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Felipe Benguria

July 2018

Institute for the Study of Free Enterprise
Working Paper 15

University of Kentucky
244 Gatton College of Business and Economics
Lexington, KY 40506-0034
http://isfe.uky.edu/

Gatton College of Business and Economics

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July 15, 2018

Abstract

This paper studies the impact of globalization on U.S. earnings inequality in the context of rapidly growing import competition from China. The increase in U.S. inequality during 2000-2007 has been driven entirely by changes within regions}. While the existing literature has established differences in wage growth across regions as a consequence of import competition, understanding the impact of globalization on rising U.S. inequality requires then focusing on its impact on inequality within regions. Exploiting variation in exposure to this unprecedented trade shock across local labor markets I find that import competition causes an increase in earnings inequality. This impact occurs primarily on the lower tail of the earnings distribution. I decompose the variation in regional inequality into changes occuring within and between industries, occupations, earnings deciles, and skill categories. While the relative share of the impact on between- and within-group inequality varies across these various dimensions, in each case the impact of trade on within-group inequality represents a relevant share of the overall impact.

[1] Department of Economics, Gatton College of Business and Economics, University of Kentucky.
Email: fbe225@uky.edu. Website: felipebenguria.weebly.com

1. Introduction

The increase in U.S. imports in the past two decades - driven mostly by imports from China - has had a significant impact on U.S. labor markets. As influential recent research documents (Autor et al. (2013)), local labor markets facing larger degrees of trade exposure have observed larger declines in manufacturing employment and slower wage growth relative to less-exposed regions. Concerns expressed in the public debate appear largely focused on the distributional consequences of this trade shock. While prior research has established that the significant increase in import competition faced by U.S. labor markets in recent decades generates spatial differences in wages, the increase in earnings inequality during the 2000-2007 period occurs entirely within rather than between regions. Motivated by this debate, this paper studies the impact of the increase in import competition from China during the period 1990-2007 on earnings inequality within local labor markets.

Earnings inequality has increased sharply in the U.S. during this period (Autor et al. (2008), Juhn et al. (1993)). A natural and widely researched question is to what extent globalization is behind this pattern, in a context of competing plausible explanations such as technological change, a decline in unionization rates or tax policies ((Autor et al. (2015)). A finer and related point also examined in this paper is through which mechanisms is overall earnings inequality increasing and through which channels is it influenced by import competition.

I study the impact of globalization on U.S. earnings inequality exploiting variation in exposure to this large trade shock across local labor markets. Differently than earlier approaches leveraging variation across industries or occupations, this method allows me to capture the impact of import competition on a wide set of outcomes, including various measures of inequality and its between-group and within-group components. I find that import competition leads to an increase in earnings inequality. A $1000 per worker increase in Chinese import competition leads to a 0.16 standard deviation increase in earnings inequality, defined as the variance of log hourly earnings. This impact is larger on the lower tail of the distribution.

A $1000 per worker increase in Chinese import competition leads to a 0.11 standard deviation increase in the 50/20 earnings ratio and a not statistically significant 0.08 standard deviation increase in the 80/50 ratio. In the 2000-2007 period, this difference is even more pronounced. Further, I find an impact on residual earnings inequality as large as the impact on the variance of raw earnings, indicating that import competition widens inequality within rather than between demographic and skill groups.

Decomposing the variation in regional inequality to changes occuring within and between industries, occupations, earnings deciles, and skill categories provides insights regarding the mechanisms at work. I find that while the exact relative share of the impact on between and within group inequality varies across these various dimensions and periods, in the case of industries, occupations, and educational attainment the impact of import competition on within-group inequality is the most relevant share of the overall impact. During the 2000-2007 period, the impact on the within component is three times larger than the impact on the between component in the case of industries, twice as large in the case of occupations, and almost six times larger in the case of educational attainment.

These results have implications for theoretical models of international trade and labor markets. They lend support to recently developed heterogeneous-firms trade models (Helpman et al. (2010), Egger and Kreickemeier (2009)) in which trade integration leads to an increase in inequality within} industries. At the same time they suggest that models capturing the impact of import competition on inequality based on differences in the relative wage of skilled and unskilled workers capture only part of the total impact on earnings inequality.

These results are also relevant from a policy perspective. They suggest policies seeking to compensate those relatively hurt by import competition will be incomplete if they are based on workers' observable educational attainment as import competition generates inequality mostly within (observable) skill groups. In the same way, policies aimed at reducing inequality generated by import competition should not benefit some industries over others as most of the impact occurs within two-digit industries.

The empirical strategy I use exploits the variation in the growth of import competition from China across industries and the variation across U.S. local labor markets in the composition of their economic activity, following an approach that has been pioneered by Topalova (2007), Autor et al. (2013), Kovak (2013), and McLaren and Hakobyan (2010) among others. This approach is based on the notion that import competition in tradable goods impacts not only workers in the tradable sectors but the entire economy of each region. This approach is more flexible than identification based on variation across industries, since it allows me to study the impact of trade on variables that are not industry-specific, such as inequality. This strategy also allows me to disentangle the impact of trade exposure on inequality within and between industries, occupations, earnings deciles, and skill groups.

My empirical strategy recognizes the possibly endogenous nature of this shock to local labor markets. While the rapid growth of Chinese import competition in the U.S. - and in many other countries - during this period is to a large extent exogenous to developments in U.S. industries and is led by the productivity growth and increased openness of China, the composition of this growth in imports across industries could be partly driven by shocks to U.S. industries that impact both imports and labor market outcomes. To account for this possible endogeneity I instrument for the growth in U.S. imports from China using the growth in imports by a set of twelve other developed economies, following the strategy of Autor et al. (2013).

Related Literature.

This paper is related to a rich literature that examines the distributional consequences of international trade.[2] [3] Earlier work used variation across industries (Bernard and Jensen (1997)) or occupations (Ebenstein et al. (2014)) in exposure to import competition and examined outcomes such as the relative wages of skilled and unskilled workers in these industries or occupations. More recently, Autor et al. (2013) identify the impact of import competition on labor market outcomes based on regional variation in trade exposure. Within regions, they examine wages of individuals with and without college education. Their results do not reject a homogeneous impact across these two groups. Autor et al. (2014) use longitudinal data to track the long-term impact of the ``China shock'' on the cumulative earnings and employment of U.S. workers. They find that workers employed in the early 1990's in industries facing larger increases in import competition during the following two decades earn lower earnings over this period, suggesting the existence of large adjustment costs. Further, they find that most of these losses are concentrated in workers with lower educational attainment.

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[2] .Surveys of this literature include Goldberg and Pavcnik (2004) and Harrison et al. (2011). Goldberg and Pavcnik (2004) is focused on the experience of developing countries undergoing trade liberalization episodes during the 1980's and 1990's. Most studies cited in this survey indicate an increase in inequality (typically captured by skilled to unskilled wage ratios) in these countries as a result of (or at least coinciding with) trade liberalization}

[3] Cross-country studies do not find a clear link between various measures of openness or trade liberalization and inequality (Edwards (1998), Dollar and Kraay (2002)).

Compared to the earlier work leveraging variation across industries or occupations in trade exposure, studying local labor markets allows to examine a wider set of outcomes, including earnings inequality. More closely related to my work, the following papers use variation across local labor markets to study the impact of import competition on inequality, with a similar empirical strategy to mine. Topalova (2007) uses the differential exposure of Indian districts to the 1990's trade liberalization and finds that real per capita expenditure in districts more exposed to trade liberalization grows more slowly in poorer relative to wealthier households. Costa et al. (2016) find an increase in inequality in Brazilian local labor markets more exposed to an increase in Chinese import competition during 2000-2010. For the U.S., Gould (2015) shows that the decline in manufacturing employment in U.S. local labor markets leads to increases in residual earnings inequality. Further, Gould (2015) uses the measure of regional trade exposure created by Autor et al. (2013) as an instrument for changes in manufacturing employment as a robustness check.[4]

This paper is also related to the vast literature that documents the large increase in U.S. earnings inequality since the 1970's (Autor et al. (2008), Juhn et al. (1993)) and examines its causes. This literature highlights several potential determinants for this trend, the main of which are skilled biased technological change, globalization, low skilled immigration, and a decline in unionization. The conclusion that emerges is that while all of these events have an impact on inequality, it is technological change that has had the main, sustained impact since the 1970's. Work measuring the role of each of these elements has typical exploited regional variation to identify their impact on inequality. While most of this literature focuses on the skill premium as an outcome, Gould (2015) focuses on residual earnings inequality. This is relevant as the skill premium explains a small fraction of changes in inequality, while residual inequality explains most of it. Gould (2015) argues that manufacturing decline has an important impact on inequality, and that low skilled immigration reinforces this impact.

[4] Differently than in my paper, Gould (2015) focuses only on residual inequaltiy, does not decompose inequality into between and within group inequality, and uses trade as an instrument for manufacturing decline in a single specification as a robustness check.

Outline.

I organize the paper as follows. In section 2 I describe the individual-level microdata obtained from the U.S. Decennial Census of Population and the American Community Survey and used to compute various measures of earnings inequality. I also describe the construction of measures of exposure of local labor markets to increases in import competition from China. Next, in section 3 I describe the evolution of earnings inequality in the U.S. during this period, document regional patterns in inequality, and decompose overall inequality into within-group and between-group components based on industries, occupations, earnings deciles, or skill groups. In section 4 I report the impact of trade shocks on various measures of inequality, including the impact in different segments of the distribution and the impact between and within industries, occupations, earnings deciles and skill groups. Finally section 5 concludes by discussing the implications of these findings.

2. Data Sources

2.1 Decennial Census of Population and American Community Survey.

The various measures of earnings inequality and its components used in this paper are computed using individual labor market outcomes from the Decennial Census of Population of 1990 and 2000 and the 3-year American Community Survey for 2006-2008 Integrated Public Use Micro Samples (Ruggles et al. (2017)). These data sources include individual characteristics such as age, gender, and educational attainment, and describe employed workers' industry, occupation and earnings. I restrict the sample to workers currently employed with non-missing earnings. Further, the data includes individuals' geographic location at the PUMA (public use microdata area) level. Throughout the paper, earnings refers to hourly earnings. I inflate earnings to 2007 US$. Industries and occupations refer to 2-digit codes. Educational attainment is divided into 16 categories (more aggregate groupings for educational attainment are also explored).

2.2 Trade Shocks to Local Labor Markets.

Trade shocks specific to each local labor market are constructed as follows. These trade shocks capture the rapid increase in import competition from China over the 1990-2007 period. This phenomena accelerated considerably precisely around 1990. During 2000-2007 imports from China increased coinciding with China's entry into the World Trade Organization.

The definition of regions in this analysis seeks to be a good approximation to the concept of local labor markets. For this purpose regions are defined as commuting zones. (Tolbert and Sizer (1996)). The criterion used to define these commuting zones by Tolbert and Sizer (1996) is that work commuting across zones is minimzed.

Outcomes are assigned to commuting zones using a cross-walk obtained from Autor et al. (2013). There are 722 commuting zones in the U.S. mainland. These are considered a good approximation to the concept of local labor market in the existing literature.

U.S. commuting zones vary substantially in their economic structure. The region-specific trade shocks take advantage of this variation and are constructed by weighting the 1990-2000 and 2000-2007 growth in industry-level imports from China with industries' employment shares in each region in the initial year of each period. These shocks are normalized by each industry's national employment. This definition is based on the model of regional economies by Autor et al. (2013)

constructed to capture the impact of changes in trade volumes on labor market outcomes. Specifically region *r* faces a trade shock:

$$\Delta IP_{rt} = \sum_{j} \frac{L_{rjt}}{L_{jt}} \frac{\Delta M_{cjt}}{L_{rt}}$$

In this expression L_{rjt} represents the employment of industry j in region r at time t, L_{rt}represents the total employment in region r at time t and L_{jt} is the national employment in industry j in at time t, where year t corresponds to the start of period. A large share of these regions' workforce is employed in non-tradable sectors. Since the employment weights in equation (1) are not restricted to tradables, regions with a small tradable sector will thus face smaller shocks.

Industry-by-year trade data on U.S. imports from China used to construct these trade exposure measures shocks to U.S. local labor markets is obtained from the United Nations' COMTRADE database. Employment weights for equation (1) are obtained from the County Business Patterns.[5]

Figure 1 shows the variation in exposure to the rise in Chinese import competition across commuting zones. This regional variation is the result of differences in the start of period share of manufacturing employment and the start of period emploment of different industries within the manufacturing sector. In both the 1990-2000 and the 2000-2007 periods, the largest impact is seen in the Northeast, Southeast, and Midwest.

The rapid growth of Chinese import competition in the U.S. during this period is to a large extent exogenous to developments in U.S. industries and has been experienced by many countries. The composition of this growth in imports across industries however could be partly driven by shocks to U.S. industries that impact both imports and labor market outcomes. To account for this possible endogeneity of industry level imports from China I instrument for the growth in U.S. imports from China with the same industry level variable for twelve other developed countries, following again the approach of Autor et al. (2013).[6] This strategy should isolate the effect of U.S. imports from China driven by the growth of Chinese industries than by other shocks to U.S. industries. The instrument is defined as follows, weighting the industry level import growth of this set of other

[5] These data are obtained from Autor et al. (2013)'s dataset.

[6] These high-income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

developed countries ($\Delta M_{rj\,t-1}^{OTHER}$) by the employment weights used in equation (1). These employment weights, however, correspond to the prior decade (as opposed to start of period employment in equation (1)), thus reducing concerns of simultaneity bias.

$$\Delta IP_{rt}^{OTHER} = \sum_j \frac{L_{rj\,t-1}}{L_{j\,t-1}} \frac{\Delta M_{rj\,t-1}^{OTHER}}{L_{r\,t-1}}$$

This instrument is highly correlated with the trade shock defined in equation (1). This indicates that the growth in import competition from China occurs to a large extent in the same industries in the U.S. and in the set of developed countries used to construct this instrument.

An assumption required for this strategy to be reasonable is that imports from this set of developed countries from China are not driven by productivity or demand shocks common to all these economies. This seems unlikely during this period, as China's export boom seems to be driven by falling trade barriers (including its integration into the World Trade Organization) (Branstetter and Lardy (2006)), and increases in its productivity as a result of domestic reforms.

To credibly identify the impact of increasing import competition on local labor markets, an additional assumption is that interregional migration flows respond slowly or in small amounts to this shock. Earlier literature suggests indeed a slow adjustment in population in response to labor demand shocks (Blanchard and Katz (1992)) and in fact Autor et al. (2013) finds no response in local labor population to growth in Chinese import competition.

3. Context: Dissecting U.S. Earnings Inequality

3.1 U.S. Earnings Inequality: 1990 - 2007.

Earnings inequality has seen an important rise in the U.S. during this period. Data from the Decennial Census of Population of 1990 and 2000 and the American Community Survey of 2007 indicates that the variance of log hourly earnings has increased from 0.516 to 0.533 between 1990 and 2000 and to 0.571 in 2007. The 90/10 ratio declined from 1.96 to 1.88 from 1990 to 2000 and increased to 1.97 in 2007.[7] In the upper tail of the distribution, the 90/50 ratio is 1.31 in 1990 and 2000 and increases to 1.33 in 2007. Regarding the lower tail, the 50/10 ratio falls from 1.5 to 1.44 from 1990 to 2000 and rises back to 1.49 in 2007. These trends in earnings inequality has been addressed by a vast literature (see for instance Autor et al. (2008) and Juhn et al. (1993)).

Figure 3 plots the evoultion over time of various percentiles of the distribution of log hourly earnings. Earnings at the 90th percentile have grown significantly faster than those at the 75th and lower percentiles, more so between 2000-2007 than between 1990-2000. During 1990-2000 earnings at the 10th percentile grew faster than those at the 25th, 50th and 75th percentile, but this trend reversed later. During 2000-2007, earnings at the 10th percentile decline strongly, and earnings at the 50th percentile remain flat. Overall, during 1990-2000 the upper half of the distribution widens, while the lower half is compressed. During 2000-2007, both halves expand.

Residual inequality also rises during this period. The variance of residual earnings after controlling for worker's age, gender and educational attainment increases from 0.378 to 0.401 between 1990-2007. Residual inequality explains a significant portion of the rise in overall earnings inequality during this period.

3.2 Earnings Inequality Between and Within Groups.

To understand the sources of the levels and changes over time in earnings inequality I decompose overall inequality into between-group and within-group inequality according to equation (3). I decompose inequality into between and within components based on the following four categories:

[7] This figures correspond to the sample used in this paper and are not restricted to full time full year (FTFY) male workers which is the sample used at times in the literature. The patterns found, however, are similar to those reported in the existing literature.

industries, occupations, deciles of the earnings distribution, and educational attainment groups. Overall earnings inequality in the economy, on the left hand side, is calculated as the variance of log hourly earnings. This is equal to the square of the sum across workers of each worker i's wage (w_i) minus the economy-wide average wage $\overline{w}$. The first term on the right hand side represents between-group inequality and is a function of the difference between a group g's average wage - $\overline{w_g}$ and the average wage in the economy - $\overline{w}$. The second term, capturing within-group inequality, is based on the difference between each worker's wage and the average wage within that worker's employer. For any given year then:

$$\frac{1}{N}\sum_{i}(w_i - \overline{w})^2 = \frac{1}{N}\sum_{g}\sum_{i\in g}(\overline{w_g} - \overline{w})^2 + \frac{1}{N}\sum_{g}\sum_{i\in g}(w_i - \overline{w_g})^2 =$$

$$\frac{1}{N}\sum_{g}N_g(\overline{w_g} - \overline{w})^2 + \frac{1}{N}\sum_{g}\sum_{i\in g}(w_i - \overline{w_g})^2$$

In this decomposition, industries and occupations are defined at the two-digit level. Educational attainmet is split into 4 groups. These are high-school dropouts, high-school graduates, workers with up to 3 years of college, and college graduates.

The results of this decomposition at a nationwide level are shown in table 2. Most of the cross-sectional variation in earnings occurs within rather than between industries (80% in 2000). Changes over time in earnings inequality are driven by changes in the within-industry component during 1990-2000 and are split evenly between both components in the subsequent period. In the case of occupations, again the within component explains most of the cross-sectional variation. However it is the between component that explains most of the changes over time. For deciles of the earnings distribution, the cross-sectional variation is primarily a result of between-decile inequality. The change over time is driven by the within component during 1990-2000 and the between component during 2000-2007. Finally, in the case of educational attainment groups, both inequality at one point in time and changes in inequality are a result primarily of the within component. It is worth noting that during 1990-2000, as overall inequality increases, there is a decline in inequality between educational groups, while inequality within groups rises.

3.3 Regional Patterns in Earnings Inequality.

There is substantial variation across commuting zones in the change over time in earnings inequality during 1990-2000 and 2000-2007. This variation is shown in figure 2. As the maps show, during 1990-2000 the east and west coasts undergo larger increases in earnings inequality. During 2000-2007, the increase in earnings inequality is more evenly spread out across the country, with larger increases in the southeast and midwest along with the coasts.

In the cross-sections of 1990, 2000 and 2007, inequality within commuting zones accounts for more than 90 percent of overall earnings inequality. Inequality within regions accounts for 93 percent of the increase in inequality during 2000-2007, but only 28 percent during 1990-2000. This is a substantial difference between both periods. For this reason I report results separately for each period (as well as combined results for the full sample) when measuring the impact of import competition on earnings inequality in the subsequent section.

Inequality within regions has seen a moderate increase between 1990 and 2000, and a much larger increase during 2000-2007. To inspect changes in the earnings distribution occuring within regions, figure 4 plots various percentiles of the distribution of log hourly earnings after removing commuting zone fixed effects. In this figure, all series are normalized to zero in the initial period. From 1990 to 2000, there is a marked difference between earnings at the 90th percentile, which increases by about 3 percent, and the 75th, 50th, 25th and 10th percentiles, which exhibit little difference between them and remain roughly flat. During the 2000-2007 period, differences widen. While earnings at he 90th percentile remain flat, earnings at all other percentiles fall, especially at the lower tail of the distribution. In particular, earnings at the 10th and 25th percentiles fall by more than 10 percent during this period.

4. Trade Shocks and Inequality

To estimate the impact of trade exposure on U.S. earnings inequality I exploit the geographical variation in exposure to growth in import competition from China across local labor markets during the period 1990-2007. I define measures of exposure to this trade shock specific to each region, as constructed by Autor et al. (2013), and estimate equations relating these trade shocks to the 1990-2000 and 2000-2007 regional change in various measures of earnings inequality and its components. As I established in the previous section, during 2000-2007 the variation in earnings inequality at a national level is almost entirely due to variation within} regions. This means the empirical strategy based on variation in trade exposure across local labor markets is especially able to capture the relevant margin of changes in nationwide earnings inequality in this period.[8]

This type of analysis -measuring the impact of import competition on various measures of inequality including inequality between and within groups - is not feasible using the earlier approaches in the literature that rely on variation in trade exposure across industries (Bernard and Jensen (1997)) or across occupations (Ebenstein et al. (2014)). The strategy used here, based on variation across local labor markets on the other hand, is more flexible and allows studying outcomes that are not industry or occupation specific.

4.1 Trade Shocks and Earnings Inequality

I estimate cross-regional regressions of the following type to asses the impact of trade exposure on inequality. The dependent variable is the change in earnings inequality in each period in each region r. These regressions are estimated separately for 1990-2000 and 2000-2007 or stacking both periods. Earnings inequality is measured as the standard deviation across workers of log hourly earnings in each region. The right hand side variable of interest is the trade shock as described in equation (1), capturing the growth in import competition from China during this period. The growth in U.S. imports from China is instrumented by the measure of imports by non-U.S. developed economies as discussed in the previous section and defined in equation (2).

[8] As shown in table 2, the change in inequality within commuting zones explains 28.4 percent of the overall change in inequality in the U.S. between 1990 and 2000, and 92.8 percent between 2000 and 2007.

I add as a set of controls to this equation, represented by X'_{rt}, various start of period commuting zone characteristics. These include the share of manufacturing employment, the share of population with a college education, the share of population that is foreign born, the share of female employment, the share of employment in routine-intensive occupations, and the average of an offshorability index of individuals' populations.[9] I also include fixed effects for nine census divisions. This implies the empirical strategy compares local labor markets facing different degrees of trade exposure within these geographic divisions. This is the preferred set of controls included in Autor et al. (2013) and used in subsequent work.

$$\Delta\, Inequality_{rt} = \delta_t + \beta_1 \Delta IP_{rt} + X'_{rt}\beta_2 + \varepsilon_{rt}$$

I report in panel A of table 3 the 2SLS results for each period (1990-2000 and 2000-2007) separately as well as for both periods stacked. These show a clear, economically and statistically significant, negative impact of trade on inequality. Regions facing stronger increases in import competition from China see larger declines in inequality. This result is robust to the inclusion of the controls mentioned earlier. The magnitude of the coefficient of interest in the 2SLS regression is such that a \$1000 per worker increase in Chinese import competition leads to a 0.162 standard deviation increase in earnings inequality in the full sample. This coefficient is larger in the 2000-2007 period (0.101) than in the 1990-2000 period, in which it is not statistically significant.

Next I study the impact on residual earnings inequality. The results are shown in panel B of table 3. The coefficients are very similar in magnitude to those obtained earlier using raw earnings. A \$1000 per worker increase in Chinese import competition leads to a 0.163 standard deviation increase in earnings inequality in the full sample. This means the import competition's effect on inequality does not act through changes in the distribution of age and education profits in the labor market.

4.2 Trade Shocks and Inequality Across the Earnings Distribution.

The previous results show that trade exposure in the form of rising import competition has a clear impact on inequality. I now turn to the question of which segments of the earnings distribution are

[9] These variables are obtained from the dataset of Autor et al. (2013).

expanding in response to the trade shock, since changes in overall inequality can mask substantial heterogeneity. For this purpose I use various ratios between percentiles of the earnings distribution as the dependent variable in equation (4). In panels C, D and E in table 3 I report the results for the 80/20, 80/50, and 50/20 percentile ratios. A $1000 per worker increase in Chinese import competition leads to a 0.11 standard deviation increase in the 80/20 percentile ratio in the full sample. The impact on the 50/20 percentile ratio, which captures the lower half of the distribution, is larger than the impact on the upper half, captured by the 80/50 ratio. A $1000 per worker increase in Chinese import competition leads to a 0.114 standard deviation increase in the 50/20 percentile ratio in the full sample, and a 0.081 standard deviation increase in the 80/50 percentile ratio, which is not statistically significant.

I also estimate equation (4) separately on each decile of the earnings distribution. These results are shown in figure 6. The results for the full sample (1990-2007) indicate that increased import competition has a negative, statistically significant impact on the lowest four deciles, and no statistically significant impact for the rest of the distribution. Coefficients for the subperiods 1990-2000 and 2000-2007 are not statistically significant.

Overall, the results indicate that trade widens} inequality at the lower half of the earnings distribution, and has little impact on the upper half.

4.3 Trade Shocks and Inequality Between and Within Groups.

Does the decline in inequality due to this trade shock occur within or between industries, occupations or skill groups? Understanding the type} of inequality generated by globalization is important because it sheds light on the mechanisms at work. This information can help discriminate existing and guide future theoretical work. For instance, in Heckscher-Ohlin type models, workers' wages depend on their skill but do not vary across industries: trade impacts inequality between skill groups. Alternatively in recently developed trade models of heterogeneous firms (Helpman et al. (2010), Egger and Kreickemeier (2009) among others) trade integration leads to an increase in inequality within industries. Understanding the channels through which trade impacts inequality is also relevant from a policy perspective. For instance, policies seeking to compensate workers at a disadvantage from import competition should not use workers' skill as a determinant if import competition generates inequality mostly within (observable) skill groups.

Alternatively, policies aimed at reducing inequality generated by import competition should not benefit some industries over others if most of the impact occurs within industries.

To estimate the impact of import competition on earnings inequality between and within groups, I first decompose inequality into its within-group and between-group components for each region r. For this purpose I use the standard identity in equation (3). I then estimate separate versions of the baseline regression in equation (4) with either between-group or within-group inequality as dependent variables.

The distribution across regions of the between} and within} components in each case are described by the kernel density estimates in figure 5. Panels e) and f) indicate that the distribution of the growth in inequality between industries shifts substantially to the right between 1990-2000 and 2000-2007. The distribution of the growth in within-industry inequality shows a much smaller rightward shift. In the case of occupations (panels g and h), earnings deciles (panels i and j), and educational attainment (panels k and l) the same is true: a larger shift in between-group inequality.

The results of the estimation of equation (4) for each of these outcomes is shown in table 4. In the case of industries (panel A), the trade shock has a larger impact on within-industry than between-industry inequality, although only the impact on within-industry inequality is statistically significant. A \$1000 per worker increase in Chinese import competition leads to a 0.118 standard deviation increase in between-industry inequality and a 0.157 standard deviation increase in within-industry inequality. Restricting the sample to the 2000-2007 period (see columns 5 and 6) the difference in the impact on these two components widens, and the impact on within-industry inequality is statistically significant. In this subperiod, a \$1000 per worker increase in Chinese import competition leads to a 0.107 standard deviation increase in within-industry inequality and a 0.031 standard deviation increase in between-industry inequality.

In the case of occupations (panel B), the impact of the trade shock is also larger on the within component. For 2000-2007, a \$1000 per worker increase in Chinese import competition leads to a statistically significant 0.103 standard deviation increase in within-occupation inequality and a not statistically significant 0.054 standard deviation increase in between-occupation inequality. A similar pattern holds for the full 1990-2007 sample, although in this case the impact on the within component is not statistically significant.

The case of earnings deciles (panel C) is different. Using the fulll 1990-2007 sample, the impact of the trade shock is similar for the between and within components. A \$1000 per worker increase in Chinese import competition leads to a 0.155 standard deviation increase in between-decile inequality and a 0.137 standard deviation increase in within-decile inequality. In the 1990-2000 period the coefficients are somewhat smaller and not statistically significant. In the 2000-2007 period the between-component is twice as large as the within component.

Finally, panel D shows the results for the case of educational attainment groups. Recall that educational attainment is divided into four categories: high-school dropouts, high-school graduates, workers with up to 3 years of college, and college graduates. For the full sample, a $1000 per worker increase in Chinese import competition leads to a statistically significant 0.165 standard deviation increase in within-group and a not statistically significant 0.099 standard deviation increase in between-group inequality.

5. Conclusions.

U.S. labor markets have faced rising import competition during 1990-2007, driven primarily by imports from China. Previous research has established that areas relatively more exposed to this trade shock have experienced reductions in manufacturing employment and lower wage growth. In this paper I examine the impact of rising import competition from China on U.S. earnings inequality. During the 2000-2007 period, the increase in U.S. earnings inequality, part of a broader trend starting in the 1970's is entirely driven by a within-region increase in inequality. That is, earnings inequality increases not because wages in some areas fall behind relative to wages in others, but because in each region wage dispersion rises over time. Exploiting regional variation in exposure to rising import competition allows me then to measure the impact of this shock on several measures of inequality.

The key findings are as follows. First, import competition led to higher degrees of earnings inequality. A $1000 per worker increase in Chinese import competition is associated to a 0.162 standard deviation increase in the variance of log hourly earnings. This impact is more pronounced during 2000-2007 than during 1990-2000. This impact occurs primarily at the lower tail of the earnings distribution. The increase in earnings inequality due to increased import competition is driven by residual earnings inequality. This means the impact on overall inequality is not driven by changes in the age or educational composition of the workforce. The empirical strategy also allows me to decompose changes over time in inequality into changes between and within industries, occupations, earnings deciles, and educational attainment groups. I find the impact on overall earnings inequality to be driven primarily by changes in the within-group component in the case of industries, occupations and educational attainment. This pattern is particularly strong in the 2000-2007 period.

These results have implications for theories of the distributional consequences of globalization. Recent models of heterogeneous firms and workers feature mechanisms through which trade integration leads to higher inequality through changes within industries (Helpman et al. (2010), Egger and Kreickemeier (2009)). The results found lend support to these models. At the same time, many models associate distributional consequences of trade to changes in the relative wage of skilled to unskilled workers. The results found indicate that this approach captures only part of the total impact on earnings inequality, as much of the impact occurs within narrow skill groups.

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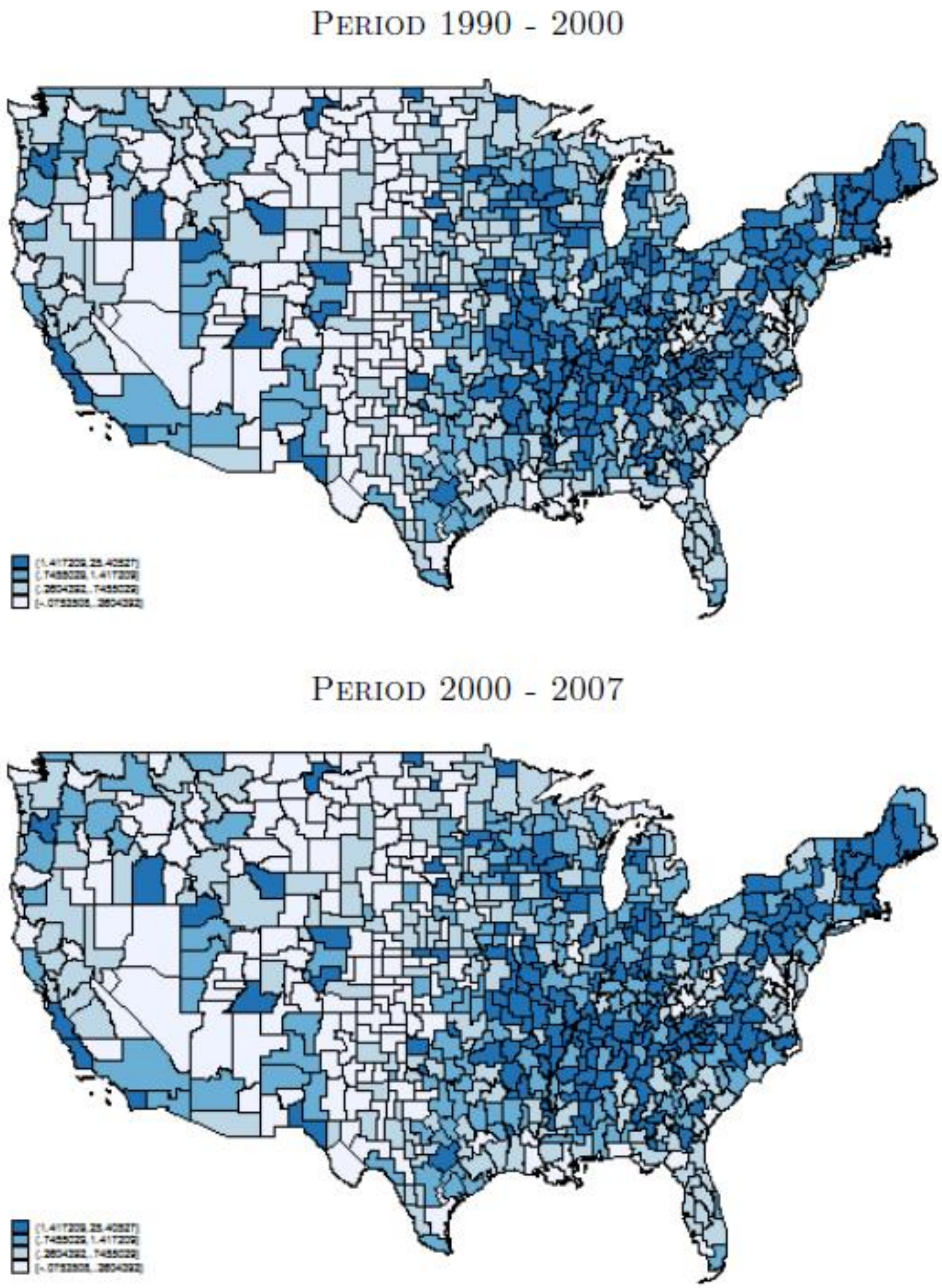
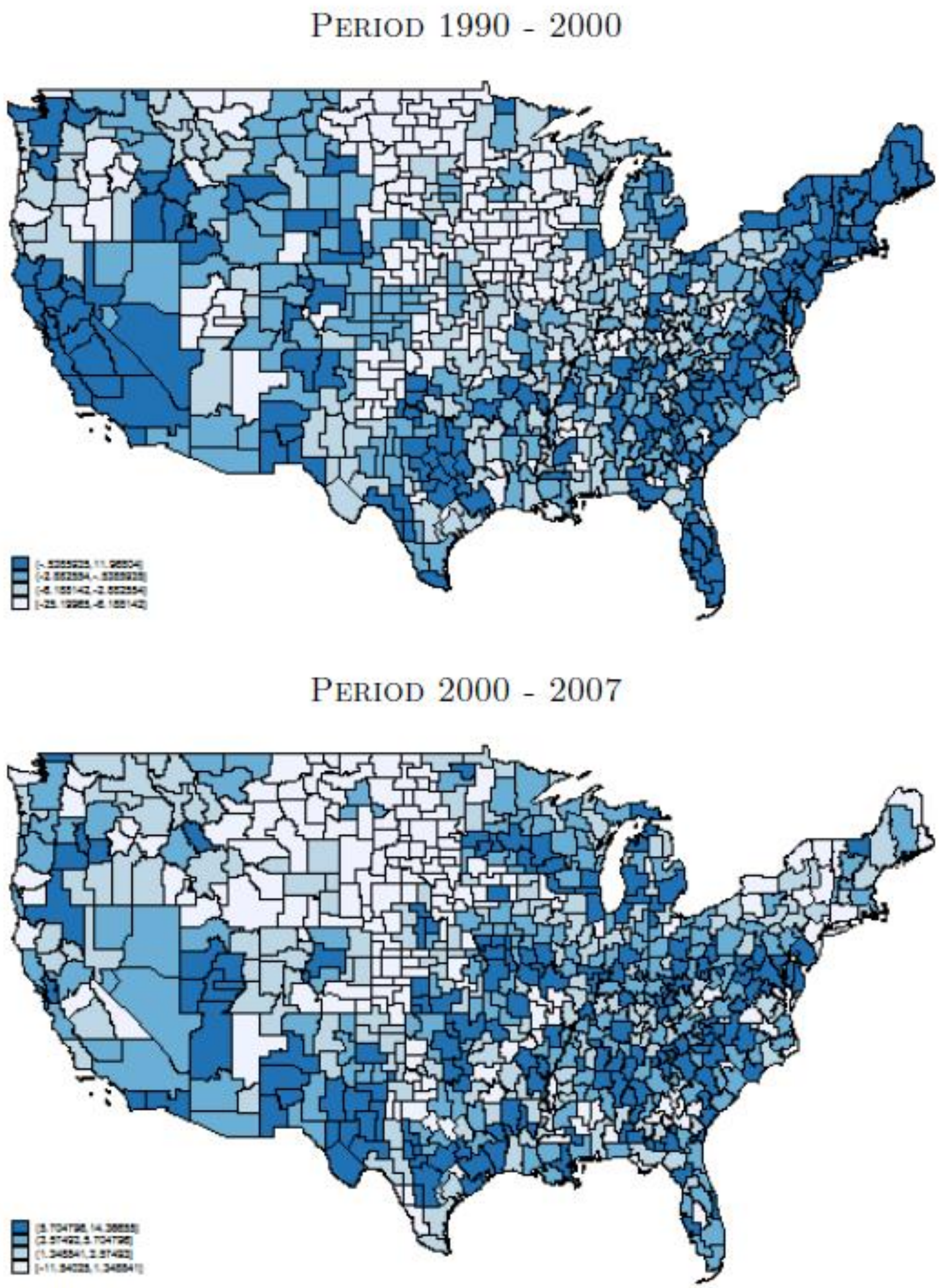
Figure 1: Increase in Chinese Import Competition Across Regions.



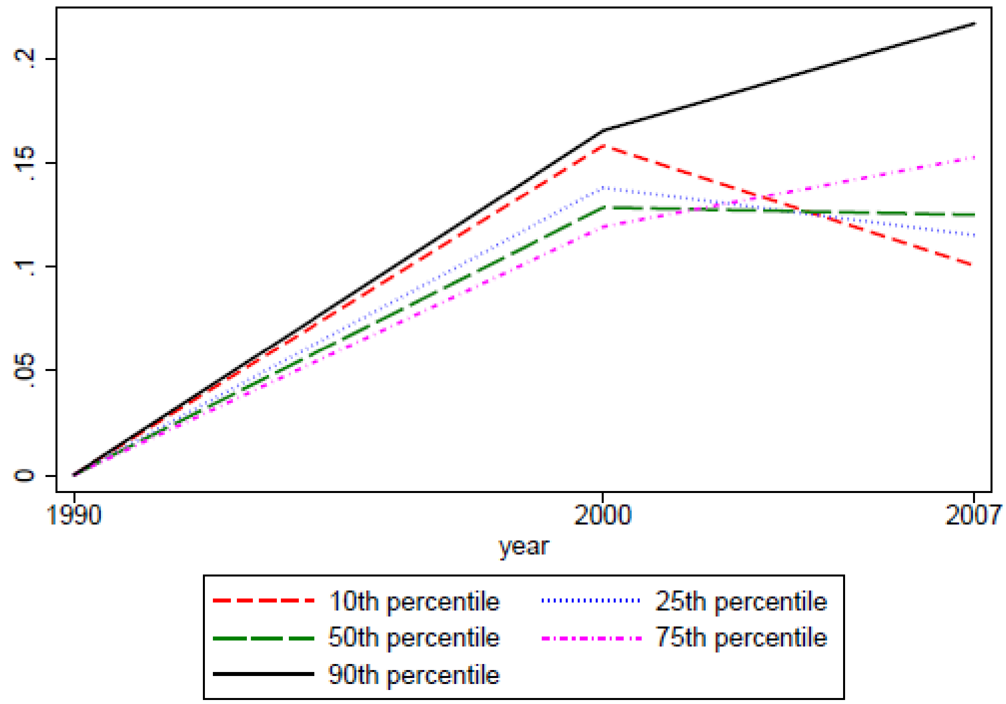
Notes: This map displays the measure of regional exposure to the increase in Chinese import competition in the periods 1990-2000 (top figure) and 2000-2007 (bottom figure). This measure is constructed according to equation (1). See text for details. Darker shades of blue indicate larger increases in Chinese import competition.

Figure 2: Increase in Earnings Inequality Across Regions.



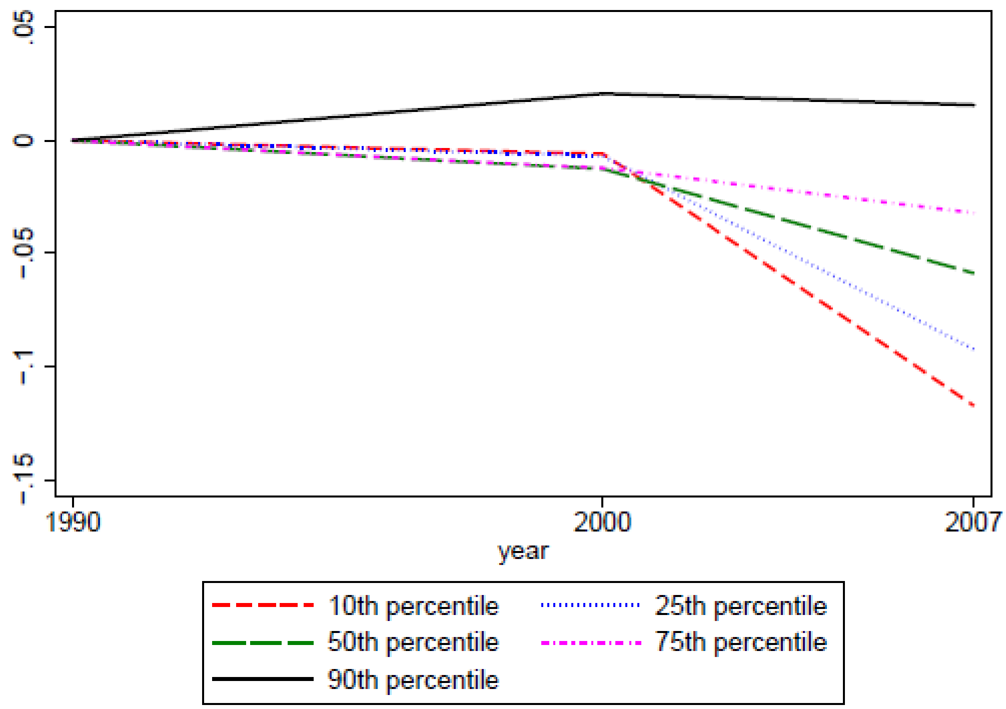
Notes: This map displays the measure of regional earnings inequality (the variance of log wage hourly earnings) in the periods 1990-2000 (top figure) and 2000-2007 (bottom figure). See text for details. Darker shades of blue indicate larger increases in earnings inequality.

Figure 3: Percentiles of the Earnings Distribution Over Time.



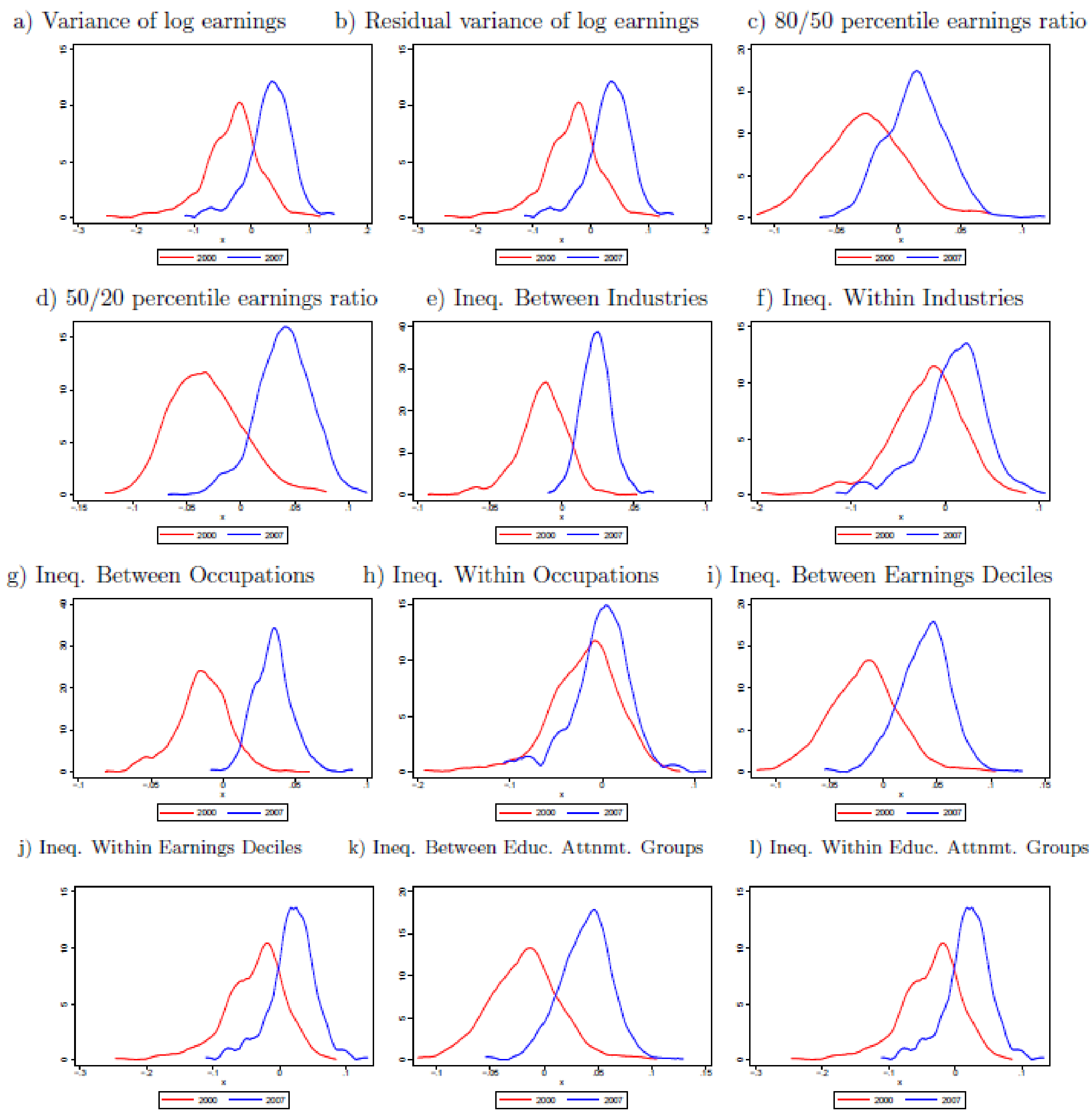
Notes: This figure displays the path over time of the 10th, 25th, 50th, 75th and 90th percentiles of log hourly earnings. All series are normalized to zero in 1990. See text for details.

Figure 4: Percentiles of the Earnings Distribution Within Regions Over Time



Notes: This figure displays the path over time of the 10th, 25th, 50th, 75th and 90th percentiles of log hourly earnings after removing commuting zone fixed effects. All series are normalized to zero in 1990. See text for details.

Figure 5: Distribution of Measures of Within-Region Earnings Inequality.



Notes: This figure displays the kernel density estimates of the distribution across commuting zones of the change over time of: (a) the variance of log earnings; (b) the variance of residual log earnings; (c) the 80/50 percentile earnings ratio; (d) the 50/20 percentile earnings ratio; and inequality between and within industries (e,f), occupations (g,h), earnings deciles (i,j), and educational attainment group (k,l).

Table 1: Summary Statistics.

		1990 - 2000		2000 - 2007	
		Mean	St. Dev.	Mean	St. Dev.
Δ Var(w)		-0.034	0.050	0.033	0.038
Δ Var(w) (Residual)		-0.031	0.047	0.008	0.034
Δ 80-50 pct. ratio		-0.027	0.033	0.014	0.024
Δ 50-20 pct. ratio		-0.032	0.034	0.040	0.026
Δ Var(w)					
	Between Industries	-0.013	0.017	0.024	0.011
	Within Industries	-0.020	0.040	0.009	0.035
Δ Var(w)					
	Between Occupations	-0.014	0.019	0.035	0.013
	Within Occupations	-0.020	0.039	-0.002	0.033
Δ Var(w)					
	Between Earnings Deciles	-0.018	0.033	0.038	0.024
	Within Earnings Deciles	-0.016	0.022	-0.006	0.019
Δ Var(w)					
	Between Educ. Attnmnt. Groups	0.004	0.010	0.014	0.009
	Within Educ. Attnmnt. Groups	-0.038	0.047	0.019	0.035

Notes: This table reports summary statistics for the various measures of changes in regional inequality and its components between 1990 - 2000 and 2000-2007. The first row refers to changes in the variance of log earnings. The second row refers to changes in the variance of residual log earnings. The third and fourth rows refer to changes in the 80/50 and the 50/20 percentiles of earnings. The subsequent rows refers to changes in earnings inequality between and within industries, occupations, earnings deciles, or educational attainment groups, computed as indicated by equation (3).

Table 2: Inequality Between and Within Groups

	1990	2000	2007	Change 1990-2000	Change 2000-2007
Industry					
Between	0.064 (12.0%)	0.061 (11.8%)	0.084 (14.9%)	-0.002 (28.3%)	0.023 (50.7%)
Within	0.466 (88.0%)	0.460 (88.2%)	0.483 (85.1%)	-0.006 (71.7%)	0.022 (49.3%)
Occupation					
Between	0.105 (19.8%)	0.100 (19.2%)	0.137 (24.2%)	-0.005 (61.9%)	0.037 (82.3%)
Within	0.425 (80.2%)	0.422 (80.8%)	0.430 (75.8%)	-0.003 (38.1%)	0.008 (17.7%)
Earnings Deciles					
Between	0.468 (88.3%)	0.466 (89.4%)	0.516 (91.0%)	-0.002 (19.4%)	0.050 (110.0%)
Within	0.062 (11.7%)	0.055 (10.6%)	0.051 (9.0%)	-0.007 (80.6%)	-0.004 (-10.0%)
Educational Attnmt.					
Between	0.060 (11.4%)	0.070 (13.5%)	0.091 (16.0%)	0.010 (-121.2%)	0.020 (45.2%)
Within	0.470 (88.6%)	0.451 (86.5%)	0.476 (84.0%)	-0.018 (221.2%)	0.025 (54.8%)
Commuting Zones					
Between	0.032 (6.0%)	0.026 (4.9%)	0.029 (5.1%)	-0.006 (71.6%)	0.003 (7.2%)
Within	0.498 (94.0%)	0.496 (95.1%)	0.538 (94.9%)	-0.002 (28.4%)	0.042 (92.8%)

Notes: This table reports levels and changes in earnings inequality between and within various categories at the national level. The first three columns of the table report the results of the decomposition of inequality (in equation (3)) measured as the variance of log earnings into within-group and between-group components. These groups are alternatively industries (at the 2-digit level), occupations (at the 2-digit level), earnings deciles, educational attainment (divided into 4 groups), and commuting zones. The last two columns report the change over time in between-group and within-group inequality during 1990-2000 and 2000-2007. The percentage in parenthesis next to each column reflects the contribution of each component to overall earnings inequality.

Table 3: Trade Shock and Overall Earnings Inequality.

	1990 - 2007 (1)	1990 - 2000 (2)	2000 - 2007 (3)
Panel A: Variance of log earnings.			
Δ Imports per Worker	0.162 ***	0.079	0.101 ***
	(0.087)	(0.071)	(0.056)
Panel B: Residual Inequality.			
Δ Imports per Worker	0.163 ***	0.067	0.103 ***
	(0.097)	(0.069)	(0.054)
Panel C: 80-20 ratio.			
Δ Imports per Worker	0.110 *	0.058	0.064
	(0.042)	(0.065)	(0.050)
Panel D: 80-50 ratio.			
Δ Imports per Worker	0.081	-0.092	0.017
	(0.058)	(0.070)	(0.071)
Panel E: 50-20 ratio.			
Δ Imports per Worker	0.114 *	0.174 **	0.072 ***
	(0.031)	(0.086)	(0.042)

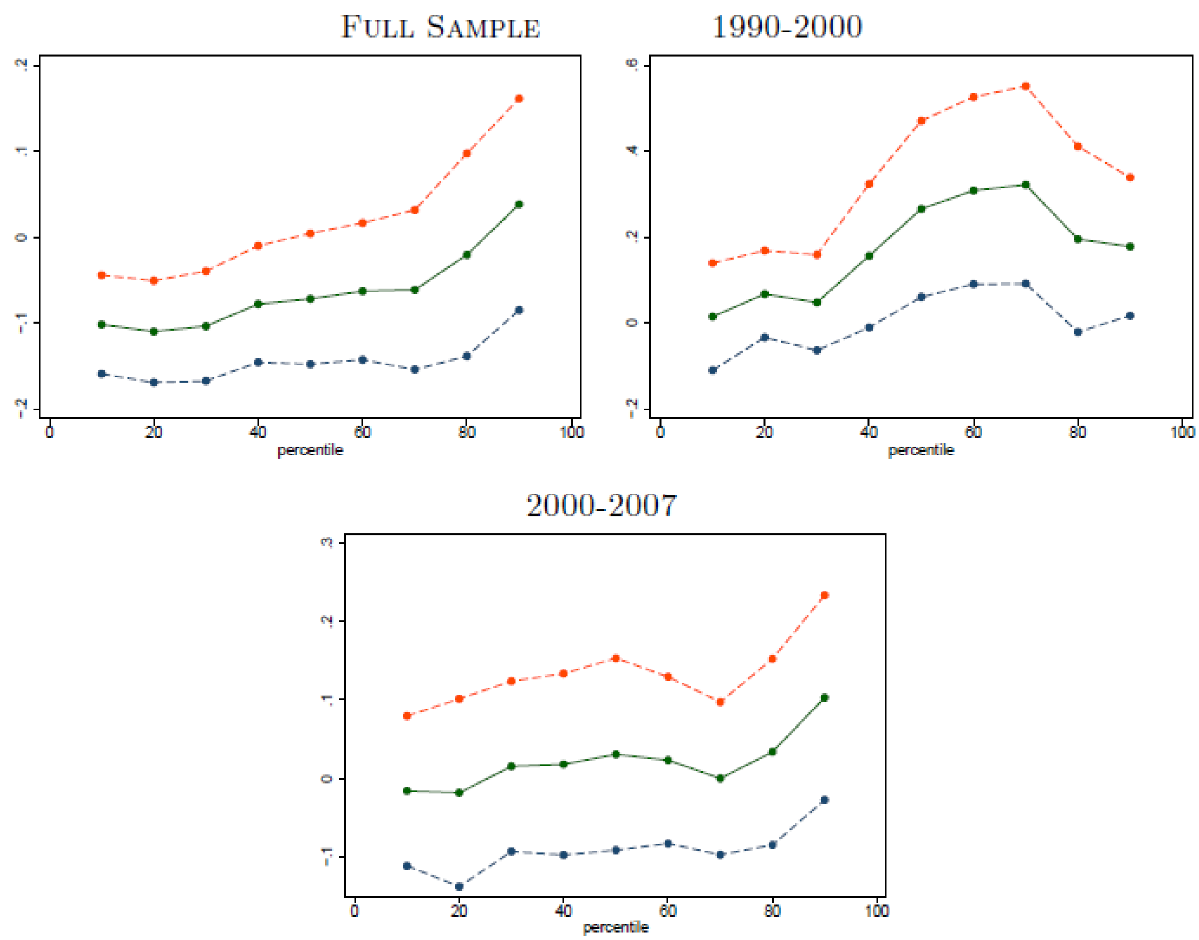
Notes: This table reports the results of the OLS and 2SLS estimation of equation (4). Each observation corresponds to a local labor market (commuting zone). The dependent variables is the variance of log earnings in panel A, the variance of residual log earnings in panel B, the 80/20 percentile earnings ratio in panel C, the 80/50 percentile earnings ratio in panel D, and the 50/20 percentile earnings ratio in panel E. The region-specific trade shock ΔIPr and the instrument are defined in equations (1) and (2). All columns include the following controls: the share of manufacturing employment, the share of population with a college education, the share of population that is foreign born, the share of female employment, the share of employment in routine-intensive occupations, the average of an offshorability index of individuals' populations, and dummies for census geographic divisions. Standard errors are clustered by state. ***, **, and * denote statistical significance at a 1, 5 and 10 percent confidence level.

Table 4: Trade Shock and Inequality Between and Within Groups.

	1990 - 2007		1990 - 2000		2000 - 2007	
	Between	Within	Between	Within	Between	Within
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Industries.						
Δ Imports per Worker	0.118 *	0.157	0.151 ***	0.041	0.031	0.107 ***
	(0.041)	(0.101)	(0.086)	(0.078)	(0.043)	(0.063)
Panel B: Occupations.						
Δ Imports per Worker	0.102 **	0.156	0.158 ***	0.034	0.054	0.103 ***
	(0.042)	(0.096)	(0.084)	(0.074)	(0.055)	(0.056)
Panel C: Earnings Deciles.						
Δ Imports per Worker	0.155 ***	0.137 ***	0.085	0.045	0.110 ***	0.060
	(0.082)	(0.080)	(0.067)	(0.088)	(0.058)	(0.050)
Panel D: Educational Attainment.						
Δ Imports per Worker	0.099	0.165 ***	0.040	0.083	0.019	0.112 ***
	(0.066)	(0.090)	(0.104)	(0.073)	(0.068)	(0.058)

Notes: This table reports the results of the 2SLS estimation of equation (4). Each observation corresponds to a local labor market (commuting zone). The dependent variables are earnings inequality between industries, occupations, earnings deciles, or educational attainment groups in columns 1 and 3 and 5, and earnings inequality within each of these categories in columns 2 4 and 6, as defined in the text. The region-specific trade shock ΔIPr and the instrument are defined in equations (1) and (2). All columns include the following controls: the share of manufacturing employment, the share of population with a college education, the share of population that is foreign born, the share of female employment, the share of employment in routine-intensive occupations, the average of an offshorability index of individuals' populations, and dummies for census geographic divisions. Standard errors are clustered by state. ***, **, and * denote statistical significance at a 1, 5 and 10 percent confidence level.

Figure 6: Trade Shock and Percentiles of the Earnings Distribution.



Notes: This table reports the results of the 2SLS estimation of equation (4) using the 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, and 90th percentiles of log hourly earnings as depedent variable. The solid line corresponds to the estimated coefficients; the dashed lines correspond to the confidence interval. Standard errors are clustered by state.