Import Competition, Technological Change, and Local Employment Dynamics

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Abstract

This paper examines how import competition and technological change affect employment and job creation by startups and existing firms in local labor markets in the US between 2000 and 2011. I do not find a statistically strong negative impact of Chinese import competition on Commuting Zone employment and job creation using the Quarterly Workforce Indicators data. This is in contrast with some of the previous studies that have found that increased exposure to Chinese imports reduces local manufacturing employment in the United States using the County Business Pattern data. On the other hand, technological change has a statistically strong and persistent negative impact on local employment and job creation. In general, this effect holds for both the manufacturing sector and non-tradable sector, and urban and rural areas. However, the effects tend to be statistically more significant among older establishments and less so for startups. I also use the County Business Pattern to examine the impact of import competition and technological change on the growth in the number of small businesses in Commuting Zones. I find strong negative effects of technological change on the number of manufacturing small businesses, but not in the non-tradable sectors.

1. Introduction

In the past several decades, global trade has grown at an unprecedented pace. Decreasing transportation and communication costs, as well as bilateral and multilateral trade agreements have created a world environment more amenable to trade. Trade has helped lift numerous people out of poverty in developing countries, and consumers across the world are able to consume a variety of goods and many of those at substantially lower prices than before. Trade has also created winners and losers within each country as each country specializes in its respective exporting sectors. Though standard trade theory predicts that workers in the losing sectors are able to relocate to the winning sectors, the pace of adjustment has been slow in reality. Especially, the increase in US trade with developing countries has led economists to reexamine the impact of globalization on US labor markets. Recent research has indeed found that import competition does affect local labor markets and lead to differential changes in employment and income (Acemoglu et al. 2016, Autor et al. 2013, Hakobyan and McLaren 2010). At the same time technological change has had a significant impact on the demand for skill. In particular, skill-biased technological change has increased the relative demand for skilled workers. Both the forces of globalization and technological change have affected labor markets around the world in recent decades and have contributed to increasingly diverging economic fortune of places based on skill and industry.

Another recent pattern of the US economy has been the decline in the rate of entrepreneurship and the decline in the share of small businesses in the economy. At the same time, the movement of workers across sectors and regions has been slowing. I do not yet have a full understanding of the causes behind such decline in business dynamism in the US. This paper examines how international trade relates to entrepreneurship activity in the US. In particular, I examine how import competition from China affects (1) employment by startups and existing firms, (2) new job creation by startups and existing firms, and (3) the number of small establishments in local labor markets in the US.

Examining China's import competition has two main advantages from an economics analysis perspective. First is that the growth and size of China's world trade generates a substantial enough variation in trade patterns to examine labor markets in the trading partner countries.

Second is that underlying the growth of China's export was China's decision to become less isolated and to join in the global economy. Such supply side effect of trade is useful for empirically identifying the impact of Chinese import competition on US local labor markets. China's export to the US has grown substantially since the 1990s, and especially more soon after China joined the World Trade Organization (WTO) in 2001. US imports from China, which was $26 billion in 1991, increased to $100 billion in 2000, and then to $483 billion in 2015. Moreover, different regions in the US were differentially affected by China's rise in global trade. Manufacturing regions that directly compete with Chinese imports would be more affected than other regions.

Ex ante, it is difficult to predict whether the impact of Chinese import competition on local entrepreneurship and job creation would be positive or negative. If import competition generates an excess supply of labor, those workers may see entrepreneurship as an alternative to unemployment. Hence, regions that see larger import shocks could see an increase in job creation by new businesses. If entrepreneurship increases with trade shocks, one could further hypothesize that entrepreneurship would increase in sectors that were less impacted by the trade shocks. On the other hand, if the negative impact of trade shocks induces potential entrepreneurs and lenders to have a pessimistic view on the future health of the local economy, entrepreneurship may decrease.

This paper empirically examines this question by constructing a Commuting Zone level panel data utilizing multiple data sources. I create a local level trade shock variable that utilizes the rise in imports from China to the US since 2000. The differences in initial industry composition generate regional variation in the trade shocks. I then merge the regional level trade shock variable with job creation by startups and existing firms using the Quarterly Workforce Indicator data and the County Business Pattern data. By analyzing the impact of Chinese import competition on local job creation and the number of small businesses, I hope to shed light on how globalization affects the patterns of employment and entrepreneurship.

In addition to the impact of import competition, this paper also focuses on the impact of technological change on local employment, job creation, and small businesses. In particular, I examine how the share of employment in routine jobs affects local employment dynamics. By comparing technological change and import competition, the paper aims to shed light on the impact of two major forces that has been affecting jobs and businesses in the United States. In doing so, I hope that the findings of this paper will be helpful for the policy discussion surrounding trade, technological change, and local labor markets and entrepreneurship.

2. Literature Review

A large body of economics research examines the impact of globalization on labor markets. The literature in the 1980s has found little impact of international trade and competition on local labor markets in the US (Feenstra and Hanson 1999). However, trade between developed countries had characterized most of US trade during that period. As China opened up to global trade in the 1990s and joined the WTO in 2001, US trade with China has increased significantly, especially in manufacturing. The increase in US trade with developing countries has led economists to reexamine the impact of globalization on US labor markets. Recent research has found that trade shocks do impact local labor markets and lead to differential changes in employment and income. Autor et al. (2013) finds that rising Chinese import lowers local labor market participation and local wages in the manufacturing sector. In a related study Acemoglu et al. (2016) finds that import competition from China was a contributing factor behind the weak US employment growth during the 2000s. Though the above studies focus on the US labor market responses to China's import competition, other studies have found that globalization and reduced trade barriers in general have an impact on labor markets in developing countries as well, especially, in terms of increasing regional and income inequality. (Topalova 2007, Kovak 2013, Verhoogen 2008). Moreover, the literature also finds negative spill over effects to the non-manufacturing sectors and that the negative labor market effects persist even when social assistance and trade adjustment programs are accounted for (Hakobyan and McLaren 2010, Autor et al. 2013). This project contributes to the literature that examines the labor market effects of globalization, by further probing into whether import competition from China affects job creation by start-ups versus existing firms in the US.

Also closely related is the literature on declining business dynamism in the United States. Pugsley and Sahin (2015), Decker et al. (2014a), and Hathaway and Litan (2014) all show that the share of new firms has been declining in recent decades while the share of older firms has been increasing. Pugsley and Sahin (2015) theoretically show how the two patterns could be related. They show that startup deficit can both drive the patterns of declining new firm share and increasing old firm share in the economy. Papers by Lazear and Spletzer (2012), Hyatt and Spletzer (2013), Decker et al. (2014b) and Davis and Haltiwanger (2014) similarly present evidence of declining business dynamism focusing on the decline in worker reallocation in the

US. Though economists have widely documented declining business dynamism in the US, I do not have a full understanding of the causes behind why business dynamism and entrepreneurship has declined in recent decades. Decker et al. (2014a) suggest that shocks such as technological change or globalization and how firms or workers respond to such shock may have had an impact. This paper sheds light on whether globalization may have had an impact on entrepreneurship.

This paper is also related to the literature that examines entrepreneurship as a catalyst for economic and employment growth. The regional variation in entrepreneurship has motivated researchers to explore the policy and economic growth implications of entrepreneurship. Fritsch (2013) emphasizes the regional context as an important factor that affects the degree to which entrepreneurship impacts economic growth. Acs et al. (2009, 2013a) incorporate endogenous growth theory to entrepreneurship and emphasize how knowledge spillover allows entrepreneurs to identify and exploit new opportunities. Bosma and Sternberg (2014) emphasize the importance of differentiating the types of entrepreneurs and show that urban areas have more entrepreneurs motivated by opportunities in the market. Glaeser et al. (2015) and Lee (2016) directly examine the economic growth implications of entrepreneurship. Using quasi-experimental designs, they both find that entrepreneurship has a positive causal impact on urban employment and wage growth.

The entrepreneurship literature has examined various factors that affect entrepreneurship, which include funding sources (Kerr et al. 2010, Samila and Sorenson 2011), housing collateral (Adelino et al. 2013, Brack et al. 2013), family (Bertrand and Schoar 2006), and peers (Lerner and Malmendier 2011). Rosenthal and Strange (2003) find evidence of agglomeration effects of entrepreneurship, i.e., more firms creating new businesses, in metropolitan areas. To the best of our knowledge, this paper contributes to the literature by examining a new dimension that has not been explored before – how globalization, and in particular, import competition affects local entrepreneurship.

3. Data

3.1 Employment change and job creation

The main dataset used to examine job creation by start-ups and existing firms is the Quarterly Workforce Indicators (QWI) dataset. The QWI is created by the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program, which combines multiple data sources including the Longitudinal Business Database, the Decennial Census, and social security records. The LEHD aggregates the above firm and worker level data to construct a county level data. The QWI reports private sector employment, job creation and job destruction for five establishment age categories - new establishments (0-1 year-olds), 2-3 year-olds, 4-5 year-olds, 6-10 year-olds, and establishments 11 years old or older. The new establishments category (0-1 year-olds) indicates startups. The data construction by establishment age allows us to examine job creation and destruction by startups as well as existing establishments. The QWI covers firms that hire employees and hence do not include the self-employed.

The QWI provides aggregate values by county, quarter and industry, where industry is defined at the 2-digit National American Industry Classification System (NAICS) level. I aggregate the data into annual data taking the average of the four quarters of each year. The fact that the QWI is available at the county level is particularly important for the analysis. The empirical analysis will be at the Commuting Zone (CZ) level. Commuting Zones are clusters of U.S. counties that are characterized by strong within-cluster and weak between-cluster commuting ties and represent a local labor market geography that covers the entire land area of the United States. Commuting Zones are especially useful in defining rural counties, which share a common market, and are increasingly being used as the geographic unit of analysis in economics research that focus on local labor markets.

The main analysis examines the change in employment, job creation, and job destruction for startups over several years. Though the QWI data is available starting in 1990, data for only 4 states are available then. Coverage increases over time and 42 states are covered by 2000, and 50 states (including Washington, D.C.) by 2007. Massachusetts is still not included in the data. Similar to other studies that utilize the QWI data, I use the data starting in 2000 to ensure adequate geographic coverage.[1] The main outcome variables, i.e., the employment change, job creation, and job destruction variables, are scaled by each Commuting Zone's working age population. Scaling the variables ensures that the variables are comparable across time and across firm groups. This is similar to Adelino et al. (2014) and Curtis et al. (2016) who scale by the region's employment.

3.2 The change in the number of small businesses

The paper also examines the change in the number of small businesses in Commuting Zones. For this I use the County Business Pattern (CBP). Unlike the QWI, which provides employment information by establishment age, the CBP data provides the number of establishments by size, that is, the number of employees. For the purpose of this paper I focus on small establishments with employees less than 20 employees. I believe this cutoff would in general include entrepreneurs, in addition to existing small businesses in the economy. I examine all small businesses in the commuting zone, as well as those specifically in the manufacturing sector and non-tradable sector.

3.3 Local import exposure from China

Information on US import from China comes from the United Nations Commodity Trade Statistics Database and can be mapped to four-digit SIC industries. To calculate the imports per worker in each Commuting Zone, I first use the County Business Patterns to construct Commuting Zone employment numbers by industry. The Commuting Zone level employment data is then merged with the Chinese import data by industry. I distribute the change in US imports from China in each industry to each Commuting Zone based on the industry employment share in that Commuting Zone relative to the entire US, and then create a per worker measure by dividing by the Commuting Zone employment. Autor et al. (2013) first introduced this trade shock measure at the commuting zone level. Section 4 describes the construction of this variable in more detail.

The UN Commodity Trade Statistics Database is also used to calculate the other country imports of Chinese goods, which is later used to construct a predicted value of US imports from China.

[1] States not included are District of Columbia, Arizona, Mississippi, New Hampshire, Arkansas, Wyoming, Kentucky, Alabama., and Massachusetts.

The other countries are composed of several high-income countries to reflect similar tastes as the US and include Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. These are a set of high-income countries in the UN Commodity Trade Statistics Database that have trade statistics with China over the same time period. Using a procedure similar to that for the US, I distribute the change in other country imports from China in each industry to each Commuting Zone.

3.4 Local exposure to technological change

One of the main objectives of the paper is to compare the impact technological change and import competition on local employment dynamics. The measure I use to proxy technological change is the share of routine task occupations that are susceptible to automation in the Commuting Zone. This measure was constructed by Autor and Dorn (2013). They measure the degree to which each Commuting Zone was historically specialized in routine and codifiable (tasks that can be turned into repeatable processes) jobs based on the occupations in 1980. Such routine and codifiable jobs are susceptible to computerization and include both white collar jobs that involve routine information processing and blue collar jobs that involve repetitive physical movement.

3.5 Control variables

The Commuting Zone level data on job creation by startups and import competition by China are merged with a number of other datasets to construct the full panel data with control variables. Annual county level population data from the Census Bureau's Population Estimates Program is used to construct the Commuting Zone level population by year. I then create the percentage of population working in manufacturing, percentage of college-educated population, percentage of female population, and percentage of foreign-born population in the Commuting Zone. The manufacturing population share is controlled to account for the fact that Chinese imports primarily compete with manufacturing goods in the US. The other variables reflect the entrepreneurship literature's general finding that entrepreneurship is higher among college-educated individuals and immigrants, but lower among the female population. I also include the nine census division dummies to control for unobserved regional characteristics that could affect the employment dynamics of startups.

4. Sample Construction and Summary Statistics

4.1 Sample construction

To construct the sample used in the analysis I first aggregate the county-industry-quarterly level QWI data to an annual county level data. In constructing the employment numbers I take the average over four quarters each year. To construct the annual job creation and destruction variables I take the sum of the quarterly values each year. I also aggregate the data so that I have the corresponding variables for all industries, manufacturing industries, and non-tradable industries. The QWI data categorizes industries in 2 digit NAICS codes. The non-tradable sector is comprised of retail trade (NAICS 44-45) and accommodation and food services (NAICS 72). This definition of non-tradable sectors matches the definition in Adelino et al. (2016) and Mian and Sufi (2014). The NAICS 31-33 sectors comprise the manufacturing sector. I then aggregate the county-year level QWI data to a Commuting Zone-year level data. Since the coverage of the QWI gradually increases by year I specify 2000 to be the start year, so that I have a sufficiently broad coverage of the US. It is important to maintain the same geographies over time when analyzing economic change within locations. If not, the additional counties that enter the data set would confound the Commuting Zone level analysis and distort estimates. Hence, I restrict our analysis to all counties that enter the dataset in 2000. This returns a panel of 650 commuting zones across the United States from 2000 to 2011.

4.2 Summary statistics

Table 1 presents the summary statistics. The empirical analysis examines 7-year differences and 10-year differences within the 2000-2011 panel. I present here some of the main variables for 2000-2006. The employment, jobs gained, and jobs lost variables by each establishment age categories are all scaled by the working age population. The first row implies that the share of all employment relative to the working age population for 2006 was 1.43 percentage points lower than that for 2000. I can see that this decline can largely be attributed to the decline in manufacturing employment. In addition to the change in the stock of employment, I are also interested in the change in the flow of employment, in particular, job creation. Especially, job creation by startups (0-1 year-olds) represents the degree of entrepreneurship in each Commuting Zone. The summary statistics imply that on average new jobs created by both startups and older establishments have been declining as a share of working age population.

Chinese imports per worker during this period increased on average by about $1,500. The Autor and Dorn (2013) measure of the share of employed in routine occupations is about 29%. Share of manufacturing employment in 2000 was on average about 18.5%, the share of college educated (including Associates Degrees) population was about 48.8%, the share of foreign-born population was about 6.3 percent, and the share of female population was about 51%.

Table 1 Summary statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
Difference in employment per working age population (2000-2006, in % pts)					
All establishments	-1.493	4.485	-34.239	16.074	650
Startups (Establishments 0-1 year-olds)	-0.245	1.071	-11.889	8.372	650
Establishments 11+ year-olds	-0.396	4.105	-20.353	24.101	650
Difference in manufacturing employment per working age population (2000-2006, in % pts)					
All establishments	-1.612	2.375	-13.045	14.345	650
Startups (Establishments 0-1 year-olds)	-0.055	0.266	-2.332	2.526	650
Establishments 11+ year-olds	-1.460	2.474	-17.650	14.966	650
Difference in non-tradable sector employment per working age population (2000-2006, in % pts)					
All establishments	-0.285	0.698	-9.017	4.635	650
Startups (Establishments 0-1 year-olds)	-0.020	0.281	-2.185	2.815	650
Establishments 11+ year-olds	-0.059	0.737	-8.824	4.693	650
Difference in jobs gained per working age population (2000-2006 in % pts)					
All establishments	-0.917	3.750	-19.221	19.129	650
Startups (Establishments 0-1 year-olds)	-0.087	0.839	-7.080	6.091	650
Establishments 11+ year-olds	-0.291	2.643	-12.401	13.522	650
Difference in manufacturing jobs gained per working age population (2000-2006, in % pts)					
All establishments	-0.269	0.968	-9.530	8.725	650
Startups (Establishments 0-1 year-olds)	-0.024	0.163	-2.848	1.342	650
Establishments 11+ year-olds	-0.213	0.887	-9.235	8.237	650
Difference in non-tradable sector jobs gained per working age population (2000-2006, in % pts)					
All establishments	-0.287	1.121	-5.922	7.827	650
Startups (Establishments 0-1 year-olds)	0.002	0.345	-1.900	2.064	650
Establishments 11+ year-olds	-0.122	0.799	-3.276	5.764	650
Difference in the number of small establishments (less than 20 employees) (2000-2006, in % pts)					
All sectors	3.810	9.308	-20.1	60.40	650
Manufacturing sector	4.220	24.591	-100	200.00	646
Non-tradable sector	6.727	34.731	-100	464.74	545
Change in imports from China to US per worker (in 2007 $1,000)	1.514	1.593	-0.460	17.850	650
Share of employed in routine occupation (in 2000)	28.815	2.916	22.227	36.656	650
Share of manufacturing employment (in 2000)	18.487	10.909	0.108	55.242	650
Share of college-educated population (in 2000)	48.802	8.365	26.320	70.555	650
Share of foreign-born population (in 2000)	6.297	6.624	0.621	48.908	650
Share of female (in 2000)	0.511	0.016	0.382	0.544	650

5. Empirical Strategy

5.1. Non-technical overview of the empirical approach

This paper's empirical analysis examines the impact of import competition and technological change on employment, job creation by startups and existing firms, and number of small businesses in a regression framework. The unit of analysis is US Commuting Zones. Hence, I are comparing how one of the outcome variables - either employment, job creation by startups, job creation by existing firms, or the number of small businesses - differ in Commuting Zones that face more Chinese import competition relative to Commuting Zones that experience less Chinese import competition. Similarly, I compare Commuting Zones that are more susceptible to technological change versus those that are less susceptible based on the share of employed in routine jobs. A regression framework allows us to simultaneously estimate the relationship between the outcome variable of interest and the variables used to proxy trade shock and technological change. There are many other variables that could explain the variation in employment, job creation, and number of small businesses. Hence, I additionally control for these variables in the regression analysis. I control for the percentage of population working in manufacturing, percentage of college-educated population, percentage of female population, and percentage of foreign-born population in the Commuting Zone. I also control for aggregate annual trends and broader regional characteristics by controlling for the year and census division. The results from such regression analysis present the relation between variables, but do not necessarily imply that the relationship is causal. For example, there may be a significant relationship between local trade shocks and local employment, but that doesn't necessarily imply that local trade shocks caused a change in local employment.

In order to examine the causal effect, one needs exogenous variation in the local import shock measure, i.e., variation that is independent from all local characteristics. But, US imports from China at the local level would likely be driven by many unobserved local economic conditions. Hence a standard OLS regression would likely return biased estimates, i.e., estimates that are different from the true causal impact. To get closer to a causal effect, I need to isolate the part of the import shock measure that is not driven by local US demand conditions, but by supply shocks in China. Following Autor et al. (2013), I construct the import shock measure with other country imports from China in the same industry. Essentially, this strategy utilizes the variation in Chinese imports driven by China's rising competitiveness (a supply shock from US's perspective) in global trade during the study period. By focusing on the variation primarily driven by China's supply shock to the world, the instrumental variable strategy produces estimates that may be less influenced by local demand shocks compared to OLS estimates. Nonetheless, it is in general difficult to generate truly exogenous variation and hence, I still include the control variables. Below describes the estimation strategy in more detail.

5.2. Base OLS regression

In practice, I use the following equation to examine the impact of Chinese imports per worker on local entrepreneurship and business dynamism:

$$y_{it1,t2} = \beta \Delta Z_{it1,t2} + TechChange_{i,1980} \cdot \delta + X_{i,2000} \cdot \gamma + Division_i + \rho_{t1} + \varepsilon_{it}. \quad (1)$$

The above equation represents a stacked first difference regression where the first differencing is between t_1 and t_2, which is specified to span a 7 years period in the main set of analyses. Since the panel data spans 2000 to 2011, equation (1) pools the first difference regressions of 2000 and 2006, 2001 and 2007, and so forth till 2005 and 2011. In certain specifications I also examine the 10 years differences.

$y_{it1,t2}$ is the change in the employment, job creation, or job destruction variables by startups in Commuting Zone (CZ) i between t_1 and t_2. I also examine the values for existing firms. $\Delta Z_{it1,t2}$ measures the change in US imports of Chinese goods per worker between t_1 and t_2. In other words, equation (1) examines how the change in import competition from China per worker affects jobs created by startups in the CZ.

Another question I explore in this paper is whether import exposure or technological change has a stronger impact on local labor market employment and business dynamism. I include the historical share of routine occupations in the commuting zone in 1980, $TechChange_{i,1980}$ in equation (1).

X_{it1} is the vector of CZ level control variables - the percentage of population working in manufacturing, percentage of college-educated population, percentage of female population, and percentage of foreign-born population in the CZ - in 2000. $Division_i$ is the set of census division dummy variables and ρ_{t1} is the initial year fixed effects. The year fixed effects are included, since multiple time periods are stacked to estimate a pooled first difference regression. The main coefficient of interested is β. If increasing Chinese import penetration decreases employment dynamics in the CZ, β would be negative.

Specifically, ΔZ_{it}, the change in US imports of Chinese goods per worker in the CZ between t_1 and t_2, is constructed based on the following equation:

$$\Delta Z_{it1,t2} = \sum_j \frac{L_{ijt1}}{L_{jt1}} \frac{\Delta M_{jt1,t2}}{L_{it1}}$$

where L_{ijt1} is the employment in CZ i in industry j in the base year t_1, L_{jt1} is total US employment in industry j in year t_1, $\Delta M_{jt1,t2}$is the change in the value of US imports from China in industry j between years t_1 and t_2, and L_{it} is the total employment in CZ *i*. The above equation basically distributes the change in US imports from China in each industry to each CZ based on the industry employment share in that CZ relative to the US, and then creates a per worker measure by dividing by the CZ employment.

5.3. Instrumental variable strategy

To examine the impact of local import exposure on local employment and business dynamics, one would need exogenous variation (variation independent from local economic conditions) in the import exposure measure. However, US imports from China at the CZ level could be driven by unobserved local economic conditions that affect the region's demand for Chinese goods. To get an unbiased estimate of β in the above equation, I need to isolate the part of Z_{it} that is not driven by local US demand conditions, but by supply shocks in China. To get plausibly exogenous variation, I use the variation in Chinese imports driven by China's rising competitiveness, which is a supply shock from US's perspective, in global trade during the study period. I instrument the import shock measure with other country imports from China in the same industry. By focusing on the variation primarily driven by China's supply shock to the world, the instrumental variable generates plausibly exogenous variation in US imports from China.

Specifically, the instrumental variable $\Delta V_{it1,t2}$ uses China's exports to eight other countries during the same period. The other countries are eight high-income countries that potentially have similar tastes as the US and have trade flow data with China. The instrumental variable is constructed as below.

$$\Delta V_{it1,t2} = \sum_j \frac{L_{ijt1}}{L_{jt1}} \frac{\Delta M'_{jt1,t2}}{L_{it1}}$$

Now, $\Delta M'_{jt1,t2}$ is the change in other country imports from China in industry j between t_1 and t_2. The 2SLS regression effectively estimates the equation where the first stage regression is

$$\Delta Z_{it1,t2} = \pi \Delta V_{it1,t2} + TechChange_{i,1980} \cdot \delta + X_{i,2000} \cdot \gamma + Division_i + \rho_{t1} + \varepsilon_{it} \qquad (2)$$

and the second stage equation is

$$y_{it1,t2} = \beta \widehat{\Delta Z}_{it1,t2} + TechChange_{i,1980} \cdot \delta + X_{i,2000} \cdot \gamma + Division_i + \rho_{t1} + \varepsilon_{it}.$$

where $\widehat{\Delta Z}$ denotes the predicted value of ΔZ from the first stage regression. The reduced form is expressed as

$$y_{it1,t2} = \theta \Delta V_{it1,t2} + TechChange_{i,1980} \cdot \delta + X_{i,2000} \cdot \gamma + Division_i + \rho_{t1} + \varepsilon_{it}.$$

The estimate of interest β is conceptually equivalent to the ratio of the reduced form coefficient to the first stage coefficient, i.e., θ / π.

The exclusion restriction for the instrumental variable strategy assumes that the demand shocks for Chinese goods at the industry level are not correlated across countries. If demand shocks across countries are correlated then the instrumental variable may fail to perfectly isolate the supply shock component of Chinese imports. Autor et al. (2013) examine results while excluding industries that are more susceptible to this concern. Since the housing and construction markets were somewhat correlated across countries they drop the steel, cement, and glass industries. However, they find that this does not change the results much. Nonetheless, the exclusion restriction can fail in ways not described here. I note that the instrumental strategy is not fool-proof and that I do not claim to have perfect exogeneity. Some of the limitations are at least partially addressed by including control variables like share employed in manufacturing and share employed in routine jobs. Though these variables do try to capture important factors, such as technological change, it is only a proxy and there could likely be additional omitted factors.

6. Regression Results

6.1. The first-stage regression.

I first present the results of the first stage regression of equation (2) in Table 2. The regression essentially examines the relationship between the change in Chinese imports to the US and the change in Chinese imports to the other countries. Column (1) presents the pooled first difference regression that examines the change over 7 years and column (2) presents results that examine the change over 10 years. Both regressions control for the share of employed in routine occupation, share of manufacturing employment, share of college-educated population, share of foreign-born population, and share of female, all in 2000. The nine US Census division fixed effects and initial year fixed effects are included as well. The main objective of Table 2 is to examine whether the instrumental variable is strongly correlated with the endogenous variable in equation (2). In column (1) the coefficient estimate on the change in imports from China to other countries per worker is 1.156 and the standard error is 0.1. This implies a t-statistic of 11.71 and returns a first-stage F-statistic that is well above 100, indicating a strong first-stage regression. Similarly, column (2) returns a large first-stage F-statistic. The Table 2 results indicate that the instrumental variable, Chinese trade with other developed countries, is indeed a strong predictor of the import competition variable used in the analysis – The change in Chinese imports to US per worker. In the following sections when I present results from the 2SLS regressions with the full set of control variables, the first-stage regression corresponds to Table 2.

Table 2 First stage regression

	(1) Change in imports from China to US per worker (seven year difference in $1,000)	(2) Change in imports from China to US per worker ten year difference in $1,000)
Change in imports from China to other countries per worker	1.156***	1.274***
	(0.0987)	(0.152)
Share of employed in routine occupation	0.00519	-0.00258
	(0.0163)	(0.0241)
Share of manufacturing employment	-0.00546	-0.0190
	(0.00640)	(0.0135)
Share of college-educated	0.00840*	0.0178***
	(0.00461)	(0.00624)
Share of foreign-born	0.00120	0.000848
	(0.00255)	(0.00384)
Share of female	-1.165	-2.330
	(2.516)	(3.676)
Census division f.e.	Yes	Yes
Year f.e.	Yes	Yes
Observations	3,900	1,950
R-squared	0.824	0.858

Notes: Standard errors in parentheses are clustered at the Commuting Zone level. *** p<0.01, ** p<0.05, * p<0.1.

6.2. Impact of import competition and technological change on local employment dynamics

In this section I examine how import competition and technological change measured by the exposure to Chinese imports and the share of employed in routine occupation affect local employment dynamics at the commuting zone level over a 7-year period. Table 3 presents the results from the 2SLS regressions that examine the difference in commuting zone level employment (Panel A), jobs gained (Panel B), and jobs lost (Panel C). Each panel examines the aggregate value for all establishments, startups (0-1 year-olds), and mature establishments (11+ year-olds). As noted previously, each regression is a stacked 7-year first difference regression using panel data that spans 2000 from 2011 over 650 commuting zones. Since the error terms could be correlated across years, I cluster standard errors at the commuting zone level.

Panel A column (1) presents results when the only control variables are the initial year fixed effects. The result indicate that a one thousand dollar increase in Chinese import per worker is negatively associated with the change in aggregate employment per working age population but the relationship is not statistically significant. On the other hand the coefficient estimate on the share of employed in routine occupation is negative and significant at -0.321. This implies that a standard deviation increase in share employed in routine jobs in 1980 is associated with about a 0.9 percentage point decrease in the Commuting Zone's aggregate employment per working age population over a 7-year period.

In column (2) I include the set of control variables, i.e., the share of manufacturing employment, share of college-educated population, share of foreign-born population, and share of female, all in 2000, in addition to the initial year fixed effects. The coefficient estimate on the Chinese import penetration variable becomes smaller in magnitude while the coefficient estimate on share employed in routine jobs becomes more negative. In column (3), I additionally include the nine-census division fixed effects to capture general regional variations that are not explicitly controlled for in the previous regression. The impact of Chinese import competition on aggregate employment remains statistically not distinguishable from zero, but the coefficient estimates on the share employed in routine occupations is a strong negative at about -0.5.

The next three columns examine the change in startup (0-1 year-olds) employment. Now the outcome variable is the employment by startups divided by the working age population in year t+7 minus the employment by startups divided by the working age population in year t. Focusing on results with the full set of control variables in column (6), again I do not find any statistically significant effect of Chinese import competition on startup employment dynamics, but a significant negative effect of having a higher share of the employed in routine jobs. In columns (7) through (9) I examine the most mature establishments in the QWI data, i.e., establishments 11 year-old or older. Again focusing on the results with all control variables, Chinese import competition has no significant impact on the employment of mature establishments but the proxy for technological change has a significant negative effect. Furthermore, Commuting Zones that have a higher share of manufacturing employment in 2000 see a decline in employment per working age population. Commuting Zones with a higher share of female population in 2000 is strongly associated with employment growth as well. Overall, Panel A indicates that the increase in Chinese import exposure did not affect the Commuting Zone employment of new or old establishments. On the other hand, having a higher share of the employed in routine jobs is a very strong predictor of negative employment growth.

In Panel B, I examine how job creation changed over time by using the number of jobs gained per working age population as the outcome variable. Panel B column (3), column (6), and column (9) all indicate that there are no statistically significant effects of Chinese import exposure on jobs gained at the commuting zone level across all establishments or startups. However, there are strong negative effects of having a higher share of employment in routine jobs on the change in gross job creation over time.

In Panel C, I examine how import competition and technological change affect gross job destruction. Again focusing on the columns with the full set of controls, I find no statistically significant effects of both Chinese import penetration and share of employed in routine jobs on job destruction by startups. However, for older establishments in column (9) the coefficient estimate on share employed in routine jobs is negative and significant. Overall, Table 3 results indicate that import competition has no effect on the change in employment, job creation, or job destruction. Rather technological change is the main driver behind the decline in employment and job creation.

Table 3 Import competition and local employment dynamics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	A. Difference in employment per working age population (7-year difference in % pts)								
		All establishments			0-1 year-olds			11+ year-olds	
(Change in imports from China to US)/worker	-0.231	-0.0623	-0.0941	0.00618	-0.00432	-0.0139	-0.301**	-0.0392	-0.0499
	(0.152)	(0.129)	(0.106)	(0.0138)	(0.0128)	(0.0111)	(0.117)	(0.0939)	(0.0801)
Share of employed in routine occupation	-0.321***	-0.466***	-0.496***	-0.0130	-0.0324***	-0.0387***	-0.221***	-0.313***	-0.339***
	(0.110)	(0.0782)	(0.0864)	(0.0112)	(0.00885)	(0.00697)	(0.0790)	(0.0539)	(0.0562)
Share of manufacturing employment		-0.0316	-0.0220		0.00448	0.00398		-0.0588***	-0.0431**
		(0.0309)	(0.0255)		(0.00279)	(0.00248)		(0.0220)	(0.0192)
Share of college-educated		-0.00587	0.00246		-0.000570	0.00117		0.00817	0.0158
		(0.0237)	(0.0287)		(0.00254)	(0.00232)		(0.0165)	(0.0205)
Share of foreign-born		0.0371*	0.0395*		0.00701***	0.00656***		0.00885	0.0212
		(0.0191)	(0.0204)		(0.00190)	(0.00220)		(0.0139)	(0.0147)
Share of female		43.15**	35.87***		4.157**	1.436		32.96**	28.49***
		(20.38)	(13.68)		(2.023)	(1.451)		(14.81)	(10.43)
Census division f.e.	No	No	Yes	No	No	Yes	No	No	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	B. Difference in jobs gained per working age population (7-year difference in % pts)								
		All establishments			0-1 year-olds			11+ year-olds	
(Change in imports from China to US)/worker	0.482***	0.0628	0.0642	0.0117	-0.0117	-0.0207	0.346***	0.0665	0.0866
	(0.141)	(0.0688)	(0.0855)	(0.0187)	(0.0133)	(0.0128)	(0.0919)	(0.0470)	(0.0533)
Share of employed in routine occupation	-0.0732	-0.0648	-0.160***	0.00314	0.000918	-0.0141**	-0.0757**	-0.0558	-0.123***
	(0.0543)	(0.0623)	(0.0622)	(0.0109)	(0.00758)	(0.00708)	(0.0355)	(0.0428)	(0.0395)
Share of manufacturing employment		0.122***	0.0976***		0.00831***	0.00910***		0.0782***	0.0591***
		(0.0274)	(0.0214)		(0.00276)	(0.00210)		(0.0178)	(0.0138)
Share of college-educated		0.0151	0.0148		-0.00120	0.00280		0.00875	0.00413
		(0.0180)	(0.0183)		(0.00235)	(0.00226)		(0.0121)	(0.0110)
Share of foreign-born		-0.00590	-0.00430		-0.00231	0.000180		-0.00386	-0.000560
		(0.0145)	(0.0139)		(0.00255)	(0.00240)		(0.00946)	(0.00910)
Share of female		0.903	24.32**		4.531*	3.223**		-6.628	16.16**
		(12.16)	(10.05)		(2.407)	(1.407)		(7.553)	(6.695)
Census division f.e.	No	No	Yes	No	No	Yes	No	No	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	C. Difference in jobs lossed per working age population (7-year difference in % pts)								
		All establishments			0-1 year-olds			11+ year-olds	
(Change in imports from China to US)/worker	0.284***	-0.0101	0.0145	0.00791	-0.00665	-0.0103	0.206***	0.00560	0.0328
	(0.110)	(0.0606)	(0.0664)	(0.00761)	(0.00605)	(0.00678)	(0.0747)	(0.0442)	(0.0488)
Share of employed in routine occupation	-0.0598	-0.0259	-0.0846	0.00141	0.00273	-0.00250	-0.0556*	-0.0262	-0.0733**
	(0.0406)	(0.0519)	(0.0530)	(0.00346)	(0.00390)	(0.00380)	(0.0295)	(0.0379)	(0.0368)
Share of manufacturing employment		0.0780***	0.0507***		0.00422***	0.00315**		0.0517***	0.0332***
		(0.0195)	(0.0154)		(0.00124)	(0.00123)		(0.0143)	(0.0111)
Share of college-educated		0.00155	-0.0133		-0.00174	-0.00120		0.00351	-0.00769
		(0.0163)	(0.0181)		(0.00121)	(0.00144)		(0.0117)	(0.0121)
Share of foreign-born		-0.000982	-0.00357		-0.000685	-0.000745		-0.000442	0.000887
		(0.0116)	(0.0100)		(0.000835)	(0.00101)		(0.00830)	(0.00740)
Share of female		-13.21	5.848		1.104	0.263		-13.94*	4.671
		(9.860)	(7.727)		(0.803)	(0.677)		(7.440)	(5.929)
Census division f.e.	No	No	Yes	No	No	Yes	No	No	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Number of observations is 3,900. Standard errors in parentheses are clustered at the Commuting Zone level. *** p<0.01, ** p<0.05, * p<0.1.

6.3. Manufacturing versus non-tradable sectors

In this section I examine how exposure to Chinese imports and the historical share of employed in routine jobs affect local employment dynamics in the manufacturing sector and the non-tradable sector, namely the retail trade (NAICS 44-45), and accommodation and food services (NAICS 72).

Table 4 Panel A presents results for the manufacturing sector and Panel B the non-tradable sector. Each column presents results from the stacked 7-year first-difference regressions with the full set of control variables and fixed effects. Standard errors are clustered at the Commuting Zone level. The employment results in Panel A columns (1) through (3) indicate that, though the estimates are negative, Chinese import competition does not have a statistically significant impact on manufacturing employment. On the other hand, the coefficient estimates on the share of employed in routine jobs is all negative and statistically significant. The coefficient estimate on the initial share of manufacturing employment is also negative and significant across all establishment age categories. Panel A columns (4) through (6) present results on gross job creation in manufacturing, and columns (7) through (9) on gross job destruction in manufacturing. As column (5) indicates both import competition and technological change have a negative impact on the change in job creation among startups. I can compare the magnitudes by translating the coefficient estimates into a one standard deviation effect. A standard deviation increase in Chinese import compeition reduces the change in job creation by about 0.01 percentage point over 7 years. On the other hand, a standard deviation increase in the share of employed in routine occupations reduces the change in job creation by about 0.0075 percentage point over 7 years. Since the mean change in job creation among startups over 7 years is 0.08, these effect amount to about 10 percent of the change. The main coefficient estimates on job destruction is also negative but are not statistically significant for startups, and the effect is mostly attributed to establishments 11 year-olds or older.

Since most of the imports from China were manufactured goods, the US manufacturing sector is likely to have been directly affected by Chinese import competition. How Chinese import competition would affect other parts of the economy is less clear. Industries not directly in competition with Chinese imports may have taken advantage of the lower priced goods for their businesses. On the other hand, the impact on the manufacturing sector could spill over to other sectors of the local economy. Routine tasks exist in both blue collar and white collar occupations and hence technological change is more likely to affect all sectors of the economy.

I examine the non-tradable sector in Panel B. Chinese import competition generally has no statistically significant impact on all three outcomes, but the coefficient estimates tends to be positive. The positive effect on the older establishments is larger and statistically more powerful than that for the startups. This is in contrast to the manufacturing sector's negative coefficient estimates. The impact of the share in routine occupations is negative and statistically significant for mature establishments. On the other hand, there is no significant effect from technological change on startups in the non-tradable sector.

Table 4 The manufacturing sector and non-tradable sector

	Difference in employment per working age population (7-year difference in % pts)			*Difference in jobs gained per working age population (7-year difference in % pts)*			*Difference in jobs lossed per working age population (7-year difference in % pts)*		
	All establishments	0-1 year-olds	11+ year-olds	All establishments	0-1 year-olds	11+ year-olds	All establishments	0-1 year-olds	11+ year-olds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				A. Manufacturing sector					
(Change in imports from China to US)/worker	-0.0890*	-0.00139	-0.0685	-0.0268*	-0.00659*	-0.0122	-0.0496**	-0.00513	-0.0379**
	(0.0506)	(0.00411)	(0.0443)	(0.0151)	(0.00353)	(0.0132)	(0.0220)	(0.00383)	(0.0175)
Share of employed in routine occupation	-0.160***	-0.00507**	-0.123***	-0.0209***	-0.00257**	-0.0133**	-0.0207**	-0.00170	-0.0136*
	(0.0309)	(0.00230)	(0.0246)	(0.00746)	(0.00130)	(0.00670)	(0.00926)	(0.00128)	(0.00734)
Share of manufacturing employment	-0.108***	-0.00447***	-0.0968***	-0.00526*	-0.000717	-0.00333	-0.0119***	-0.000379	-0.0101***
	(0.00958)	(0.00101)	(0.00937)	(0.00284)	(0.000491)	(0.00253)	(0.00319)	(0.000453)	(0.00291)
Share of college-educated	0.00211	0.000134	0.00125	0.00128	0.000681*	0.000597	-0.00239	0.000156	-0.00242
	(0.00827)	(0.000643)	(0.00709)	(0.00250)	(0.000369)	(0.00217)	(0.00275)	(0.000309)	(0.00228)
Share of foreign-born	0.00374	-0.000732	0.00654	-0.000861	-0.000722***	0.00108	-0.000280	-0.000524**	0.00165
	(0.00603)	(0.000451)	(0.00476)	(0.00206)	(0.000243)	(0.00201)	(0.00208)	(0.000245)	(0.00187)
Share of female	0.0380	0.00137	-1.658	1.422	0.133	0.869	-0.909	-0.350*	-0.726
	(4.365)	(0.337)	(4.100)	(1.522)	(0.204)	(1.394)	(1.436)	(0.210)	(1.314)
Census division f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900
				B. Non-tradable sector					
(Change in imports from China to US)/worker	0.00697	0.00138	0.00945	0.0265	-0.00126	0.0218*	0.0200	0.000378	0.0182
	(0.0128)	(0.00230)	(0.00994)	(0.0177)	(0.00361)	(0.0133)	(0.0145)	(0.00231)	(0.0113)
Share of employed in routine occupation	-0.0362***	-0.000343	-0.0364***	-0.0290***	0.00192	-0.0356***	-0.0131	0.00151	-0.0234***
	(0.0109)	(0.00145)	(0.00913)	(0.00958)	(0.00198)	(0.00727)	(0.0101)	(0.00110)	(0.00815)
Share of manufacturing employment	0.00864**	-0.000120	0.00850**	0.0169***	0.000469	0.0139***	0.0109***	0.000201	0.0103***
	(0.00379)	(0.000570)	(0.00338)	(0.00357)	(0.000617)	(0.00289)	(0.00356)	(0.000408)	(0.00292)
Share of college-educated	0.00284	0.000275	0.00111	-0.00163	0.000491	-0.00299	-0.00252	-2.42e-05	-0.00128
	(0.00396)	(0.000553)	(0.00310)	(0.00272)	(0.000692)	(0.00216)	(0.00327)	(0.000395)	(0.00247)
Share of foreign-born	0.0101***	0.00177***	0.00588***	0.00428	0.00138	0.00262	0.00280	0.000685**	0.00186
	(0.00286)	(0.000573)	(0.00220)	(0.00322)	(0.000884)	(0.00195)	(0.00317)	(0.000347)	(0.00223)
Share of female	6.268***	0.327	6.041***	6.758***	0.983**	5.133***	2.300	0.242	2.668
	(2.190)	(0.315)	(1.790)	(2.364)	(0.454)	(1.843)	(2.138)	(0.269)	(1.691)
Census division f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900

Notes: Number of observations is 3,900. Standard errors in parentheses are clustered at the Commuting Zone level. *** p<0.01, ** p<0.05, * p<0.1.

6.4 Urban and rural commuting zones

I next examine urban and rural Commuting Zones separately. Urban Commuting Zones are those that are part of a Metropolitan Statistical Area (MSA) and rural Commuting Zones are those outside of MSAs. Table 5 presents the results on the change in jobs gained per working age population. Panel A presents results for urban Commuting Zones and Panel B rural Commuting Zones. I first discuss the urban Commuting Zone results. The change in job creation across all sectors from technological change is negative for both the 0-1 year-olds and the 11+ year-olds and statistically significant for the latter. When I split by industry, I find that the negative job creation effect by startups is primarily coming from the manufacturing sector. The negative job creation effect by older firms (11+ year-olds) is more pronounced in the non-tradable sector. The results for the rural Commuting Zones are generally qualitatively similar but statistically weaker. The negative job creation effect from technological change among older firms (11+ year-olds) is significant for the non-tradable sector, but not the manufacturing sector. Overall, the urban versus rural results in Table 5 indicate that the impact of import competition on job creation is statistically weak – none of the coefficient estimates are significant at the 5 percent level – but there are negative impacts from technological change, especially among urban manufacturing establishments and older non-tradable sector establishments.

Table 5 Urban versus rural commuting zones

	All sectors			*Manufacturing sectors*			*Non-tradable sectors*		
	All establishments	0-1 year-olds	11+ year-olds	All establishments	0-1 year-olds	11+ year-olds	All establishments	0-1 year-olds	11+ year-olds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A.Difference in jobs gained per working age population in urban commuting zones (7-year difference in % pts)									
(Change in imports from China to US)/worker	0.0627	-0.0211	0.0847	-0.0317*	-0.00688*	-0.0185	0.0248	-0.00131	0.0211
	(0.0955)	(0.0136)	(0.0599)	(0.0171)	(0.00380)	(0.0146)	(0.0191)	(0.00398)	(0.0143)
Share of employed in routine occupation	-0.154**	-0.0102	-0.123**	-0.0220**	-0.00273**	-0.0138*	-0.0328***	0.00187	-0.0384***
	(0.0778)	(0.00875)	(0.0490)	(0.00879)	(0.00133)	(0.00814)	(0.0119)	(0.00236)	(0.00915)
Share of manufacturing employment	0.141***	0.0130***	0.0862***	-0.00507	-0.000833	-0.00228	0.0246***	0.000632	0.0194***
	(0.0287)	(0.00271)	(0.0187)	(0.00378)	(0.000642)	(0.00335)	(0.00465)	(0.000806)	(0.00383)
Share of college-educated	0.0491**	0.00701***	0.0242*	0.00305	0.000912**	0.00220	0.00448	0.000865	0.00117
	(0.0228)	(0.00255)	(0.0139)	(0.00283)	(0.000394)	(0.00253)	(0.00322)	(0.000793)	(0.00271)
Share of foreign-born	0.00308	0.000573	0.00443	-0.000767	-0.000778***	0.00152	0.00579*	0.00133	0.00386*
	(0.0148)	(0.00242)	(0.00964)	(0.00215)	(0.000249)	(0.00212)	(0.00331)	(0.000911)	(0.00201)
Share of female	46.64***	5.724***	29.86***	1.667	0.206	0.846	9.903***	1.059	7.477***
	(16.17)	(2.141)	(10.92)	(2.446)	(0.267)	(2.260)	(3.342)	(0.680)	(2.591)
Census division f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,542	1,542	1,542	1,542	1,542	1,542	1,542	1,542	1,542
B.Difference in jobs gained per working age population in rural commuting zones (7-year difference in % pts)									
(Change in imports from China to US)/worker	0.0167	-0.00784	0.0699	0.0311	-0.00740	0.0519*	-0.00746	-0.00161	0.00512
	(0.0784)	(0.0241)	(0.0598)	(0.0328)	(0.0123)	(0.0302)	(0.0247)	(0.00715)	(0.0186)
Share of employed in routine occupation	-0.0940*	-0.0107	-0.0777**	0.0114	0.00518*	0.00313	-0.0330**	-0.00290	-0.0260**
	(0.0517)	(0.0119)	(0.0360)	(0.0166)	(0.00283)	(0.0160)	(0.0147)	(0.00458)	(0.0113)
Share of manufacturing employment	-0.0129	-0.00173	-0.0111	-0.0121***	-0.00125*	-0.0108***	0.00113	0.000246	0.000907
	(0.0115)	(0.00250)	(0.00816)	(0.00336)	(0.000670)	(0.00332)	(0.00374)	(0.00107)	(0.00287)
Share of college-educated	-0.0384**	-0.00689**	-0.0198*	-0.00720*	-0.000681	-0.00473	-0.0184***	-0.00120	-0.0116**
	(0.0172)	(0.00342)	(0.0105)	(0.00419)	(0.000651)	(0.00397)	(0.00616)	(0.00143)	(0.00458)
Share of foreign-born	-0.0183	-0.00508	-0.00297	0.0145**	0.00202**	0.00335	-0.00684	0.00254	-0.00530
	(0.0241)	(0.00560)	(0.0162)	(0.00565)	(0.00101)	(0.00698)	(0.00805)	(0.00184)	(0.00613)
Share of female	9.207	0.626	7.487**	1.118	0.0419	1.163	5.036*	0.989**	3.896*
	(6.167)	(1.134)	(3.585)	(0.978)	(0.339)	(0.894)	(2.811)	(0.495)	(2.361)
Census division f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,538	2,538	2,538	2,538	2,538	2,538	2,538	2,538	2,538

Notes: Standard errors in parentheses are clustered at the Commuting Zone level. *** p<0.01, ** p<0.05, * p<0.1.

6.5 Does import competition interact with the impact of technological change?

One of the main objectives of this paper is to compare the impact of import competition and technological change on local employment dynamics. The results up to now indicate that technological change has a strong negative impact on local employment and job creation, but that import competition does not. In this section, I explore whether import competition and technological change have compounding effects? That is, I examine whether Commuting Zones that had a higher employment share of routine jobs suffer a stronger negative employment and job creation effect when Chinese import competition increases. In order to examine this effect, I include the interaction term between Chinese import competition and the share of employees in routine occupation to equation (1).

I first examine the employment effects in Panel A. The coefficient estimate on the interaction term tends to be positive. However, other than in column (7) the estimates are not statistically very strong, i.e., most are not significant at the 5 percent level. The coefficient estimates on Chinese import penetration per worker tends to be negative but again not statistically very strong. In particular, the manufacturing sector results in column (4) to column (6) indicate no effects from the interaction term and Chinese import competition. On the other hand, the negative impact from technological change persists across all columns. Next, I examine job creation in Panel B. Similar to the Panel A results, the share of employment in routine occupation has a significant negative effect on the jobs gained per working age population and the effect is more pronounced among older establishments. The coefficient estimates on the interaction term and Chinese import penetration is not significant in all columns. Overall the results in this section indicate no compounding effect between import competition and technological change.

Table 6 Trade versus technological change

	All sectors			*Manufacturing sectors*			*Non-tradable sectors*		
	All establishments	0-1 year-olds	11+ year-olds	All establishments	0-1 year-olds	11+ year-olds	All establishments	0-1 year-olds	11+ year-olds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Difference in employment per working age population (7-year difference in % pts)									
Interaction of trade and technology variables	0.0884*	0.0117*	0.0482	-0.0227	0.000697	-0.0257	0.0141**	0.00351	0.00923*
	(0.0522)	(0.00710)	(0.0345)	(0.0282)	(0.00162)	(0.0239)	(0.00670)	(0.00225)	(0.00520)
(Change in imports from China to US)/worker	-2.813*	-0.369*	-1.545	0.605	-0.0197	0.701	-0.430**	-0.106	-0.278*
	(1.603)	(0.217)	(1.043)	(0.866)	(0.0500)	(0.727)	(0.203)	(0.0681)	(0.158)
Share of employed in routine occupation	-0.626***	-0.0558***	-0.410***	-0.126***	-0.00599**	-0.0857***	-0.0571***	-0.00547	-0.0501***
	(0.108)	(0.0124)	(0.0733)	(0.0337)	(0.00244)	(0.0314)	(0.0155)	(0.00366)	(0.0128)
Share of manufacturing employment	-0.0207	0.00364	-0.0412**	-0.108***	-0.00477***	-0.0950***	0.00903**	-0.000156	0.00896***
	(0.0256)	(0.00243)	(0.0192)	(0.00950)	(0.000981)	(0.00877)	(0.00372)	(0.000568)	(0.00330)
Share of college-educated	0.0130	0.00235	0.0220	-0.000360	8.52e-05	-0.000893	0.00461	0.000657	0.00235
	(0.0274)	(0.00241)	(0.0200)	(0.00793)	(0.000620)	(0.00700)	(0.00412)	(0.000654)	(0.00321)
Share of foreign-born	0.0416**	0.00673***	0.0226	0.00333	-0.000785*	0.00642	0.0104***	0.00184***	0.00617***
	(0.0204)	(0.00218)	(0.0147)	(0.00608)	(0.000444)	(0.00473)	(0.00286)	(0.000586)	(0.00220)
Share of female	38.97***	1.872	30.12***	-0.788	0.0412	-2.668	6.755***	0.454	6.349***
	(13.52)	(1.429)	(10.31)	(4.326)	(0.337)	(3.973)	(2.198)	(0.309)	(1.793)
Census division f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900
R-squared	0.384	0.250	0.309	0.535	0.060	0.490	0.244	0.246	0.140
B. Difference in jobs gained per working age population (7-year difference in % pts)									
Interaction of trade and technology variables	0.0140	0.00134	0.0158	0.00307	-0.00110	0.00467	-0.00141	-0.000339	0.000835
	(0.0316)	(0.00589)	(0.0204)	(0.00520)	(0.00154)	(0.00422)	(0.00638)	(0.00165)	(0.00473)
(Change in imports from China to US)/worker	-0.373	-0.0586	-0.417	-0.0970	0.0286	-0.137	0.0703	0.00969	-0.00392
	(0.995)	(0.183)	(0.639)	(0.159)	(0.0458)	(0.128)	(0.199)	(0.0509)	(0.148)
Share of employed in routine occupation	-0.181**	-0.0160*	-0.147**	-0.0246**	-0.000909	-0.0196**	-0.0269*	0.00244	-0.0368***
	(0.0902)	(0.00956)	(0.0573)	(0.0109)	(0.00169)	(0.00962)	(0.0140)	(0.00300)	(0.0106)
Share of manufacturing employment	0.0983***	0.00879***	0.0609***	-0.00763***	-0.000871*	-0.00514**	0.0168***	0.000411	0.0140***
	(0.0205)	(0.00206)	(0.0132)	(0.00260)	(0.000448)	(0.00240)	(0.00337)	(0.000595)	(0.00278)
Share of college-educated	0.0167	0.00281	0.00671	0.000617	0.000490	0.000353	-0.00182	0.000428	-0.00288
	(0.0189)	(0.00222)	(0.0114)	(0.00275)	(0.000353)	(0.00241)	(0.00287)	(0.000734)	(0.00223)
Share of foreign-born	-0.00385	0.000136	0.000184	-0.00133	-0.000780***	0.000768	0.00424	0.00136	0.00265
	(0.0139)	(0.00238)	(0.00909)	(0.00206)	(0.000232)	(0.00203)	(0.00319)	(0.000881)	(0.00193)
Share of female	24.79**	3.286**	16.64**	1.649	0.101	1.126	6.711***	0.973**	5.161***
	(10.11)	(1.380)	(6.780)	(1.522)	(0.190)	(1.404)	(2.324)	(0.443)	(1.832)
Census division f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900	3,900
R-squared	0.274	0.275	0.247	0.088	0.031	0.077	0.262	0.242	0.238

Notes: Standard errors in parentheses are clustered at the Commuting Zone level. *** p<0.01, ** p<0.05, * p<0.1.

6.6. Results from 10-year differences

The results up to now have focused on the 7-year differences in employment and job creation. I also examine the longer time horizon of 10 years to allow for longer adjustment times in the local economy. Since the panel spans 2000 to 2011, the regression pools the first differences over 2000-2009, 2001-2010, and 2002-2011. This returns 1,950 observations and as before I cluster standard errors at the commuting zone level. The results are presented in Table 7. In general the results are qualitatively very similar to that of from Table 1 and Table 2. Panel B column (9) does indicate a positive impact of Chinese import competition on job creation among older establishments in the non-tradable sector. However, this effect doesn't result in sustained employment growth in Panel A.

Table 7 Results using 10-year differences

	All employment			*Manufacturing employment*			*Non-tradable employment*		
	Aggregate	0-1 year-olds	11+ year-olds	Aggregate	0-1 year-olds	11+ year-olds	Aggregate	0-1 year-olds	11+ year-olds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	A. Difference in employment per working age population (10-year difference in % pts)								
(Change in imports from China to US)/worker	-0.0290	-0.0167	0.0171	-0.0690	-0.00453	-0.0512	0.00446	-0.000225	0.0133
	(0.117)	(0.0150)	(0.0852)	(0.0545)	(0.00443)	(0.0510)	(0.0145)	(0.00224)	(0.0104)
Share of employed in routine occupation	-0.822***	-0.0359***	-0.588***	-0.244***	-0.00705**	-0.188***	-0.0622***	0.00149	-0.0573***
	(0.140)	(0.0112)	(0.0973)	(0.0494)	(0.00330)	(0.0396)	(0.0171)	(0.00188)	(0.0145)
Share of manufacturing employment	-0.0618*	0.00453	-0.0865***	-0.191***	-0.00402***	-0.173***	0.0121**	-0.000459	0.0113**
	(0.0375)	(0.00347)	(0.0283)	(0.0153)	(0.00139)	(0.0142)	(0.00579)	(0.000651)	(0.00505)
Share of college-educated	-0.0323	-0.00485	-0.00299	-0.00845	0.000864	-0.0108	0.00214	-0.000331	-0.000546
	(0.0485)	(0.00351)	(0.0350)	(0.0135)	(0.000926)	(0.0114)	(0.00610)	(0.000642)	(0.00477)
Share of foreign-born	0.0418	0.00566**	0.0282	0.00452	-0.00126**	0.00984	0.0152***	0.00194***	0.00971***
	(0.0307)	(0.00262)	(0.0217)	(0.00955)	(0.000617)	(0.00743)	(0.00405)	(0.000650)	(0.00315)
Share of female	57.19***	2.048	43.59***	0.539	0.0712	-2.372	9.989***	0.276	9.166***
	(20.94)	(1.917)	(15.71)	(6.394)	(0.488)	(5.961)	(3.335)	(0.390)	(2.715)
Census division f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,950	1,950	1,950	1,950	1,950	1,950	1,950	1,950	1,950
R-squared	0.420	0.242	0.373	0.638	0.079	0.613	0.280	0.142	0.177
	B. Difference in jobs gained per working age population (10-year difference in % pts)								
(Change in imports from China to US)/worker	0.0502	-0.0106	0.0528	-0.0194	-0.00856*	-0.00688	0.0292**	0.000556	0.0258**
	(0.0651)	(0.0113)	(0.0419)	(0.0137)	(0.00508)	(0.00982)	(0.0134)	(0.00327)	(0.0108)
Share of employed in routine occupation	-0.227**	-0.00983	-0.184***	-0.0267*	-0.00392	-0.0160	-0.0406**	0.00635**	-0.0474***
	(0.0919)	(0.0113)	(0.0584)	(0.0140)	(0.00241)	(0.0104)	(0.0170)	(0.00267)	(0.0134)
Share of manufacturing employment	0.132***	0.00840***	0.0879***	-0.0122***	-0.000542	-0.00872**	0.0249***	-0.000264	0.0220***
	(0.0297)	(0.00322)	(0.0197)	(0.00451)	(0.000880)	(0.00366)	(0.00582)	(0.000905)	(0.00489)
Share of college-educated	0.00765	-0.00146	0.00546	-0.00155	0.00122**	-0.00203	-0.00241	0.000260	-0.00373
	(0.0290)	(0.00363)	(0.0179)	(0.00462)	(0.000601)	(0.00349)	(0.00541)	(0.000982)	(0.00438)
Share of foreign-born	-0.0123	-0.000162	-0.00272	-0.00419	-0.000986**	-0.000965	0.00536	0.00219	0.00262
	(0.0212)	(0.00356)	(0.0140)	(0.00365)	(0.000418)	(0.00315)	(0.00599)	(0.00141)	(0.00410)
Share of female	26.57*	4.436**	16.48*	1.858	0.116	1.032	6.872*	1.754**	4.256
	(14.39)	(1.914)	(9.851)	(2.267)	(0.303)	(2.022)	(3.925)	(0.701)	(3.078)
Census division f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,950	1,950	1,950	1,950	1,950	1,950	1,950	1,950	1,950
R-squared	0.345	0.320	0.332	0.252	0.055	0.207	0.311	0.175	0.318

Notes: Standard errors in parentheses are clustered at the Commuting Zone level. *** p<0.01, ** p<0.05, * p<0.1.

6.7. Comparing results using the County Business Pattern data

Our analysis utilizes the QWI data to examine the impact of trade and technology on local employment and job creation dynamics. Currently, the QWI is the only publically available data that allows researchers to examine job creation or destruction at the Commuting Zone level by establishment age. Other scholars have used the County Business Pattern (CBP) to examine employment patterns across Commuting Zones. In particular, Autor et al. (2013) have used the CBP to examine how trade affects manufacturing employment. In this section, I use the CBP to examine how the results I find differ from our analysis that utilizes the QWI data. Since, the CBP does not have job dynamics data and establishment age information, I present result on aggregate employment change only. Table 8 presents the results.

In columns (1) and (2) I examine the 2SLS regressions of all employment and manufacturing sector employment, which correspond to Table 3 column (3) and Table 4 column (1). The coefficient estimates on Chinese import competition are both negative, and the column (2) estimate is statistically significant at the 1 percent level. The result implies that a $1,000 increase in Chinese imports per worker reduces the employment share of working age population by 0.14 percentage points. The estimates from Table 3 and Table 4 were also negative and somewhat smaller at around -0.09 but were not as statistically significant. The rest of the columns present results from the 10-year differences and show similar results.

Overall, The negative impact from import competition is consistent with findings from other papers that use the County Business Patterns. However, when I use the QWI data the negative effects tend to be smaller and statistically insignificant. On the other hand, the impact of technological change on employment is also statistically significant and negative when using the CBP data.

Table 8 Employment Results using the County Business Pattern data

	Difference in employment per working age population from CBP			
	7-year difference in % pts		10-year difference in % pts	
	All sectors	Manufacturing sector	All sectors	Manufacturing sector
	(1)	(2)	(3)	(4)
(Change in imports from China to US)/worker	-0.144	-0.142***	-0.189	-0.156***
	(0.184)	(0.0404)	(0.208)	(0.0442)
Share of employed in routine occupation	-0.687***	-0.136***	-1.124***	-0.213***
	(0.157)	(0.0284)	(0.251)	(0.0497)
Share of manufacturing employment	-0.0267	-0.104***	-0.0387	-0.178***
	(0.0299)	(0.00834)	(0.0477)	(0.0126)
Share of college-educated	0.0505	-0.00345	0.0542	-0.00983
	(0.0755)	(0.00803)	(0.119)	(0.0140)
Share of foreign-born	0.0355	0.000481	0.0542	0.00222
	(0.0308)	(0.00540)	(0.0483)	(0.00904)
Share of female	50.16**	0.162	81.32***	-0.165
	(19.71)	(3.704)	(30.03)	(5.481)
Census division f.e.	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes
Observations	3,900	3,900	1,950	1,950
R-squared	0.429	0.576	0.361	0.709

Notes: Standard errors in parentheses are clustered at the Commuting Zone level. *** p<0.01, ** p<0.05, * p<0.1.

6.8. Impact on the number of small businesses

Finally, I examine how import competition and technological change affects the growth in the number of small businesses in Commuting Zones. For this analysis I use the County Business Pattern (CBP) data. The CBP data provides the number of establishments by size, that is, the number of employees. For the purpose of this paper I focus on small establishments with employees less than 20 employees, which would generally include new businesses. I examine all small businesses in the commuting zone, as well as those specifically in the manufacturing sector and non-tradable sector. Table 9 presents the results. Columns (1) to (3) present the 7-year difference results and columns (4) to (6) the 10-year difference results. The coefficient estimates on Chinese import penetration are not statistically significant, other than one estimate that is at the 10 percent level. On the other, there is a strong negative impact from technological change in the manufacturing sector. Column (5) implies that a standard deviation increase in the share of employed in routine occupations decreases the number of small establishments by about 2.73 percentage points over 10 years. This effect is statistically significant at the 1 percent level. Technological change has a negative impact on the number of small businesses in manufacturing but not in the non-tradable sector, while import competition has no significant effect.

Table 9 Number of Small Businesses form the County Business Pattern data

	Difference in number of small businesses from CBP					
	7-year difference in % pts			10-year difference in % pts		
	All sectors	Manufacturing sector	Non-tradable sector	All sectors	Manufacturing sector	Non-tradable sector
	(1)	(2)	(3)	(4)	(5)	(6)
(Change in imports from China to US)/worker	0.431	-0.0937	0.522	0.559*	-0.0145	0.669
	(0.309)	(0.320)	(0.412)	(0.326)	(0.310)	(0.417)
Share of employed in routine occupation	0.215	-0.606***	0.235	0.333	-0.937***	0.333
	(0.233)	(0.180)	(0.300)	(0.353)	(0.260)	(0.454)
Share of manufacturing employment	-0.177***	0.0961	-0.0760	-0.278***	0.164*	-0.116
	(0.0586)	(0.0612)	(0.0918)	(0.0900)	(0.0872)	(0.143)
Share of college-educated	0.126	0.0316	0.154	0.170	0.0637	0.253
	(0.0997)	(0.0651)	(0.121)	(0.159)	(0.0922)	(0.193)
Share of foreign-born	0.0967*	-0.160***	0.115*	0.159*	-0.227***	0.183*
	(0.0570)	(0.0353)	(0.0685)	(0.0833)	(0.0496)	(0.101)
Share of female	-95.10***	-104.7***	-95.12*	-125.1***	-128.9**	-111.8
	(33.91)	(38.87)	(53.48)	(47.92)	(54.97)	(79.26)
Census division f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,900	3,879	3,304	1,950	1,940	1,643
R-squared	0.429	0.576	0.429	0.576	0.361	0.709

7. Conclusion and Policy Implications

In the past several decades, global trade has grown at an unprecedented pace. Especially, the increase in US trade with developing countries has had an impact on local labor markets. At the same time technological change has had a significant impact on the demand for skill. In particular, skill-biased technological change has increased the relative demand for skilled workers. Both globalization and technological change have contributed to the increasingly diverging economic fortune of places based on skill and industry in the United States.

Another recent pattern of the US economy has been the decline in business dynamism. The rate of entrepreneurship at the aggregate level has been declining and the share of small businesses in the economy has been decreasing. At the same time worker reallocation has been slowing. I do not yet have a full understanding of the causes behind declining business dynamism in the US.

In this regard, this paper examined the following questions:

- How does foreign import competition and technological change affect U.S. local employment and job creation? Which is the more important factor behind recent job dynamics in the U.S.?
- How do the effects differ by *establishment age*, i.e., between startups and older establishments, by *industry*, i.e., the manufacturing sector and non-tradable sector, and by *region,* i.e., urban versus rural areas?
- How does foreign import competition and technological change affect the number of small businesses in the local economy?

I summarize the main findings from the empirical results below.

I find no evidence that import competition affects the change in local employment and job creation. Using the Quarterly Workforce Indicators data I do not find a statistically strong negative impact of Chinese import competition on local employment and job creation. This is in contrast with some of the previous studies that have found that increased exposure to Chinese imports reduces local manufacturing employment in the United States using the County Business Pattern data.

Technological change is more critical to declining local employment and job creation than import competition. Technological change has a statistically strong and persistent negative impact on local employment and job creation. In general, this effect holds for both the manufacturing sector and non-tradable sector, and urban and rural areas. However, the effects tends to statistically more significant among older establishment and less so for startups.

Technological change also has a negative effect on the number of small businesses. I use the County Business Pattern data to examine the impact of import competition and technological change on the growth in the number of small businesses in Commuting Zones. I find strong negative effects of technological change on the number of manufacturing small businesses, but not in the non-tradable sectors.

Policy Implications

Globalization and technological change are two main factors that are believed to be driving the change in employment and job patterns in the United States. However, to formulate appropriate and adequate policies that address this issue, I need to have a clearer understanding of the impacts of globalization and technological change on labor market and job dynamics. The aim of this paper was to provide some empirical evidence that can help us in this regard.

The main finding of this paper is that technological change and not import competition is the driving force behind the decline in local employment, job creation, and small businesses. The strong and persistent negative effect of the share of employed in routine jobs in the local economy, compared to the muted impact from Chinese import competition, presents a policy challenge. Currently, there is a substantial gap between technologists and policy makers in understanding what new technologies, such as artificial intelligence or robotics, can do. Most of the public and policy makers do not follow the rapid developments in technology and those who are at the frontier of research and development are more focused on advancing the technologies and have less concern on the social ramifications of such technology. In this regard, there seems to be a policy void in how the government should help train the future work force and future cohorts of entrepreneurs. Though the impact of trade on labor markets is important, technological change will likely have a more significant impact on regional labor markets. The government should actively be engaged in assessing the implications of recent technological developments for the labor market. It would be fruitful to start developing ideas and policies that could help mitigate the potential negative impact of artificial intelligence, robotics, online economies, etc. on labor and businesses.

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