECD has been limited to examining the relationship between productivity and wage differentials or wages and firm size (e.g. Hellerstein et al. 1999; Troske 1999); it has not been applied to investigate the impacts of trade. The Census Bureau's ongoing Longitudinal Employer-Household Dynamics (LEHD) program will certainly help fill the void. However, given the sheer complexity and magnitude of this project, it will be some time before a comprehensive (all state) and fully operational data set is complete (Abowd et al. 2004), not to mention readily accessible to researchers.

Thus, to more carefully explore the trade-inequality link, a matched employer-employee database has to be constructed. We developed such a database for the Los Angeles Consolidated Metropolitan Statistical Area (CMSA) for 1990 and 2000. The steps involved in this process are outlined below.

Because there are no variables in the US Census Bureau's products that directly link workers to individual business units, connections have to be produced. We establish these by exploiting information on the industry and census tract of work and plant location contained in various US Census Bureau products. Specifically, the matched employee-employer data set is constructed from three different sources:

- Longitudinal Research Database (LRD);
- Standard Statistical Establishment List or Business Register (SSEL);
- One-in-six sample long form of the Decennial Household Census (Decennial).

The Census Bureau's Longitudinal Research Database provides an incredibly rich set of information on manufacturing establishments and is the only source of data on real, as opposed to estimated, US exports at the sub-national level (see McGuckin and Pascoe 1988 for more details). Employing the LRD in years for which a Census of Manufactures is conducted (years ending in a two or seven) provides data for the population of manufacturing establishments in the US, approximately 350,000 records in 1997. The Business Register (SSEL) contains street level addresses for each of the establishments in the LRD, as well as non-manufacturing establishments, and is available annually. The one-in-six long form of the Decennial Household Census provides detailed information on individual person characteristics such as age, gender, education, race, nationality and income, as well as sector and place of work, if applicable. As its name suggests, the long form samples approximately one of every six individuals or households. A set of weights accompanies the one-in-six data that allows construction of populations of individuals along with their characteristics for designated regions. The Decennial is only available for 1990 and 2000.

The matching of workers to establishments across the LRD and Decennial data sets is done in a series of general steps (for both 1990 and 2000). The *first* stage of the employee-employer matching procedure involves selecting a sub-sample of manufacturing plants and worker records from the raw data files for the Los Angeles CMSA (Los Angeles, Orange, Riverside, San Bernardino and Ventura counties). This is done in the years for which the one-in-six long form of the Decennial Household Census is produced -1990 and 2000. Only workers employed in manufacturing plants are retained for the matching process. Because LRD data are unavailable for 1990 and 2000, we employ manufacturing plant data from 1987 as a surrogate for 1990 and manufacturing data for 1997 as a surrogate for 2000. Given the timing mismatch between datasets, we acknowledge the possibility that establishments may have altered their workforce during those three years. However, it is unclear whether such changes in aggregate will introduce significant bias in the results discussed below.

Administrative Record plants were dropped from the sample because they do not contain real data. After 1963, the Census Bureau exempted small, single-plant firms from completing the Census of Manufactures. These small firms were designated as Administrative Record (AR) cases and data for these firms are imputed from industry averages and other information from the Internal Revenue Service and the Social Security

Administration. The AR cases typically represent less than 2% of industry output. The AR establishments tend to be relatively small and so the resultant sample will be somewhat biased toward larger producers and those that are part of multi-unit firms.

Although the LRD files include a vast array of information on plant characteristics, they are stripped of name and address information below the metropolitan area or county level. In order to find the street-level addresses for each manufacturing plant, the LRD must be linked to the SSEL that contains the street-level address information. This linking is straightforward and exploits unique permanent plant numbers found in both files.

In a *second* step, a Geographic Information System (ARC View GIS 3.2 for Unix) is used to geocode and identify the census tract within which each manufacturing plant address is located. It would be preferable to employ the higher resolution street-level address data, but worker data from the Decennial identifies place of work down to the census tract level only. Census tracts are the highest resolution geographic data consistent for all regions and both time periods in both worker and plant records. Note that census tract boundaries shifted between 1990 and 2000 and so the analysis here employs consistent 2000 census tracts.

Finding census tracts of operation for every manufacturing plant is not possible because of errors in the SSEL address data, either in the form of incomplete or inconsistent location information, non-existent or missing zip codes or the use of P.O. boxes instead of the physical location of the establishment itself. In analysis of this problem, Breau and Rigby (2006) report that about 10-20% of establishments cannot be geocoded. These establishments are dropped from the analysis.

Further, since the goal of this exercise is to link individual workers to unique manufacturing establishments by industry and census tract of worker/plant location, we delete all records where more than one manufacturing plant in a given industry is found in the same census tract. Doing so ensures that we do not misallocate workers between plants.

The *final* step is to link workers and manufacturing plants using common industry and location identifiers. We emphasise that the resulting match assigns workers to a unique establishment. To merge the manufacturing establishment data with individual worker characteristics taken from the Decennial, requires standardizing the industry definitions in each data set. Industries in the LRD are classified according to 1987-based 4-digit Standard Industrial Classification (SIC) codes, whereas industries in the Decennial are classified using a different scheme. In many cases the Census categories are roughly equivalent to 3-digit SIC codes so building a bridge between the classification schemes is relatively straightforward, especially for the 1987 LRD and the 1990 Decennial. Bridging the 1997 LRD and 2000 Decennial industry codes is more difficult because the latter is based on the 1997 North American Industry Classification System (NAICS) classification. This matching takes two steps. First, the LRD's 1987-based SIC codes are converted to 1997 NAICS codes using the Census Bureau's standard correspondence tables (http://www.census.gov/epcd/www/naicstab.htm). Second, the 1997 NAICS codes are converted to 2000 Census code equivalents yielding a total of 82 possible industry categories. Finally, an industry code crosswalk (http://www.census.gov/

hhes/ www/ioindex/indcswk2k.pdf) is used to make the 1990 and 2000 Decennial codes consistent through time.

Evidence of Increasing Wage Inequality in Los Angeles, 1990-2000

The final matched employee-employer sample for Los Angeles contains information on 17,043 workers across 2,835 manufacturing plants in 2000. Consistent with the employee-employer matched data generated by Troske (1998), our final matched data is biased toward larger manufacturing plants and the usual characteristics displayed by such plants. It is unclear whether this sampling bias alters the relationship between imports and wage inequality in the matched data relative to the original population.

From this dataset, we are able to generate a series of indices to show how wage inequality in Los Angeles has evolved over the last decade. Table 2 shows the value of the Gini coefficient, the Theil entropy index and the Atkinson index for 1990 and 2000, as well as the percentage change in these indices from one period to the next. Each measure of inequality is calculated from the annual wages and salaries data of individual workers reported in our matched dataset. Wages and salaries data reflect a person's wages, salaries, commissions, tips and monetary bonuses received from all jobs the year prior to the actual Decennial Census year. We analyze earnings data instead of a broader definition of income (that typically includes dividends, rents, public transfers and other income from non-wage sources) because of our interest in the possible impacts of international competition on local labor markets.

[Insert Table 2 about here]

The indices reported in Table 2 reflect three different classes of inequality measures, each with different assumptions and "sensitivities". The Gini coefficient, arguably the most commonly used measure of inequality because of its ease of interpretation, tends to be most sensitive to changes in the middle of the income distribution, whereas the Theil and Atkinson indices tend to be more sensitive to changes at the bottom of the distribution (Coulter 1989; Jenkins 1991). Regardless of the index used, wage inequality in Los Angeles increased through the 1990s. The Gini reports an increase in wage inequality of approximately 9% from 1990 to 2000, the Atkinson index shows a gain of 11%, while the Theil indicates an increase in inequality of some 20%.

Indices of Foreign Competition

In order to link inequality to trade, a measure of trade competition is required. Three measures of foreign competition are developed from National Bureau of Economic Research (NBER) data and from the work of Bernard et al. (2006) and Feenstra et al. (2002). Real, as opposed to estimated, US import data for individual industries are only available at the national level. Various branches of the Department of Commerce provide some state data, but not across a consistent and detailed set of manufacturing sectors. The Massachusetts Institute for Social and Economic Research (MISER) provides estimates of sub-national data by industry, but these estimates are based on a very crude methodology. Real export data are available in the Longitudinal Research Database discussed below. There is no other source of real sub-national export data. Estimates of such from shippers declarations are unreliable and do not necessarily reflect production location.

National data on U.S. merchandise exports and imports at the 4-digit industry level of the Standard Industrial Classification (SIC) come from Feenstra et al.'s (2002) international trade dataset, that is spliced over two different time periods: (1) 1958-1994 containing trade files based on 1972 4-digit SICs and (2) 1989-2001 containing trade records based on 1987 4-digit SICs. Of the 459 possible 4-digit SIC industries, import and export values cannot be computed for 73 industries because the international transactions recorded via the Harmonized System (HS) codes cannot be assigned a unique 4-digit SIC. The result is a maximum of 386 possible "super-SIC4" trade-industry classifications.

To analyze the impacts of international trade on wage inequality, the first measure employed is an index of trade openness for each industry,

$$TRADOP_{it} = \left(\frac{EXPORTS_{it} + IMPORTS_{it}}{SHIPMENTS_{it}} \right),$$

where $EXPORTS_{it}$ and $IMPORTS_{it}$ represent the values of U.S. exports and imports for industry i at time t (1990, 2000) and where $SHIPMENTS_{it}$ represents the total value of shipments, taken from the Bartelsman, Becker, Gray NBER-CES manufacturing industry database (Bartelsman et al. 2000).

A second measure focuses solely on import competition, defined as

$$IMPOP_{it} = \left(\frac{IMPORTS_{it}}{SHIPMENTS_{it}} \right).$$

A third measure of trade competition is based on Bernard et al.'s (2006) work that captures US exposure to import competition from low-wage countries. This index focuses on the geographical origins of imports to the US and incorporates import data from 52 low-wage countries. The value share of total (VSH_{it}) US imports originating from these countries is defined as

$$VSH_{it} = \left(\frac{IMPORTS_{it}^{LWC}}{IMPORTS_{it}} \right),$$

where $IMPORTS^{LWC}{}_{it}$ represent the value of imports from low-wage countries and $IMPORTS_{it}$ the value of total US imports. Using this value share, a low-wage country import competition index can be constructed as

$$LWC\_COMP_{it} = \left(\frac{VSH_{it} * IMPORTS_{it}}{SHIPMENTS_{it}} \right).$$

Models and Estimation

The central focus of this paper is how trade affects wage inequality. In order to examine this question, we estimate two regression models. The first looks at the relationship between foreign competition and the wages of workers in Los Angeles across different educational categories and is specified as:

Model 1

$$\begin{aligned} \ln AWS_{jit} = \alpha + \beta_1 AGE_{jit} + \beta_2 MALE\_D_{jit} + \beta_3 RACE\_D_{jit} + \beta_4 NAT\_D_{jit} + \\ \beta_5 \ln SIZE_{jit} + \beta_6 \ln KLRATIO_{jit} + \beta_7 FORCOMP_{jit} + \varepsilon_{jit}, \end{aligned}$$

where the dependent variable (AWS_{jit}), real annual wages and salaries for individual worker j in plant i at time t is a function of the worker's personal characteristics such as age (AGE_{jit}), sex ($MALE\_D_{jit}$), race ($RACE\_D_{jit}$), nativity (NAT_D_{jit}) and the plant characteristics to which he or she is linked, the size of the manufacturing plant ($SIZE_{jit}$), the size of the capital stock per worker in the plant ($KLRATIO_{jit}$) and an industry measure of foreign competition ($FORCOMP_{jit}$).

To capture the effect of foreign competition on skills, note that Model 1 is estimated separately for workers in each of four education categories that are used as a proxy for skills. Education group 1 denotes individuals with less than a high school education. Education group 2 denotes high school graduates. Education group 3 defines individuals with some college but no diploma. Education group 4 identifies workers with at least a BA/BSc degree. Our primary interest is on the foreign competition coefficient, β_7, that theory suggests should be negative and significant for workers toward the bottom end of the education/skill distribution. Estimation of Model 1, over the four different education groups, is performed for 1990 and 2000 to see how the impact of trade has shifted over the 1990s, a period during which the ratio of imports to GDP, especially from developing economies, increased substantially in the US. We also estimate the model using all three measures of foreign competition.

The worker characteristics included in the model cover a standard set of characteristics that theory suggests impact wages (Machin et al. 1996; Anderton and Brenton 1999). Similarly, in past work, plant characteristics such as size and the level of capitalization are found to be correlated with wages (Baldwin 1995; Troske 1999). The KLRATIO variable also serves as a measure of technology within the plant. Note also that the error term in Model 1 is not assumed to possess the usual properties. This is discussed in more detail below.

The second model examines the influence of foreign competition on the relative wages of less-skilled workers versus high-skilled workers (i.e. wage inequality) in Los Angeles and is specified as:

Model 2

$$\ln DIFF_{jit} = \alpha + \beta_1 AGE_{jit} + \beta_2 MALE\_D_{jit} + \beta_3 RACE\_D_{jit} + \beta_4 NAT\_D_{jit} + \\ \beta_5 \ln SIZE_{jit} + \beta_6 \ln KLRATIO_{jit} + \beta_7 FORCOMP_{jit} + \varepsilon_{jit},$$

where the terms on the right-hand side are the same as those in Model 1. The dependent variable in Model 2 more directly addresses the question of the impacts of trade on wage inequality. $DIFF_{jit}$ measures the difference between the annual wages and salary of an individual worker in educational category 1 or 2 and the average annual wage and salary of workers in educational category 4 within the same industry. Thus, *DIFF1-4* (*DIFF2-4* etc) measures the difference in annual earnings between individual workers in education category 1 (2 etc) and the average earnings of workers in education category 4. In other words, instead of looking at the distributional characteristics of different shares of workers in the matched dataset, $DIFF_{jit}$ is a simple deviation measure capturing the difference between the annual wages and salary of workers in different educational categories. The comparative standard, in this case is not the usual mean of the entire distribution of workers (see Coulter 1989) but only that of workers in educational category 4. This difference in earnings is computed on workers within the same industry.

The coefficients to be estimated in Model 2 reveal how that earnings difference is influenced by worker and plant characteristics, by skill-biased technical change and by foreign competition. Interest in Model 2 will focus on β_6 as well as β_7. Existing literature on the impacts of trade on earnings inequality suggest that both coefficients will be positive, especially when the earnings difference, as a measure of inequality, compares workers in the lowest educational category with those in the highest. However, that work has rarely included measures of technical change and foreign competition in the same model, and has not to date employed reasonable measures of skills and controls for additional worker and plant characteristics. The relative sizes of the trade and technology coefficients are of interest, along with how those coefficients move between 1990 and 2000.

Models 1 and 2 are estimated using ordinary least squares (OLS). Note that the error term in both models is not assumed to possess the usual properties, for individual workers employed by the same establishment share common measures of establishment characteristics, and because import data, available only at the industry level, are shared by all establishments within a particular industry. For these reasons standard errors are biased downwards (Moulton 1990). Consider the following standard linear model,

$$\mathbf{y} = \alpha + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

where $\mathbf{y}$ is an *n* x *1* vector of observations on a dependent variable, $\mathbf{X}$ is an *n* x *k* matrix of explanatory variables, $\boldsymbol{\beta}$ is a *k* x *1* vector of parameters to be estimated, α is an unknown scalar and $\boldsymbol{\varepsilon}$ represents an nx1 vector of random disturbances. Typically, we assume that $E(\varepsilon) = 0$ and that $E(\varepsilon\varepsilon') = \sigma^2$. However, when aggregate data are distributed across micro-level units it is likely that there is substantial correlation of disturbance terms across those units that share the same values of the aggregate variable. In this case, we know

$$E(\varepsilon\varepsilon') = \sigma^2\mathbf{V} = \sigma^2[(1-\rho)\mathbf{I}_n + \rho\mathbf{ZZ}']$$

where ρ is the intraclass correlation of the disturbances, that is the correlation of elements of ε that share the same value of the aggregate variable (belong to the same aggregate group), and $\mathbf{Z}$ is an *n* x *p* matrix of 0-1 indicators indicating membership in each of the p groups of the aggregate variable. When applied to data with correlated disturbances, coefficient estimators are unbiased, but inefficient, while standard errors are biased. Therefore, the true variance-covariance matrix of the OLS estimator of $\boldsymbol{\beta}$ is no longer $\sigma^2(\mathbf{X'X})^{-1}$, but rather $\sigma_2(\mathbf{X'X})^{-1}\mathbf{X'VX}(\mathbf{X'X})^{-1}$.

This correction for correlated disturbance terms is employed throughout the estimation. We correct for possible heteroscedasticity using the Huber-White sandwich estimator throughout the analysis.

4. RESULTS

Changes in Wage Levels

Tables 3 and 4 below reveal how foreign competition impacts the wages of workers with different levels of education in the Los Angeles CMSA in 1990 and 2000. Both tables report results for the three different measures of foreign competition defined above. Recall that the first of these measures is trade openness (*TRADEOP*), the second is import competition (*IMPOP*) and the third is import competition from low-wage countries (*LWC_COMP*). The number of worker observations in these tables is larger than the actual number of workers in the matched employer-employee data because of the use of worker observation weights taken directly from the long form of the Decennial Census. Estimation of these same models using unweighted data produces almost identical results.

[Tables 3 and 4 about here]

Tables 3 and 4 show that worker characteristics impact wages in a fashion that is well-known and consistent with theoretical expectations (see Ashenfelter et al. 1986). Across all educational categories, wage levels increase with age, they are higher for male versus female workers, for white versus non-white workers and for native-born versus foreign-born workers. Similarly, there is a positive establishment-size wage effect, consistent with the findings of Brown and Medoff 1989, and worker wages increase with the capital-labor ratio.

The results generated for our measures of foreign competition are most important given the rationale of this paper. Table 3 reveals that all three indices of foreign competition significantly reduced the wages of workers with the lowest level of education across the manufacturing sector of the Los Angeles CMSA in 1990. In other words, we find clear evidence that an increase in international trade has a negative effect on the wages of workers in educational category 1. Of all three, the largest impact comes from the measure of import competition (*IMPOP*). In 1990, as we move up the education/skills ladder, the wages of workers with a high school diploma (education category 2) or with higher levels of education are not significantly influenced by imports. Thus, workers with at least a high school education appear to be immune to the effects of import competition. Interestingly, the coefficient estimate for trade openness becomes positive and significant for workers with some college education (i.e. education categories 3 and 4). We suspect that these significant, positive coefficients are capturing the benefits of exports on the wages of more skilled workers.

The results from 2000 (Table 4) are broadly consistent with those from 1990. Perhaps most important, Table 4 shows that the impact of trade on wages has climbed the skill ladder. Whereas in 1990 only workers in educational group 1 had wages depressed by trade, by 2000, foreign competition depresses the wages of workers in education groups one and two. This finding raises interesting questions of the future, and of the belief that education insulates workers in the developed world from global competition. With the wage levels of workers in education categories 3 and 4 not significantly affected by trade, the relationship between foreign competition and earnings inequality is clear in these results, if only implicitly.

Changes in Relative Wages

Table 5 provides a more direct measure of the impact of foreign competition on wage inequality in Los Angeles. Recall that the dependent variable in Table 5 measures the difference between the wage of a worker in education category 1 (*DIFF1-4*) or education category 2 (*DIFF2-4*) and the average wage of workers in education category 4. These comparisons are made between workers in the same manufacturing sectors. Once more, Table 5 shows that worker characteristics operate as expected. In general, workers in the lower education categories have wages that move closer to that of the average wages of workers in the highest education category in the same industry, as they get older, if they are male, white and born in the US. Less educated workers found in smaller or larger plants appear to be no closer, in terms of wages, to the average wages of workers in the highest education category.

[Tables 5 and 6 about here]

Of much more interest, in 1990 the difference between the wages of the least skilled workers and average wages of the most highly skilled workers increased significantly as the capital-labor ratio of the establishment in which the least skilled worker was employed increased. This is evidence of skill-biased technical change: an increase in capital investment per worker raises the wages of the high-skilled relative to the wages of the low-skilled. Increased trade (*TRADEOP*) also widened the gulf between the wages of those at either end of the skill distribution in 1990. The elasticity of wage inequality to skill-biased technical change was almost three times greater than that of trade for workers in education category 1 in 1990.

By 2000 (Table 6), skill-biased technical change no longer has a significant influence on wage differences across education categories, but the influence of trade on inequality has increased. The coefficient estimates for trade openness (*TRADEOP*) are larger in 2000 than in 1990, and the estimates for import competition (*IMPOP*) are now also positive and significant. Table 6 provides strong evidence that through the 1990s the influence of trade on wage inequality increased and overtook that of skill-biased technical change.

These results are extremely important in terms of understanding how foreign competition, in the form of trade pressures, impact wage inequality. Unlike most previous work, the analysis here makes use of micro-data that controls for worker and plant characteristics that are known to influence wages. In addition, the results were obtained using much clearer measures of worker skill (educational attainment) than those typically employed in previous empirical studies. Tables 3-6 show clearly that trade significantly dampens the wages of less-skilled workers and contributes to rising levels of inequality. While the influence of technical change on wages is potentially larger than the influence of trade in 1990, that is not the case, for Los Angeles at least, in 2000.

5. CONCLUSION

Debate over the relationship between international trade and the recent rise in inequality in the US and elsewhere continues to generate much controversy in social sciences and policy circles. As we have seen, the consensus that has emerged among academics over the last 10 to 15 years is that international trade plays a secondary role in explaining changes in relative wages and that skills-biased technological change is most likely the primary driver of inequality. The results presented in this paper challenge these claims.

By exploiting sectoral and geographical information contained in the US Census Bureau’s Longitudinal Research Database and the one-in-six long form of the Decennial Census, we developed a matched employee-employer dataset for the Los Angeles CMSA for 1990 and 2000. This dataset allowed us to circumvent some of the methodological limitations of existing empirical studies of the trade-inequality link, most importantly the failure to adequately measure worker skills and the inability to control for a range of worker and plant characteristics that impact wages.

Our findings confirm the theoretical predictions of Stolper-Samuelson arguments: an increase in foreign competition significantly reduces the wages of less-skilled workers in the Los Angeles CMSA. The wages of more highly educated workers are unaffected by imports and appear to rise with exports. Between 1990 and 2000, the negative impact of import competition moves up the skills ladder, suggesting that higher education may not insulate all workers from the pressures of the global economy over the long-run.

Greater trade openness has a positive and significant impact on wage inequality both in 1990 and 2000. In 1990 skill-biased technological change exerts a larger impact on wage inequality than trade. However, by 2000, skill-biased technological change no longer has a significant impact on inequality, while the impact of foreign competition increases strongly from its 1990 levels. Thus, the impact of trade on wage inequality eclipses the influence of technological change through the 1990s, at least in our study region.

The next step in this analysis is to develop the matched employer-employee data for the US as a whole, for individual states and for selected metropolitan areas. We seek to understand whether or not the results we have presented here hold for the nation, and how the impacts of trade vary across the US space-economy.

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Table 1 – Key Empirical Studies of the Trade-Inequality Link

Author(s) (year of publication)	Area of Study (period)	Remarks	Main Results
Factor-Content Studies			
Borjas, Freeman & Katz (1992)	US (1980-88)	Use CPS data to look at effects of trade and immigration in the effective supply of high school dropouts.	Estimates for 1980-85 suggest that trade contributed to approximately 15% of the rise in wage inequality.
Sachs & Shatz (1994)	US (1978-90)	Focus on imports from developing countries (use production Vs. non-production ratio as skills proxy).	Impact of trade on wage inequality is unclear, very small at best.
Wood (1994)	North-South regions (1980s)	Looks at factor content of imports from less developed countries (uses skilled Vs. unskilled labor proxy).	Trade (combined with induced technological change) can explain a large part of rising earnings inequality in 1980s.
Product-Price Studies			
Bhagwati (1991)			
Lawrence & Slaughter (1993)	US (1980-89)	Production Vs. non-production workers.	Trade has no impact on relative prices of low-skilled to high-skilled labor intensive goods. Impact of technological change more important.
Leamer (1996)	US (1958-91)	Uses Bartelsman & Gray NBER productivity database (looking at production Vs. non-production workers).	Trade has a significant effect on wage inequality in the 1970s, less so in the 1980s.
Baldwin & Cain (2000)	US (1967-93)	13+ years of education as proxy for skilled workers.	Increased import competition does not account for rise in wage inequality during 1980s.

Table 2: Wage Inequality in Los Angeles, 1990-2000

Index of inequality	1990	2000	Percentage change (1990-2000)
Gini coefficient	.391	.426	8.9%
Theil entropy index (GE(1))	.298	.356	19.5%
Atkinson index (AK(1))	.259	.287	10.8%

Note: All inequality indices were generated using Jenkins' (2001) *Ineqdeco Version 1.6* Stata ado-file.

Table 3: Trade and Wage Levels by Education Category, 1990

	Education 1			Education 2			Education 3			Education 4		
	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)
Worker characteristics												
Age	0.017**	0.017**	0.017**	0.016**	0.016**	0.017**	0.017**	0.017**	0.017**	0.017**	0.017**	0.016**
	(17.51)	(17.64)	(17.14)	(16.43)	(16.54)	(16.10)	(16.92)	(16.85)	(14.68)	(15.11)	(15.37)	(10.41)
Male	0.342**	0.340**	0.308**	0.333**	0.332**	0.344**	0.358**	0.358**	0.369**	0.325**	0.329**	0.393**
	(17.70)	(15.68)	(14.18)	(14.64)	(14.61)	(13.67)	(17.90)	(17.89)	(17.76)	(10.09)	(10.07)	(10.48)
White	0.042*	0.041*	0.046*	0.092**	0.092**	0.092**	0.144**	0.143**	0.169**	0.146**	0.144**	0.206**
	(2.02)	(1.98)	(2.18)	(3.71)	(3.70)	(3.33)	(7.25)	(7.16)	(6.94)	(4.25)	(4.24)	(4.83)
U.S. National	0.278**	0.272**	0.256**	0.281**	0.279**	0.294**	0.216**	0.214**	0.214**	0.217**	0.213**	0.272**
	(10.16)	(9.94)	(8.98)	(9.42)	(9.30)	(9.27)	(9.30)	(9.19)	(8.14)	(5.34)	(5.19)	(5.77)
Plant characteristics												
ln(TE)	0.043**	0.041**	0.037**	0.056**	0.056**	0.051**	0.036**	0.037**	0.033**	0.053**	0.051**	0.037**
	(4.97)	(4.76)	(3.87)	(6.84)	(6.96)	(6.13)	(6.53)	(6.44)	(5.35)	(7.67)	(6.63)	(3.83)
ln(KL)	0.088**	0.083**	0.072**	0.054**	0.053**	0.046**	0.056**	0.055**	0.051**	0.078**	0.080**	0.078**
	(8.97)	(8.46)	(6.89)	(4.52)	(4.40)	(3.60)	(4.86)	(4.85)	(4.20)	(5.23)	(5.23)	(4.66)
ln(TRADEOP)	-0.022**			0.010			0.020**			0.031**		
	(2.60)			(1.05)			(2.68)			(3.17)		
ln(IMPOP)		-0.030**			0.002			0.011			0.012	
		(3.93)			(0.28)			(1.79)			(1.31)	
ln(LWC_COMP)			-0.027**			-0.002			-0.007			-0.001
			(5.88)			(0.37)			(1.36)			(0.10)
Constant	1.176**	1.170**	1.146**	1.488**	1.479**	1.445**	1.785**	1.771**	1.682**	1.966**	1.931**	1.877**
	(21.36)	(21.65)	(20.01)	(24.75)	(24.93)	(21.77)	(33.20)	(33.11)	(26.31)	(25.21)	(24.50)	(17.38)
Observations	50260	50260	48196	34173	34173	29084	49785	49785	37983	39682	39682	22193
R^2	0.22	0.22	0.22	0.23	0.22	0.22	0.23	0.22	0.23	0.24	0.24	0.22

Notes: Robust t-statistics in parentheses. * indicates significant at the 0.05 level. ** indicates significant at the 0.01 level. Industry fixed effects included.

Table 4: Trade and Wage Levels by Education Category, 2000

	Education 1			Education 2			Education 3			Education 4		
	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)	ln(AWS)
Worker characteristics												
Age	0.018**	0.018**	0.018**	0.018**	0.018**	0.018**	0.018**	0.018**	0.018**	0.011**	0.011**	0.012**
	(13.92)	(13.94)	(13.56)	(14.51)	(14.51)	(14.97)	(15.45)	(15.42)	(15.54)	(8.34)	(8.34)	(7.68)
Male	0.360**	0.356**	0.342**	0.333**	0.331**	0.324**	0.307**	0.306**	0.311**	0.377**	0.378**	0.388**
	(14.98)	(14.76)	(13.90)	(12.02)	(11.90)	(11.53)	(13.18)	(13.16)	(12.44)	(11.13)	(11.18)	(10.15)
White	0.087**	0.086**	0.085**	0.162**	0.162**	0.155**	0.143**	0.143**	0.154**	0.093**	0.093**	0.108**
	(3.75)	(3.73)	(3.57)	(5.67)	(5.67)	(5.36)	(5.84)	(5.86)	(6.04)	(2.71)	(2.71)	(2.91)
U.S. National	0.103*	0.102*	0.093*	0.129**	0.127**	0.138**	0.154**	0.154**	0.154**	0.277**	0.277**	0.311**
	(2.48)	(2.46)	(2.15)	(4.56)	(4.50)	(4.87)	(5.80)	(5.77)	(5.64)	(7.28)	(7.27)	(8.34)
Plant characteristics												
ln(TE)	0.043**	0.043**	0.040**	0.041**	0.042**	0.038**	0.044**	0.044**	0.042**	0.039**	0.031**	0.029**
	(3.69)	(3.79)	(3.41)	(4.79)	(4.82)	(3.96)	(6.49)	(6.49)	(5.12)	(5.85)	(2.61)	(2.46)
ln(KL)	0.056**	0.055**	0.048**	0.052**	0.051**	0.049**	0.027*	0.027*	0.027*	0.030*	0.031**	0.029*
	(4.68)	(4.66)	(3.97)	(3.56)	(3.46)	(3.46)	(2.27)	(2.24)	(2.10)	(2.56)	(2.61)	(2.46)
ln(TRADEOP)	-0.020*			-0.013			-0.008			0.019*		
	(2.51)			(1.68)			(1.11)			(2.21)		
ln(IMPOP)		-0.025**			-0.017*			-0.008			0.019	
		(3.53)			(2.42)			(1.18)			(1.93)	
ln(LWC_COMP)			-0.022**			-0.016**			-0.006			0.004
			(4.40)			(3.04)			(1.16)			(0.56)
Constant	1.456**	1.437**	1.434**	1.761**	1.746**	1.705**	2.066**	2.060**	2.026**	2.711**	2.725**	2.592**
	(22.19)	(22.03)	(21.29)	(23.12)	(22.87)	(20.95)	(32.94)	(32.97)	(30.01)	(30.07)	(28.62)	(29.19)
Observations	38856	38856	37355	25780	25780	24415	34370	34370	31918	24857	24857	20739
R^2	0.16	0.16	0.16	0.21	0.21	0.22	0.20	0.20	0.20	0.17	0.17	0.18

Notes: Robust t-statistics in parentheses. * indicates significant at the 0.05 level. ** indicates significant at the 0.01 level. Industry fixed effects included.

Table 5: Trade and Wage Inequality by Education Category, 1990

	Education 1 Vs. 4			Education 2 Vs. 4		
	ln(diff_ed)	ln(diff_ed)	ln(diff_ed)	ln(diff_ed)	Ln(diff_ed)	ln(diff_ed)
Worker characteristics						
Age	-0.008**	-0.008**	-0.009**	-0.011**	-0.011**	-0.011**
	(8.12)	(8.00)	(7.88)	(9.77)	(9.61)	(8.55)
Male	-0.100**	-0.104**	-0.115**	-0.235**	-0.238**	-0.230**
	(3.61)	(3.73)	(4.05)	(6.07)	(6.11)	(5.44)
White	-0.003	-0.004	-0.012	-0.090**	-0.090**	-0.094*
	(0.15)	(0.17)	(0.54)	(3.33)	(2.73)	(2.55)
U.S. National	-0.191**	-0.193**	-0.207**	-0.132**	-0.140**	-0.158**
	(5.75)	(5.79)	(6.14)	(3.46)	(3.62)	(3.95)
Plant characteristics						
ln(TE)	-0.029	-0.209	-0.025	-0.028*	-0.028	-0.048*
	(1.88)	(1.80)	(1.32)	(1.97)	(1.91)	(2.49)
ln(KL)	0.091**	0.089**	0.078**	0.016	0.013	0.025
	(4.84)	(4.61)	(3.77)	(0.65)	(0.51)	(0.91)
ln(TRADEOP)	0.037*			0.037**		
	(2.28)			(2.62)		
ln(IMPOP)		0.019			0.013	
		(1.22)			(0.92)	
ln(LWC_COMP)			-0.011			0.008
			(1.13)			(0.70)
Constant	3.596**	3.570**	3.495**	3.928**	3.895**	3.972**
	(36.57)	(37.01)	(32.19)	(39.84)	(40.25)	(29.49)
Observations	48242	48242	46317	31092	31092	26364
R^2	0.05	0.05	0.05	0.07	0.06	0.06

Notes: Robust t-statistics in parentheses. * indicates significant at the 0.05 level. ** indicates significant at the 0.01 level.

Table 6: Trade and Wage Inequality by Education Category, 2000

	Education 1 Vs. 4			Education 2 Vs. 4		
	ln(diff_ed)	ln(diff_ed)	ln(diff_ed)	ln(diff_ed)	Ln(diff_ed)	ln(diff_ed)
Worker characteristics						
Age	-0.005**	-0.005**	-0.005**	-0.010**	-0.010**	-0.010**
	(5.53)	(5.56)	(5.31)	(7.92)	(7.86)	(7.41)
Male	-0.136**	-0.138**	-0.144**	-0.156**	-0.154**	-0.160**
	(5.70)	(5.77)	(6.11)	(4.80)	(4.74)	(4.63)
White	-0.048*	-0.048*	-0.039	-0.073*	-0.074*	-0.071*
	(2.14)	(2.16)	(1.77)	(2.32)	(2.24)	(2.10)
U.S. National	-0.099**	-0.097**	-0.099**	-0.134**	-0.135**	-0.145**
	(2.92)	(2.85)	(2.91)	(4.24)	(4.26)	(4.45)
Plant characteristics						
ln(TE)	0.035*	0.036**	0.034*	-0.001	0.001	0.007
	(2.55)	(2.62)	(2.45)	(0.11)	(0.04)	(0.51)
ln(KL)	0.021	0.022	0.026	0.005	0.003	-0.003
	(1.56)	(1.61)	(1.95)	(0.25)	(0.18)	(0.14)
ln(TRADEOP)	0.042**			0.058**		
	(2.82)			(4.02)		
ln(IMPOP)		0.030*			0.049**	
		(2.20)			(3.36)	
ln(LWC_COMP)			0.002			0.007
			(0.29)			(0.65)
Constant	3.833**	3.826**	3.766**	4.200**	4.213**	4.132**
	(47.43)	(46.80)	(46.22)	(40.20)	(39.82)	(37.16)
Observations	35848	35848	34546	22867	22867	21738
R^2	0.04	0.04	0.03	0.07	0.06	0.05

Notes: Robust t-statistics in parentheses. * indicates significant at the 0.05 level. ** indicates significant at the 0.01 level.