Import Competition, Regional Divergence, and the Rise of the Skilled City

Javier Quintana González[*]

Bocconi University

Abstract

Over the last decades, regions in the United States have been diverging. More skill-intensive areas have experienced a higher wage and skill premium growth at the same time that they became even more skill-intensive. This process deepened inequality both between and within urban areas, concentrating educated and high-earning workers into few cities. In this paper, I show that the substantial decline of manufacturing industries following the sharp rise of Chinese exports, and how local economies adapted to the loss of employment in those sectors, contributed significantly to the divergence among metropolitan areas in the US. Nonetheless, differences in local outcomes are not only the consequence of variations in industrial composition or exposure to foreign competition. Instead, I show in this paper that the consequences of international competition on local labor markets are highly heterogeneous. Even conditional on having manufacturing sectors with similar size and characteristics, the sign and magnitude of the effects of rising import competition depend critically on the characteristics of the rest of the local economy. In particular, I focus on how the share of local workforce with college education shapes the reaction to adverse shocks. Among more skill-intensive regions, greater exposure to import competition makes cities to attract college-educated workers and to increase college-wages and skill premium. On the other hand, among less educated regions, foreign competition has negative effects in terms of college-educated workforce and wages. These results are robust to the inclusion of potential confounders such as skill intensity of directly exposed sectors or city size. This result highlights that the contribution of trade to regional divergence critically depends on the ability of cities to adapt to adverse shocks, and the importance of accounting for local characteristics beyond the directly exposed sectors.

JEL codes: F14, F16, F66, I24, J24, J61, R12

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[*]javier.quintana@phd.unibocconi.it

1 Introduction

Over the last decades, metropolitan areas in the United States have been diverging. More skill-intensive regions have experienced a faster wage and skill premium growth at the same time that they became even more skill-intensive. In other words, college-educated[1] workers have been moving to areas with already higher levels of education, and they have been getting relatively higher wages in those places. The concentration of educated and high-earning workers into few cities deepened inequalities within and between cities. This is in contrast with the convergence in wages and education that took place among US metropolitan areas in the first decades of the post-war period. In this paper, I show that the substantial decline of manufacturing industries following the sharp rise of Chinese exports, and how local economies transformed after the loss of employment in those sectors, contributed significantly to the divergence among metropolitan areas in the US.

It is well documented[2] that the increase in Chinese imports had a negative impact on manufacturing employment in the US. The loss of employment was concentrated in those labor markets with a greater share of local workforce employed in the exposed sectors. Thus, exposure to foreign competition creates a difference between metropolitan areas according to their industrial composition, manufacturing-intensive regions performed worse than the rest of the country. However, I show that the contribution of the 'China shock' to the divergence among US metropolitan areas does not arise only from differences in industrial composition. Taking into account only the size of exposed sectors leaves out relevant consequences of increased import competition. Indeed, the contribution of the 'China shock' to the sorting of skilled workers and disparities on skill premium only appears when the analysis considers other characteristics of the local markets, beyond the size of the manufacturing sector.[3]

In this paper, I document how the characteristics of the non-manufacturing sector of local economies influence the impact of foreign competition. One of the main findings of this paper is that the level of education of regions with similar exposure to the 'China shock' determines the sign and magnitude of its impact on relevant economic results such as skill sorting or disparities in skill premium.

The reason why the share of employment on exposed sectors is not enough to fully understand changes in the overall local economy has to do with the relative size of manufacturing with respect to total employment. Even in the most manufacturing-intensive areas, the percentage of workers employed in the sector is a minority of the local labor force[4]. Thus,

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[1]Throughout the paper I use indistinctly the terms skills and education. I discuss the equivalence in Section 6

[2] Autor et al. (2013) initiated an extensive literature on the 'China shock'

[3]Regressing the growth of college-educated population or the change in skill premium on import penetration as in Autor et al. (2013) delivers non-significant effects

[4]In 1990, the share of working-age population in manufacturing was 12.7%, the median commuting zone employed 12.9% of working-age population in manufacturing, and the 95th percentile was 20.7%

any indirect effect on the non-exposed industries might be as relevant as the direct effect to determine the fate of the overall local economy. While the manufacturing sector typically employs a minor share of the local workforce, a negative shock to it may shape the industrial composition of the rest of the local economy. The ability of a city to absorb the idle resources from the shrinking industries, and the kind of sectors that will grow to replace them will determine the consequences on the overall economy. In this paper, I show that a large share of college-educated workforce at the time of arrival of the negative shock is a crucial factor for cities to undergo a successful adaptation to the 'China shock'.

I find that comparing commuting zones with similar size and characteristics of exposed manufacturing sector, the effects of foreign competition will be different depending on the share of college-educated workers in the region. Among more skill-intensive regions, greater exposure to import competition makes cities to attract college-educated workers and to increase college-wages and skill premium. On the other hand, among less educated regions, foreign competition has negative effects in terms of college-educated workforce and wages.

Namely, metropolitan areas such as San Jose, CA, Raleigh, NC or Austin, TX (with large and highly exposed manufacturing sectors, and a large share of college-educated workforce by 1990) will do better not only than cities in the Rust Belt such as Reading, PA or Dayton, OH (large and exposed manufacturing and low share of college education), but also than cities like Washington, DC (with similarly large college-educated population but negligible exposure to trade). On the other hand, those regions in the Rust Belt will do worse than other areas with a similarly low share of college-educated population but lower exposure to import competition such as Las Vegas, NV or Jacksonville, FL[5].

Empirically, I study the effects of the rapid growth of the volume of Chinese imports between 1990 and 2007 on urban commuting zones in the US. To capture the heterogeneity in the effects of higher import competition I interact the measure of exposure to trade competition with the share of the workforce with a college degree at the beginning of the period. Results are robust to the inclusion of controls to isolate other potentially correlated sources of heterogeneity such as productivity of the manufacturing sector, occupational composition or city characteristics as size or share of foreign-born population.

The estimated effects are sizable and significant. I find that among regions exposed to a rise of \$1700 per worker in Chinese imports per decade (median value), a 6.6% higher share of workers with a college degree (1 standard deviation) means a growth of college-educated population of 10.11% faster per decade (equivalent to 0.52 standard deviations), average real wages for college-educated workers grow a 3.78% more per decade (0.45 standard deviations) and college wage premium becomes 3.86 percentage points higher per decade (0.47 standard deviations) due to the effect of Chinese import competition.

[5]Figure 2 shows the ranking of change in import penetration between 2000-2007, horizontal axis, and the ranking in share of workforce with college education in 1990, vertical axis.
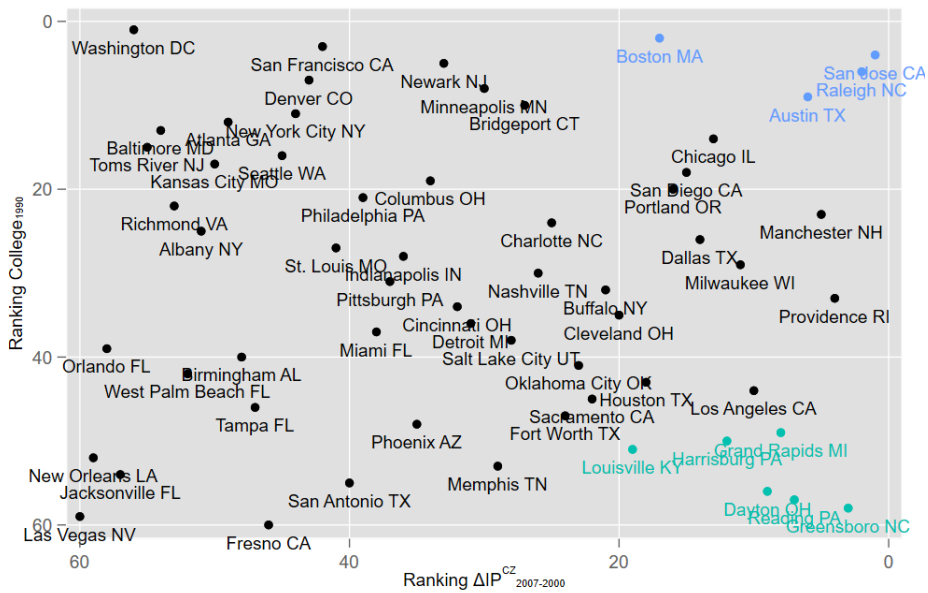
Figure 1: Ranking of college-educated workforce and change in import penetration

There results are relevant for two reasons. First, they provide an explanation to why some cities successfully transition from an industrial to a post-industrial economy. Second, because accounting for heterogeneous effects provides previously unreported effects of the 'China shock'. The average effect on variables like college-workers migration or dispersion of skill premium with a standard analysis as in Autor et al. (2013) are not significantly different from zero.

The remainder of this paper is organized as follows. Section 2 discusses the contribution of this paper to the existing literature. Section 3 introduces the hypothesis of skill-biased sector reallocation and section 4 formalizes a theoretical model and its testable implications. Section 6 includes the description of variables and data sources. I discuss the empirical analysis and identification strategy in section 7. Section 8 contains the summary of results and section 9 concludes.

2 Related Work

The first strand of literature that this work speaks to is the regional divergence in the US. This process, coined as "The Great Divergence" by Moretti (2012), involves dispersion among US cities in many dimensions. The two features that this work addresses are the sorting of college-educated workers into college-abundant regions and the dispersion in college wage premium.

Concerning the literature on the regional divergence in the US over the last decades, I introduce import competition as a novel causal factor of growing disparities in wages and

college education. Growth in exposure to trade contributes to deepening inequalities between and within metropolitan areas. While skill-abundant regions will benefit from the negative shock to manufacturing as they will undergo a positive and skill-oriented transformation; less educated regions will lose part of their college-educated population in favor of the later. Thus, import competition from China makes skilled workers sort into high-skill areas and makes college wages to grow faster in those regions than in the rest of the country.

This work also complements previous theories attempting to explain these features, such as skill-biased technological change or sectoral change. Extensive literature, with Katz and Murphy (1992) as a seminal paper, has focused on the role that skill-biased technological change plays on the rise of skill wage premium at the national level. At the local level, Autor and Dorn (2013) finds that the effect of computerization is larger in those regions where jobs are more intensive in routine tasks. Giannone (2017) quantifies the large contribution of SBTC and agglomeration economies to the end of wage convergence. Beaudry et al. (2006) examines the faster PC adoption in skill-abundant metropolitan areas and the subsequent increase in skill premium.

Concerning technological progress, I show that the growth of Chinese imports competition might accelerate SBTC. Among high-skilled regions, the effect of greater exposure to trade increases both the share and the overall size of the college-educated population, whereas the opposite happens among areas with low college intensity. By increasing disparities in skill intensity, the growth of import competition places skill-intensive regions in a better position to exploit skill-biased technical improvements. Then, the findings on this paper are complementary to the SBTC literature.

Empirically, I test that for the most college-educated regions, exposure to trade has a positive effect on the growth of STEM-intensive occupations or patents per capita. This effect is significant even after controlling for the interaction between the growth of import competition and other variables usually correlated with the automation of jobs, such as the fraction of employment in routine task occupations or the skill composition of the manufacturing sector.

Buera et al. (2015) focuses instead on skill-biased structural changes, where the larger demand for skilled workers comes from a sectoral reallocation toward high-skill intensive industries. Authors show that economic development is associated with a shift in value added to high-skill intensive sectors and a subsequent increase in skill-premium.

Concerning to sectoral changes, I show that highly-educated regions facing a high exposure to Chinese import competition reallocate relatively more employment to STEM-intensive sector and to STEM-related occupations.

The second literature strand that this work speaks to is the effect on local labor markets of trade liberalization. An essential reference is Autor et al. (2013), showing that the growth

of Chinese import competition had a substantial impact on wages and employment in local labor markets in the US between 1990 and 2007. When a region is specialized in manufacturing industries which are highly exposed to Chinese imports competition, employment and wages decrease.

As a novelty, this work shows the importance of accounting for heterogeneous consequences of the 'China shock' and the critical role of overall characteristics of local labor markets, beyond just the relative size of those directly exposed industries. This is particularly relevant because the average effect is not significantly different from zero on key aspects of regional divergence such as change of college-educated population, skill premium or directed migration flows.

Following the seminal work by Autor et al. (2013) a large literature sprung reporting about the effects of Chinese import competition on a wide variety of outcomes. The set of variables for which the effect of the China shock has been found to be significant ranges from local labor markets, innovation[6] or provision of public goods[7] to electoral outcomes[8], mental health[9] or marriage market[10].

This paper steps out from that trend. Unlike most of the literature, the main contribution of this paper is not finding a novel dependent variable on which rising import competition has an effect. Instead, this paper focuses on the analysis of how the China shock affects regions differently depending on local characteristics. In other words, this paper is not about the dependent variable, but about the right-hand side of the equation, and the way in which the 'China shock' variable interacts with other local characteristics.

In the same context of trade shocks, Monte (2015) develops a general equilibrium framework and shows that even if exposure to trade in comparative disadvantage sectors lowers nominal wages, all real wages grow. The reason is that local services and housing prices adjust and workers change commuting patterns within local labor markets. In this work, I show that the positive effect of import exposure in highly educated regions still holds after controlling for local prices. Also, I show that there are significant effects of migration between local labor markets, not only within them.

Dix-Carneiro and Kovak (2015) finds, in the context of Brazilian regions from 1990 to 2010, a significant but small adverse effect on skill premium in regions that allocate a larger fraction of their skilled workers in sectors facing a larger tariff reduction.

An essential difference of this work with respect to prior literature it highlights the importance of characteristics beyond the manufacturing sector. An important determinant of differential effects of exposure to trade is the total share of college-educated population

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[6] Dorn et al. (2016)

[7] Feler and Senses (2017)

[8] Autor et al. (2016), Colantone and Stanig (2018)

[9] Colantone et al. (2015)

[10] Dorn et al. (2017)

in the region. I show that neglecting the overall characteristics of regions, focusing instead only on the size or composition of those directly exposed industries, misses a relevant part of the total effect of import competition.

Finally, this work connects with Glaeser and Saiz (2003) and the 'reinvention city' hypothesis. The authors document that skilled cities are better at adapting to adverse economic shocks because human capital enables to adapt well to change. Findings in this work support the 'reinvention city' view; areas with a higher college education dodge the adverse effects of exposure to Chinese imports, and they leverage out the losses in employment in manufacturing to grow more skill-intensive sectors. Also Glaeser and Ponzetto (2007) looks at the differences in fate of US cities according to their skill levels. The later focuses on the decline of communication costs as the source of divergence. Similarly than in the case of SBTC, this is a compatible argument with the one of uneven skilled transformation that this paper proposes.

3 Hypothesis

The impact on local economies of the increase of Chinese imports has been widely studied. An increase in import competition directly affects local economies by decreasing employment in sectors with a higher level of exposure. Therefore, the level of intensity in manufacturing in the different areas will influence the extent to which trade competition affects local economic outcomes.

However, I argue in this paper that this is not enough to fully describe the induced changes in local economies.

Beyond the manufacturing sector, the rest of the local economy, even if it is not directly exposed to trade competition, is also affected by its consequences. An important transmission channel is the reallocation of productive factors. Part of the resources that were employed in manufacturing, such as labor or office space, turn idle after the negative shock hits the sector. These productive factors can be reallocated to other parts of the local economy where returns stay higher.

Even if this is an indirect way in which rising trade competition affects local labor markets, its weight on final outcomes might not be small. Given that the share of the labor force that is employed in the manufacturing sector is a minority fraction, even in the most intensive regions, any transmission of effects into the nonmanufacturing part of the economy will be highly amplified. Thus, the ability of the rest of the economy to absorb the trade shock will be decisive in determining changes in the economic performance of the area as a whole.

The magnitude of this reallocation will depend on the relative size of manufacturing industries in each local market, but also the overall characteristics of the local economy will

play a relevant role. The importance of local characteristics will be inversely proportional to the geographic mobility of productive factors. If factors such as industrial space or unskilled labor are perfectly or partially immobile, elasticity between sectors will be determined by local characteristics.

However, not all the relevant productive factors are equally immobile. For instante, empirical evidence shows that college-educated workers are more mobile than those without a college education[11]. Concerning relatively mobile factors, differences in the reallocation process within local markets will imply a reallocation of factors across regions. Those markets that reallocate more local resources to the skill-intensive nonmanufacturing sector, will become a better destination for skilled workers.

4   Theoretical Model

To illustrate the reason why the level of skill intensity in a region would play a relevant role when it interacts with higher import competition, I introduce a model of structural transformation in local economies. The model exemplifies the reaction of regions to a trade shock hitting their manufacturing sector. I show that, even if the shock is the same for every local labor market, areas with a higher skill-intensity react by shifting their production from manufacturing to more skill-intensive sectors. Stickiness of production factors such as unskilled labor or office space and the migration of skilled workers from low to high-skill regions are the primary drivers of the differences in effects of trade competition.

The model has four main ingredients: 1) local economies with two productive sectors that differ in their intensity of skilled employment; 2) positive agglomeration externalities for skilled workers; 3) existence of local production factors supplied in a fixed quantity, and 4) a spatial equilibrium that solves the allocation of skilled workers across locations.

This is a partial analysis focused on the production side of the economy, so it neglects the consumption side. Each local economy is composed of two different productive sectors: manufacturing sector and an advanced sector. Regions are assumed to be small open economies, and their firms sell their products in the international market taking prices as given.

The only ex-ante difference between cities that I feed into the model are the parameters $\mathbb{M}_c$ and $\mathbb{H}_c$. The first one represents the idiosyncratic productivity of cities in the production of manufacturing goods, while the second parameter pins down the stock of skilled workers at the beginning of the period. The variation in $\mathbb{M}_c$ and $\mathbb{H}_c$ determines the initial diversity in manufacturing and skill intensity across cities. These two parameters are necessary to replicate the initial variation in manufacturing and skill intensity across cities in the data. Figure 2 plots the ranking in skill and manufacturing intensity among the 60 largest local

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[11]Wozniak (2010)

Figure 2: Ranking of college-educated workforce and change in import penetration

labor markets in US. It is clear from the plot that a perfect (negative) correlation between skill intensity and manufacturing employment does not fit actual data. Thus, variation in the two variables is needed to replicate observed differences. Including variation only in manufacturing productivity or prior stock of skilled workers will result in a perfect sorting of skill-abundant regions to specialize only in the advanced sector, and vice versa.

Productive sectors

Local economies consist of two productive sectors, manufacturing and advanced sector, that differ in their skill intensity. Manufacturing sector uses office space and employs unskilled workers following a Cobb Douglas function with constant returns to scale. Cities have an idiosyncratic productivity level in manufacturing $\mathbb{M}_c$ that determines the relative size of the two sectors in the local equilibrium. Production is sold at price $P_{M,c}$. The growth in competition due to Chinese imports is represented in the model as a negative shock to the price of the good produced in the manufacturing sector.

$$P_{M,c} \cdot Y_{M,c} = P_{M,c} \cdot \mathbb{M}_c \cdot O_{M,c}^{\alpha} L_{M,c}^{1-\alpha}$$

The advanced sector also follows a Cobb Douglas production function with office space and labor as inputs. However, the labor component combines both skilled and unskilled workers with a constant elasticity of substitution. Its price is normalized to 1.

$$P_{A,c} \cdot Y_{A,c} = O_{A,c}^{\alpha} \left(\psi \cdot L_{A,c}^{\sigma} + (1-\psi) \cdot \mathbb{X}_c H_c^{\sigma} \right)^{\frac{1-\alpha}{\sigma}}$$

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where
$$\mathbb{X}_c = \left(\frac{H_c}{H_c + L_{A,c}} \right)^{\beta} \text{ with } 0 < \beta < 1$$

Additionally, the agglomeration of skilled workers in the advanced sector creates a positive skill-specific productivity externality. Skilled workers benefit from the skill intensity of the local advanced sector. Agglomeration externalities for skilled workers help to replicate the empirical evidence of positive relationship among skill intensity in the local market and wages for skilled workers.

This captures that firms in the advanced sector with a high share of skilled workers can implement organizational or managerial practices that improves the productivity of those workers. Concavity reflects that when the advanced sector employs a vast majority of skilled workers, changes in skill density affect little to their productivity as those practices are well established. Instead, when the skill density is low, productivity of skilled workers is more sensitive to changes in skill density.

Production factors

There are three production factors in the economy: office space, unskilled and skilled labor. There is a fixed amount of office space in the region that is competitively allocated by the owners between the manufacturing and the advanced sector $O_c = O_c^M + O_c^A$. Unskilled workers are also geographically immobile[12] and they are also employed in both sectors $L_c = L_c^M + L_c^A$.

Skilled workers are employed only in the advanced sector, and they are imperfectly mobile across regions[13]. Migration of skilled workers has an elasticity with respect to the relative salary in the region of $0 < s < \infty$

$$H_c = \mathbb{H}_c \cdot \left(\frac{w_{H,c}}{\tilde{w}_H} \right)^{s}$$

where $\mathbb{H}_c$ is a local idiosyncratic parameter that sets pre-existing differences in skill intensity and $\tilde{w}_H = \left(\sum_c w_c^s \cdot \frac{H_c^c}{H} \right)^{\frac{1}{s}}$ is the national weighted average wage for skilled workers[14][15].

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[12]This assumption is a simplification of the empirical finding that college educated workers are more mobile than workers without college education (Wozniak (2010);Malamud and Wozniak (2012)).

[13]This assumption is a simplification of the empirical finding that manufacturing sector is relatively more intensive in low-skilled labor (Bound and Holzer (2000); Notowidigdo (2011); Buera et al. (2015)).

[14]This is a direct derivation from models of spatial equilibrium as in Rosen (1979) and Roback (1982). A recent update can be found in Moretti (2011).

[15]The rationale for s can be twofold. First, it is assuming that each worker has location specific preferences for every region drawn from a given distribution. The value of s is inversely related to the variance of such distribution. If workers draw their location specific preferences from an infinite variance distribution then $s = 0$ and they do not migrate as any potential salary gain from doing so is offset by their strong preferences for their current location. If the distribution is zero variance $s = \infty$ and wages are perfectly equalized across regions as the only thing workers value about a region is the potential wage. Second, if we consider that

It is important to point out that, even if the amount of skilled population depends positively on the wages of skilled workers, the relevant quantity is the wage relative to the national average. Even if at first a trade shock might rise skilled wages across the board, in a spatial equilibrium skilled workers will reallocate only to those regions where skilled wages grew the most.

Then, the driving force for changes in the model is the competition for productive factors. This competition takes places in two dimensions. In the first place, within each region, the advanced sector competes against the manufacturing sector for the locally supplied business space and unskilled labor. The negative import competitions shock sector reduces their returns in manufacturing. On the other hand, the return to local factors in the advanced sector depends positively on the number of skilled workers due to factor complementarity.

In the second place, advanced sectors from every region compete at the national level against other regions' advanced sectors to attract skilled labor. The direction of the flow depends on the competitive salary offered to workers. Again, the productivity of skilled employees in a region depends positively on how intensive in the advanced sector is the region.

Both flows feedback each other. A region that displaces more factors from manufacturing to the advanced sector increases its productivity in the latter, attracting skilled workers. An advanced sector with more skilled workers hoards up a larger fraction of local factors.

5 Impact of Trade

As stated above, I show the differential relocation of productive factors between sectors following a negative trade shock. I model the import competition shock as a drop in the price at which manufacturing producers in a city sell their products ($P_1 < P_0$). It is important to notice that the price drop is the same in every region. However, the magnitude of the shock will not be the same in every city as long as the share of factors employed in the manufacturing sector differs. Therefore, the magnitude of sector change will be directly affected by $\mathbb{M}_c$.

In order to properly understand the underlying mechanism, I present the case without skilled-workers mobility as an intermediate step. I show how the reallocation of locally supplied factors depends on regional characteristics. Afterwards, I analyze the uneven consequences of such reallocation of local factors on the productivity of skilled workers. Finally, as long as skilled workers are geographically mobile, there will be a migration of this type of workers following the reallocation of local factors.

local housing supply has positive slope, elasticity of migration with respect to nominal wage changes will be attenuated by the hike of local housing prices. Thus, s will be proportional to the inverse of the sum of the slope of local housing supply and the strength of idiosyncratic location preferences.

5.1 Trade shock without geographical mobility

The negative shock to the price of manufacturing goods decreases the profitability of employing locally-supplied factors (office space and unskilled workers), so part of those resources are transferred to the advanced one. This transfer happens in every region, but the magnitude will depend on the relative size of the local manufacturing sector. Those regions with a high specialization in manufacturing will have a larger inflow of factors to the advanced sector. Assuming that skilled workers are not geographically mobile, the relevant elasticities are the ones of sectoral reallocations. The elasticity of office space in the advanced sector with respect to the price of manufacturing goods is proportional to the share of local office space used in the manufacturing sector.

$$\frac{\partial \ln O_A}{\partial \ln P_M} = -\frac{1}{1-\alpha} \frac{O_M}{O}$$

And the elasticity of unskilled labor employed in the advanced sector with respect to the price of manufacturing goods is

$$\frac{\partial \ln L_A}{\partial \ln P_M} = -\frac{1}{(1-\alpha)(1-\sigma)} \left[1 + \frac{1-\psi}{\psi} \left(\frac{L_A}{\mathbb{X}H} \right)^\sigma \right]$$

Productivity of skilled workers

Producers in the advanced sector pay competitive wages for skilled workers. The total effect from reallocating locally-supplied factors from manufacturing to the advanced sector on the productivity of skilled workers breaks down into two terms with opposite signs. On the one hand, employing a larger fraction of office space in the advanced sector has a net positive effect on the productivity of skilled workers. This is due to the complementarity of labor component and office space. As argued above, this magnitude will be larger in more manufacturing-intensive regions.

On the other hand, the cheaper unskilled labor will have a negative effect on the demand for skilled labor. There are two reasons for that. First, the substitution effect between the two types of labor. Second, the flood of unskilled workers reduces the skill-enhancing externalities. However, the extent of this effect depends on the prior level of skill intensity of the advanced sector. Given the concavity of $\mathbb{X}_c$ with respect to the skill density in the advanced sector, the drop is larger in areas where the non-manufacturing sector is less skill-intensive. The same inflow of unskilled workers can critically affect organizational or managerial practices that benefit skilled labor if the share of skilled workers is low. Instead, if the advanced sector employs a vast majority of skilled labor, the inflow of unskilled workers will barely affect the productivity of their skilled counterparts.

$$\frac{\partial \ln w_H}{\partial \ln P_M} = \alpha \underbrace{\frac{\ln O_A}{\partial \ln P_M}}_{\mathbb{M}_c} + \underbrace{\left[(1 - \alpha - \sigma)\frac{\psi L_A^\sigma}{\psi L_A^\sigma + (1 - \psi)\,\mathbb{X} H^\sigma} + \frac{\partial \ln \mathbb{X}}{\partial \ln L_A}\right]}_{\mathbb{H}_c} \cdot \underbrace{\frac{\partial \ln L_A}{\partial \ln P_M}}_{\mathbb{M}_c} \quad (1)$$

Then the trade shock will shift the demand for skilled workers in the advanced. However, the direction will depend on the prior characteristics of the region. On those cities a large existing stock of skilled the first term in eq. (1) will dominate, as long as the loss in specialization externalities will be low. Instead, in regions where the advanced sector was not highly skill intensive, the second term will dominate. The gains from using a larger share of office space in the advanced sector will be offset by the losses in externalities. Thus, $\mathbb{H}_c$ (skill intensity) determines the sign of the effect on skilled wages, while $\mathbb{M}_c$ (manufacturing intensity) determines the absolute magnitude of the effect.

5.2 Trade shock with geographical mobility

The uneven change in wages of skilled workers across regions induces movement of this type of workers to cities with higher wages. This ignites a spiral of divergence. In regions attracting skilled workers, its wage will further increase. This is a consequence of an even higher skill density in the advanced sector, as well as the fact that those regions will reallocate even more office space away from the manufacturing to the advanced sector. On the other hand, the reallocation of factor will unravel in regions losing skilled workers. In regions with outflows of skilled workers, the return of local factors in the advanced sector decreases. Then, the factors previously reallocated away from manufacturing return to the sector.

A nation-wide negative shock in the manufacturing sector makes the advanced sector in skill-intensive regions to grow at the expense of their respective manufacturing sectors (by using more offices space and unskilled workers) and at the expense of the advanced sector in low-skill intensity regions (by attracting skilled workers).

On the other hand, the reallocation of factors from manufacturing to the advanced sector is reversed in regions with low prior skill intensity. The dry up of skilled labor intensity inflicts a negative productivity shock in the advanced sector. Then, the negative productivity shock in the advanced sector compensates the negative shock in manufacturing.

The model provides testable implications. The effect of a national negative shock to manufacturing will have a different effect according to the prior manufacturing and skill-intensive of the region.

- A skill-intensive region with high exposure to competition:

  - becomes relatively more skill intensive
  - increases its skill wage premium

– reallocates more resources from manufacturing to the advanced sector

- A low skill-intensity region with high exposure to competition:

  – losses skilled population

  – reduces its skilled wages

- A region with low exposure to competition:

  – smaller effects than regions with similar education and higher exposure

6 Data and Sample

I test the effects of the rapid growth of the volume of Chinese imports between 1990 and 2007 on US local labor market markets, how these implications are different depending on prior local characteristics, and its implications for regional divergence. Following closely the previous literature (Autor et al. (2013), Acemoglu et al. (2016)), the sample consists of two stacked quasi-decadal differences in the outcomes of interest for the periods 1990-2000 and 2000-2007 in each region. Geographical units are 320 urban commuting zones[16] (CZ), as developed by Tolbert and Sizer (1996). These commuting zones are clusters of US counties intended to replicate local labor markets. The 320 selected CZ are the ones overlapping metropolitan areas.

Local labor markets

The primary data sources for local labor markets' characteristics are the Census Integrated Public Use Micro Samples for the years 1970, 1980, 1990 and 2000 (Ruggles et al. (2016)), and American Community Survey (ACS) for 2006 through 2008, again Ruggles et al. (2016). I use these samples of individuals between age 25 and 60 to compute average weekly wages, local levels of educational attainment, and migrations rates across commuting zones.

Real wages and wage premium

The computation of wages excludes self-employed workers, public employees and individuals with missing wages or weeks. Log weekly wages are the log of total wage income over the number of worked weeks for workers employed at least for 26 weeks in the previous year. Wages below the first percentile of the national weekly wage distribution are set to the value of the first percentile.

   In order to have a more meaningful estimation of changes in labor conditions across regions, it is necessary to take into account changes in real wages rather than in nominal

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[16]I drop the observations of New Orleans, LA, Hawaii and Alaska

ones. As long as import competition affects the demand for local goods through nominal wages and local employment, prices in more exposed regions could potentially fall (Feler and Senses (2017)). Similarly, higher housing prices may offset nominal gains in booming areas (Hsieh and Moretti (2015)). Thus, it is necessary to have a city-specific deflator. However, there is no off-the-shelf index that covers the entire sample. Then, I follow Moretti (2013) and I deflate changes in nominal wages as

$$\Delta LogRealWage_{i,t} = \Delta LogNominalWage_{i,t} - \frac{1}{3} \cdot \Delta MedianRentalPrice_{i,t} - \frac{2}{3} \cdot \Delta CPU_t$$

In order to get city-specific prices, I discount log changes in nominal weekly wages by one third of the log change of the median rental house price. The underlying logic is that most of the differences in the cost of living between cities comes from housing prices. Following Albouy (2016), housing expenditure accounts for roughly one third of disposable income.

On the other hand, the change in prices of tradable goods, under the assumption that their price changes are homogeneous across CZs, is captured by CPU index and it affects to two thirds of the nominal wage. Among observations from the same period, it is irrelevant for the analysis, as it vanishes when comparing differences in differences among CZs on a given year. I define wage premium as the log difference of wages for college-educated workers minus non-college-educated workers.

Migration

Migration rates are defined as

$$\text{Migration rate}_{i,s,t} = \frac{F_{i,s,t}}{N_{i,s,t-1}}$$

Where $F_{i,t}$ is the in-migration or out-migration flow of population group s in commuting zone i during period t. I compute migration flows for total population, college and non-college educated groups. Migration rate are computed as the fraction of the population group at the beginning of the period. Hence, the migration rate can be read as the contribution of migration to the growth rate of the respective education subgroup.[17][18] Additionally, I compute migration flows for college-educated individuals between 25 and 35-year-old at the time of the sample. I express this flow as a percentage of the respective college-educated population at the beginning of the sample.

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[17] To avoid the concern of individual moving to contiguous CZs while keeping their place of work, I restrict the sample to migrants changing their state of residence.

[18] Census provides information of the place of living 5 years ago and ACS in the place of living 1 year ago. I multiply proportionally the migration flows so they can be expressed in decade-equivalent terms

Import exposure

I shall use the sharp rise that Chinese exports to the US experienced since 1990 as the measure the growth of import competition for each local labor market. Two reasons support this decision. First, China has a strong comparative advantage in labor-intensive goods relative to the US. Second, trade with China is responsible for nearly all of the expansion in U.S. imports from low-income countries since the early 1990s.

The variable of growth of import exposure of a commuting zone is the same as in Acemoglu et al. (2016). It consists of a shift-share procedure, apportioning the growth of Chinese imports per worker in each manufacturing industry j according to each region i's proportion of employment in the industry.

$$\Delta IP_{i,t}^{CZ} = \sum_j \frac{L_{i,j,t_0}}{L_{i,t_0}} \cdot \frac{\Delta M_{j,t}^{UC}}{Y_{j,t_0} + M_{j,t_0} - E_{j,t_0}}$$

where $\Delta M_{j,t}^{UC}$ denotes the change in US imports from China in sector j and period t. This value is normalized by the domestic absorption at the beginning of the period. L_{i,j,t_0} represents the start-of-the-period employment in sector j in local market i, and L_{i,t_0} represents the total -manufacturing and non-manufacturing- local employment. Thus, variation in $\Delta IP_{i,t}^{CZ}$ comes entirely from differences in local industry structure at the beginning of the period.

The measure of CZ import exposure is likely to suffer from an endogeneity problem. To tell the supply-driven component (e.g. productivity growth in China's producers) from US local demand shocks, the instrumental variable uses applies the Bartik formula to the change in eight other developed economies in import from China normalized by local domestic absorption

$$\Delta IP_{i,t}^{Ot} = \sum_j \frac{L_{i,j,t_0}}{L_{i,t_0}} \cdot \frac{\Delta M_{j,t}^{OC}}{Y_{j,t_0} + M_{j,t_0} - E_{j,t_0}}$$

Identification relies on the assumption that high-income countries face similar supply-driven Chinese import competition, while demand shocks are uncorrelated between these eight countries and the United States.

Skill intensity

Following Acemoglu and Autor (2011) I use educational attainment as a proxy for skills. Thus, skill intensity is proxied by the share of the population between age 25 and 60 with at least a bachelor's degree.

As long as the hypothesis I am working with implies a causal effect for the interaction between import competition and prior skill intensity, I need to instrument the proportion

of college-educated population with a variable that is not affected by potential underlying trends confounding educational attainment and import competition growth.

Not doing so could bias the estimations as long as college share could be endogenous to the expectation in relative wage changes or industrial composition. To address that issue, I instrument for the share of the population with a college degree with the percentage of college-educated population in 1970, introducing a two-decade lag.

Including a two-decade lag also helps to mitigate the potential bias introduced by the contemporaneous process of skilled-bias technological change taking place from the 1980s by using a predetermined instrumental variable. Thus, this strategy exploits the long-term persistence of college education level, and it relates to the approach of Valero and Van Reenen (2016), that analyzes the long-term implication of the number of established colleges an area.

Industrial composition

Finally, I use the County Business Patterns (CBP) to retrieve data on local industrial structure. CBP provides information on employment by county and industry. In many cases, information at the most disaggregated level is not fully disclosed and it is only reported on brackets. I use the algorithm in Autor et al. (2013) to impute employment by county and 4-digit SIC.

Exports

I take the measure of exposure to exports constructed by Feenstra et al. (2017). This is a Bartik measure of export exposure of CZ constructed in an analogous way to the import exposure variable in Acemoglu et al. (2016). National growth in exports in each industry, divided by of start-of-the-period shipments, are proportionally imputed to CZs according to their share of employment in each of the industry sectors.

Patents per capita

The first dependent variable to proxy for skilled biased change is the variation in the number of patents per capita. I take data from Porter (2011). Data of patents comes from the US Patents and Trademark Office, it is fractionated by the number of inventors, and they are geographically assigned according to the location of the inventors.

STEM intensive employment

I compute the change in employment in STEM-intensive sectors in the CZ and the overall growth in STEM-intensive occupation. I define an occupation as STEM-intensive following the definitions of the O*Net database (Farr and Shatkin (2004)). Additionally, I compute

the change in the share of employment in these occupations and changes in real wages for workers STEM-intensive occupations.

7 Empirical analysis

The goal of the empirical analysis is to assess whether the lasting consequences of the China trade shock on local labor markets are heterogeneous depending on their prior level of education. In other words, this exercise can be also seen as a test on whether skilled cities adapt better to an adverse shock to their manufacturing sector and whether they can reverse its initial negative consequences.

Hence, the aim of the econometric specification is to identify the effect of the interaction of the exposure to import competition and the prior skill-intensity of local economies. A straightforward step is to set up an econometric specification as in (2), adding to the baseline specification in Autor et al. (2013) the interaction of interest.

$$\Delta Y_{t,i} = \beta_1 \cdot \Delta IP_{t,s}^{US} + \beta_2 \cdot \Delta IP_{t,s}^{US} \cdot College_{t-1,i} +$$
$$+ \alpha \cdot College_{t-1,i} + \Gamma_1 \cdot X_{t-1} + \Gamma_2 \cdot \Delta IP_{t,s}^{US} \cdot X_{t-1} + \epsilon_{t,i} \tag{2}$$

where $College_{i,t-1}^{\mathrm{CZ}}$ is the share of local workforce outside the manufacturing sector between age 25 and 60 with a college degree.

Columns 1 and 2 of tables 1 and 3 to 5 present respectively the results of the specification in (2) without including the interactive term (columns 1) and including the interaction (columns 2). Thus, columns 1 are simply a replication of the regressions in Autor et al. (2013).

As stated in the introduction, when in a standard analysis, allowing only for homogeneous effects, the consequences of being exposed to higher import competition are not statistically significant for outcomes such as population growth, college premium or the growth of STEM-intensive sectors. The apparent lack of significant effects over these variables of such a salient fact as the introduction of China into the market economy motivates further research.

The first step is the introduction of $\Delta IP_{i,t}^{\mathrm{CZ}} \cdot College_{i,t-1}^{\mathrm{CZ}}$, allowing the share of college-educated workforce to be a relevant source of heterogeneity in the effects of rising import competition.

In general, the estimated effects of the specification including the interactive term are not significant. In general, the sign of the effect of $\Delta IP_{i,t}^{\mathrm{CZ}} \cdot College_{i,t-1}^{\mathrm{CZ}}$ is positive for real wages and population growth, but it is not statistically different from zero. The point estimates are more positive for college-educated workers' real wages and population growth, but only the change in the share of the college-educated workforce is marginally significant.

Broadly, the estimated effects of the interactive term seem to mechanically counteract the intercept effect of the trade shock, neutralizing the effect of increasing Chinese competition. However, it is unlikely that the estimations provided by this specification will reflect the real effects of trade competition. The main reason is that the interaction of the share of college-educated workforce with the growth in import penetration will be highly correlated with the interaction of the latter with many other relevant variables.

Next, I discuss the shortfalls of this specification and the main econometric issue that must be addressed to identify the heterogeneous effects of trade competition correctly.

First, a necessary condition for the validity of the analysis is appropriately untangling actual differences in exposure of local economies to the trade shock from differences in the consequences of the shock. In the next section, I discuss how local employment in manufacturing across CZs, even within the same industry, might be differently exposed to competition from Chinese imports and why these differences are potentially correlated with the local level of education.

Second, the share of college-educated workforce is also correlated with other local characteristics. For instance, more educated cities are typically larger, have a higher share of foreign-born population and are unevenly distributed across Census regions. Failing to take these facts into account could make the estimate of interest to show a spurious correlation between college education and other potential sources of heterogeneity in the effect of the trade shock.

7.1   Manufacturing Sector Heterogeneity

One of the main empirical challenges of this paper deals with the way in which the exposure to import competition is measured in Autor et al. (2013) and Acemoglu et al. (2016). The Bartik strategy in these works implicitly assumes homogeneity within manufacturing industries. The weighting factor for the imputation of the growth of imports in industry j to each CZ i is the share of employment of industry j that works in location i. Hence, every worker within an industry contributes to the same extent to the degree of import exposure of their corresponding area, regardless of the nature of the tasks carried out in their jobs.

$$\Delta IP_{i,t}^{cz} = \sum_j \frac{L_{i,j,t_0}}{L_{i,t_0}} \cdot \frac{\Delta M_{j,t}^{UC}}{Y_{j,t_0} + M_{j,t_0} - E_{j,t_0}}$$

However, this assumption is not neutral when the analysis includes the interaction of the trade exposure variable with local characteristics, as long as they might be highly correlated with the composition of the local manufacturing sector.

For instance, take the example of a company operating in any given manufacturing subsector that has its workforce split into two establishments located in two different CZs. The first region hosts the headquarters, with typically white collar workers carrying out

executive, marketing, design or legal tasks. The second region hosts production facilities with typically blue collar workers doing hands-on-the-product jobs directly related to the production process.

Due to the nature of their occupations, it is less likely that the workforce in the first facility will be offshored or substituted by imports. However, as stated above, as long as all the workers belong to the same manufacturing industry, they will be all contributing to the same extent to the measure of import competition exposure of their respective regions.

If the previous example is an extended pattern and more educated local labor markets tend to employ their manufacturing workers in management occupations, it would mean that the 'nominal' import exposure variable would be overestimating the actual exposure to trade in those highly educated regions.

Thus, if the manufacturing sector heterogeneity across local labor markets is correlated with the share of college-educated workforce, the estimated effect for the interactive term would be biased. If manufacturing subsectors in college-educated regions are particularly protected from trade due to their composition, the estimator would be biasing down the effect of the interaction. If manufacturing subsectors in college-intensive regions were especially prone to suffer the effect of import competition, the estimator in the regression would be overestimating the effects.

A similar argument could be made for other attributes of local manufacturing sectors, also related with college intensity and neglected with a headcount weighting criteria, such as the productivity levels, the relative size of the manufacturing, exporting potential or degree of offshorability.

7.2   Interactive controls

I deal with the concern described in the previous section by including a broad set of interactive controls. As long as the variable of interest is the interaction between trade exposure and the share of college-educated workforce, it is not enough to include CZ characteristics as controls. Instead, it is necessary to add also the interaction of the trade exposure variable with the set of controls. Not doing so could lead the estimation to show heterogeneity in the effects of import competition depending on prior college intensity, even if the relevant source of variation in the impact of the trade shock were another CZ characteristic potentially correlated with education

The set of controls can be divided into two main groups. On the one hand, characteristics of local manufacturing sectors, such as the share of management occupations, skill intensity on manufacturing, average manufacturing wages, the percentage of employment in routine occupations, and index of offshorability. On the other, I include controls related to CZ characteristics, beyond the manufacturing sector, such as population, the share of foreign-

born population or female employment participation.

College education and manufacturing intensity have a negative correlation. Also, exposure to import competition is on average more significant the larger is the size of the local manufacturing sector.[19] Hence, the inclusion of this control, both in levels and in interaction, avoids a clear source of bias.

Following the example discussed in the previous section, I also control for the share of employment in the manufacturing sector classified as management occupations. Third, as a raw proxy for average productivity, I add as a control average log wages in manufacturing.

Finally, this battery of controls includes the share of employment in routine occupations and the average offshorability index of occupations. Within manufacturing subsectors, offshorable occupations are more inclined to suffer consequences of rising Chinese competitiveness. Autor and Dorn (2013) shows that routine occupations are more susceptible to computerization. The share of employment in routine occupations is used to untangle the effects of skill-biased technological change from the ones of trade competition (Autor et al. (2015)). As long as the rise in Chinese import competition and SBTC are contemporaneous, not including the interaction with these variables could make the interaction of interest to reflect that more college-educated regions are differently affected by technological progress or job automation process.

The second set of controls deals with local demographic characteristics. I include as controls log population, the share of foreign-born population and female employment participation. These variables are highly correlated with the share of college-educated workforce. More educated cities are typically larger, have a larger share of foreign-born population and women participate more in the labor market.[20] The inclusion of these controls, again in levels and interacted with the trade shock variable, isolates the potential agglomeration effects or a better ability of large cities to absorb negative economic shocks. Given any effect of rising import competition on local labor conditions, local population elasticities might be different for diverse urban sizes or with a different share of foreign-born population. These controls might be particularly relevant in regressions with population changes or migration flows as dependent variables.

Finally, I include the variable of exposure to exports from Feenstra et al. (2017). The entry of China into the world market economy meant a massive supply shock, but also a demand one. Those regions that were more exposed to Chinese import competition could also benefit from a larger exposure to the growth of exports[21]. The inclusion of this control

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[19]Population-weighted correlation of share of manufacturing employment with the share of college-educated workforce and import exposure is respectively -0.31 and 0.49 in 1990

[20] Population-weighted correlations with the share of college-educated workforce are respectively 0.31, 0.32 and 0.41 in 1990. With the measure of import exposure, -0.06, -0.06 and 0.07

[21]Population-weighted correlation of the measure of exposure to export and the variable of exposure to imports is 0.52 for 1990-2000 and 0.21 for 2000-2007. The correlation with college education is 0.01 in 1990

rules out the potential effects of within-sector specialization. A sector could lose employment in one part of the production chain because of imports and, at the same time, gaining jobs in another part of the chain due to exporting. This changes could not be neutral for college or non-college-educated workers.

7.3 Complete specification

Equation (3) shows the full econometric specification. This specification includes the interaction $\Delta\text{IP}_{i,t}^{\text{CZ}}\cdot\text{College}_{i,t-1}^{\text{CZ}}$ as well as the interaction of the trade variable with the battery of controls discussed in the previous section. Columns 3-6 in Tables 1 and 3 to 5 add sequentially each group of interacted controls. The full set of control variables in levels are included in every regression.

$$
\begin{aligned}
\Delta Y_{t,i} = {} & \beta_1 \cdot \Delta IP_{t,s}^{US} + \beta_2 \cdot \Delta IP_{t,s}^{US} \cdot College_{t-1,i} + \\
& + \alpha \cdot College_{t-1,i} + \Gamma_1 \cdot X_{t-1} + \Gamma_2 \cdot \Delta IP_{t,s}^{US} \cdot X_{t-1} \\
& + CensusRegion_i + Year_t \cdot College_{t-1,i} + Year_t + \epsilon_{t,i}
\end{aligned}
\tag{3}
$$

Tables 1 and 3 to 5 report the 2SLS estimates of (3) for each of the dependent variables. The instrumental variables for import exposure and the share of college-educated workforce are the ones described in the data section. The interaction of the two instrumental variables is the instrument for $\Delta\text{IP}_{i,t}^{\text{CZ}}\cdot\text{College}_{i,t-1}^{\text{CZ}}$.

The battery of interacted controls are also potentially endogenous. As long as they involve the interaction with the trade shock variable, they need to be instrumented as well. For each of the interacted controls, I include the interaction of the start-of-the-period value of the control with the instrument for the trade shock variable, $\Delta\text{IP}_{i,t}^{\text{Ot}}$

Every variable except $\Delta\text{IP}_{i,t}^{\text{CZ}}$ and $\text{College}_{i,t-1}^{\text{CZ}}$ is normalized substracting its population-weighted mean. This normalization helps to interpret the relative sizes of $\hat{\alpha}$ and $\hat{\beta}$. When the rest of the variables are demeaned, the ratio of the two coefficients is the share of college-educated workforce at which the predicted effect of import exposure changes its sign (under the assumption that the rest of characteristics are at the national mean for every CZ).

Regressions are weighted by start-of-the-sample population. Robust standard errors are clustered at the state level.

First stage

Table 6 shows the first stage regression of the main endogenous variables. As stated in the previous section, the first stage regression for each endogenous variable includes a large

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and -0.22 in 2000

set of instruments. Many of these instruments are the interaction of $\Delta\text{IP}_{i,t}^{\text{Ot}}$ with other local variables. Then, it should be expected that in the first-stage regression for $\Delta\text{IP}_{i,t}^{\text{CZ}}$ the estimated effect of $\Delta\text{IP}_{i,t}^{\text{Ot}}$ loses significance. The size of the F-statistic and SW F-statistic are well above the usual critical values, and they show that the strength of the first-stage.

Predicted values explain a large share of the variability of the endogenous variables, as fig. 11 shows.

8 Results

8.1 Population changes and skill sorting

Table 1 shows the results for the main demographic variables. The dependent variables are the log change of population between age 25 and 60, the change in the percentage of the workforce with a college degree and the log change of college-educated and non college-educated working-age workforce. Column 1 shows the estimates of the regression on the change of import penetration without including any interaction. In other words, it replicates the original analysis in Autor et al. (2013). Column 2 shows the estimation of eq. (2). Columns 3-5 show the estimates of the specification in eq. (3), adding sequentially the interacted controls with characteristics of the local manufacturing sector, local demographic variables, and exposure to exports.

Results in Table 1 exemplify the main findings in the paper. From Column 1, it arises that the average effect of import competition on the demographic changes is not significantly different from zero. However, this does not mean that the 'China shock' is not relevant for population changes. When the analysis takes into account local characteristics, it arises that the null mean effect is the consequence of positive effect among highly educated regions and negative among less educated areas.

The effects of the trade shock are significantly heterogeneous, but only for the growth rate of the college-educated workforce. While the intercept coefficient is negative, the estimated effect has a significant positive slope with respect to the prior level of college education. This result implies a population movement of college-educated workers from low-educated regions with high exposure to import competition to exposed regions with a higher level of educated.

Concerning the growth rate of non-college-educated workforce, results are less conclusive. The sign of the estimators change with the different set of controls, the magnitude are smaller and not statistically significant.

Consequently, the effect of trade competition on the share of college-educated population has a positive and significant slope with respect to the prior level of college education. Exposure to import competition makes more educated regions to become even more ed-

Table 1

	(1)	(2)	(3)	(4)	(5)
	Log Population 25-60 (change)				
$\Delta\mathrm{IP}^{\mathrm{CZ}}_{i,t}$	0.05	-1.8	-2.48**	-1.97	-1.97
	[0.068]	[1.439]	[1.248]	[1.627]	[1.771]
$\mathrm{College}^{\mathrm{CZ}}_{i,t-1}$	-0.71***	-1.31**	-2.23***	-1.85*	-1.86*
	[0.117]	[0.607]	[0.770]	[0.973]	[1.013]
$\Delta\mathrm{IP}^{\mathrm{CZ}}_{i,t} \cdot \mathrm{College}^{\mathrm{CZ}}_{i,t-1}$		6.11	9.31*	7.71	7.83
		[5.247]	[4.807]	[6.742]	[7.210]
	Share of College Workforce (p.p. change)				
$\Delta\mathrm{IP}^{\mathrm{CZ}}_{i,t}$	0.01	-0.57***	-0.73***	-1.33***	-1.42***
	[0.016]	[0.134]	[0.208]	[0.473]	[0.542]
$\mathrm{College}^{\mathrm{CZ}}_{i,t-1}$	0.09*	-0.14	-0.30**	-0.62**	-0.65**
	[0.045]	[0.116]	[0.129]	[0.253]	[0.287]
$\Delta\mathrm{IP}^{\mathrm{CZ}}_{i,t} \cdot \mathrm{College}^{\mathrm{CZ}}_{i,t-1}$		2.06***	2.55***	5.18***	5.47***
		[0.443]	[0.733]	[1.753]	[1.965]
	Log College Workforce (change)				
$\Delta\mathrm{IP}^{\mathrm{CZ}}_{i,t}$	0.05	-3.46***	-4.65**	-6.12***	-6.33**
	[0.091]	[1.223]	[1.808]	[2.231]	[2.472]
$\mathrm{College}^{\mathrm{CZ}}_{i,t-1}$	-1.01***	-2.27***	-3.78***	-4.45***	-4.54***
	[0.212]	[0.759]	[0.935]	[1.129]	[1.205]
$\Delta\mathrm{IP}^{\mathrm{CZ}}_{i,t} \cdot \mathrm{College}^{\mathrm{CZ}}_{i,t-1}$		11.98***	16.73**	23.91***	24.64***
		[4.539]	[6.756]	[8.624]	[9.246]
	Log Non College Workforce (change)				
$\Delta\mathrm{IP}^{\mathrm{CZ}}_{i,t}$	0.04	-0.21	-0.39	1.97	2.5
	[0.088]	[1.937]	[1.005]	[1.955]	[2.258]
$\mathrm{College}^{\mathrm{CZ}}_{i,t-1}$	-0.95***	-1.17*	-1.65***	-0.23	-0.05
	[0.148]	[0.654]	[0.621]	[1.096]	[1.221]
$\Delta\mathrm{IP}^{\mathrm{CZ}}_{i,t} \cdot \mathrm{College}^{\mathrm{CZ}}_{i,t-1}$		0.41	2.42	-7.04	-8.68
		[6.806]	[3.959]	[8.069]	[9.054]
Interacted Controls:					
Mfg. Sector Controls			✓	✓	✓
Demographics				✓	✓
Exports					✓
Observations	640	640	640	640	640

NOTE - Controls in levels are included in every regression. Controls interacted with $\Delta\mathrm{IP}^{\mathrm{CZ}}_{i,t}$ are included as stated. All the regressions include the interaction of $\mathrm{College}^{\mathrm{CZ}}_{i,t-1}$ with a time dummy. Regressions are weighted by start-of-the-sample population. Robust standard errors are clustered at the state level. All the variables, except $\Delta\mathrm{IP}^{\mathrm{CZ}}_{i,t}$ and $\mathrm{College}^{\mathrm{CZ}}_{i,t-1}$, are population-weighted demeaned. * $p < .1$, ** $p < .05$, *** $p < .01$

ucated, while it decimates college-education workforce among less educated regions. The effect on the growth rate of the total population between age 25 and 60 is positive, but only marginally significant.

Columns 4 and 5 include the interacted controls of demographic characteristics and exposure to export. When the analysis incorporates demographics controls, the effects for the two subpopulation groups differ. The effects are larger and more significant for the growth rate of college-educated workforce, while the effect for the growth of non-college-educated workforce remains not significant.

These changes are consistent with the existence of unobserved characteristics of firms and individuals that self-sort into larger cities. If there is positive self-selection in terms of productivity, larger cities would be relatively shielded to the same 'nominal' trade shock. Then, the reallocation effect induced by the combination of $\Delta \text{IP}_{i,t}^{\text{CZ}}$ and $\text{College}_{i,t-1}^{\text{CZ}}$ would be attenuated. Also, larger cities might offer a better buffer for affected workers due to the size of the local economy.

Comparative results

To provide a more meaningful interpretation of the estimated coefficients of table 1, I shall compute the predicted differences in outcomes for three pairs of cities. The first pair consists of a high and a low-education commuting zones exposed to the median level of import penetration. This comparison conditions on the same level of exposure to trade and exploits existing differences in college education. The second pair consists of two high-education regions, one with a high exposure to import competition and the other one with a low level of exposure to trade. Similarly, the third pair consists of two regions with a low level of college education that differ in their level of growth of exposure to trade. The second and third comparisons conditions on similar existing levels of college education, and exploits differences in manufacturing intensity.

Namely, the second example compares educated cities with a large pre-existing manufacturing sector such as Austin, TX or Raleigh, NC versus other educated cities with specialization in other economic sectors, such as Washington, DC. On the other hand, the third comparison compares low-education areas and manufacturing intense areas, such as Rust Belt's Reading, PA or Dayton, OH versus regions with low-educational attainment and little manufacturing intensity, such as Las Vegas, NV.[22]

The first comparison takes two regions at the median level of growth of exposure to Chinese imports.[23] The first one is at the 75th percentile of the education ranking in 1990,

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[22] Figure 2 plots the ranking of college education in 2000 and the raking of the growth of import penetration in the period 2000-20007 for the 60 largest metropolitan areas.

[23] The measure of import penetration that I use in the analysis is normalized by the level of absorption of the manufacturing sector. The median value of $\Delta \text{IP}_{i,t}^{\text{CZ}}$ is 11.21% for CZs at the bottom quartile of the

whereas the second one is at the 25th percentile[24]. In this case, the more college-educated region will have an 8.66% faster population growth per decade, which accounts for 0.72 standard deviations of the dependent variable. The difference is more substantial concerning the growth of college-educated population is larger. The number of college-educated workers will grow 12.33% faster per decade in the skill-intensive region; this magnitude is equal to 0.63 standard deviations. The share of workers with a college degree in the skill-intensive region will increase 0.89 percentage points more per decade respect to the one in the low-educated region; this means a difference equal to 0.45 standard deviations.

On top of that, among highly educated areas, higher exposure to trade has net positive effects for its college-educated workforce. To show it, I compare two regions at the 75th percentile of the college-education ranking in 1990. One of them is highly exposed to trade, at the 75th percentile of the distribution ($\sim \$2100/\text{worker}$), whereas the other one is at the 25th percentile ($\sim \$900/\text{worker}$)[25].

The more exposed region will have a 2.35% faster population growth per decade due to higher import higher competition than the one with little exposure. Concerning college-educated workers, it grows 7.47% per decade faster in the highly exposed region, which accounts for 0.48 standard deviations. The share of college-educated workers increases 0.9 percentage points more per decade in the highly exposed area; this is equivalent to 0.47 standard deviations.

Among regions with a low share of college-educated workers, the effect is the opposite. Comparing two areas at the 25th percentile of education raking in 1990, an area at the 75th percentile of exposure to trade ($\sim \$3400/\text{worker}$) loses the 3.17% of college-educated workers per decade compared to a region in the 25th percentile of exposure to import competition ($\sim \$1200/\text{worker}$)[26].

education ranking and 6.59% for CZs at the top quartile. For the sake of clarity, I provide the approximate equivalents figures in dollars per worker.

[24]Median exposure to China; 75th percentile in college ranking in 1990 vs. one at the 25th

$$\Delta\hat{y}_{\Delta\text{IP}50,\text{Edu}75} - \Delta\hat{y}_{\Delta\text{IP}50,\text{Edu}25} \quad = \quad \underbrace{\hat{\beta}_{\Delta\text{IP}\cdot\text{Edu}}}_{+} \cdot \left[\Delta\text{IP}^{50} \cdot \left(\text{Edu}^{75} - \text{Edu}^{25}\right)\right]$$

[25]Highly educated CZs (75th percentile); 75th percentile in exposure to China vs. 25th percentile in exposure

$$\Delta\hat{y}_{\Delta\text{IP}25,\text{Edu}75} - \Delta\hat{y}_{\Delta\text{IP}75,\text{Edu}75} \quad = \quad \hat{\beta}_{\Delta\text{IP}} \cdot \left[\Delta\text{IP}^{25} - \Delta\text{IP}^{75}\right] + \hat{\beta}_{\Delta\text{IP}\cdot\text{Edu}} \cdot \left[\left(\Delta\text{IP}^{25} - \Delta\text{IP}^{75}\right) \cdot \text{Edu}^{75}\right]$$
$$= \quad \underbrace{\left(\hat{\beta}_{\Delta\text{IP}} + \hat{\beta}_{\Delta\text{IP}\cdot\text{Edu}} \cdot \text{Edu}^{75}\right)}_{+} \cdot \left[\Delta\text{IP}^{25} - \Delta\text{IP}^{75}\right]$$

[26]Low educated CZs (25th percentile); 75th percentile in exposure to China vs. 25th percentile in exposure

$$\Delta\hat{y}_{\Delta\text{IP}25,\text{Edu}25} - \Delta\hat{y}_{\Delta\text{IP}75,\text{Edu}25} \quad = \quad \hat{\beta}_{\Delta\text{IP}} \cdot \left[\Delta\text{IP}^{25} - \Delta\text{IP}^{75}\right] + \hat{\beta}_{\Delta\text{IP}\cdot\text{Edu}} \cdot \left[\left(\Delta\text{IP}^{25} - \Delta\text{IP}^{75}\right) \cdot \text{Edu}^{25}\right]$$
$$= \quad \underbrace{\left(\hat{\beta}_{\Delta\text{IP}} + \hat{\beta}_{\Delta\text{IP}\cdot\text{Edu}} \cdot \text{Edu}^{25}\right)}_{-} \cdot \left[\Delta\text{IP}^{25} - \Delta\text{IP}^{75}\right]$$

Finally, I introduce a graphical representation of the results. As long as the analysis decomposes the effect of the 'China shock' into many components, I can compute the aggregation in order to get the CZ-specific estimate

$$\tilde{\beta}_{\Delta\text{IP}}^{cz} = \hat{\beta}_{\Delta\text{IP}} + \sum_{\gamma \in \Gamma} \hat{\beta}_{\Delta\text{IP} \cdot \gamma} \gamma^{cz} \tag{4}$$

Figure 3 plots the conditional predicted effect on college population against the initial share of college-educated workforce. The figure illustrates that zero mean effect of the 'China shock' on the change of college-educated population is the consequence of positive effect among regions at the top of the skill-intensity distribution and a negative one among those at the bottom of the distribution.

On top of that, I compute the total predicted effect of the 'China shock' as the product of the CZ-specfic estimate above and the level of import penetration of each commuting zone.

$$\Delta\hat{y}_{cz} = \left[\hat{\beta}_{\Delta\text{IP}} + \sum_{\gamma \in \Gamma} \hat{\beta}_{\Delta\text{IP} \cdot \gamma} \gamma^{cz} \right] \cdot \Delta\text{IP}_{cz} \tag{5}$$

Section 8.1 shows the estimated effects for the 60 largest commuting zones. The two figures illustrates the contribution of import competition to regional diverge. First, the conditional estimated effects it creates differences between the most and the least educated regions. This is the consequence of the positive slope of the predicted effect. Second, conditional on a similar level of skill intensity, differences in exposure to import competition have differential effects. Among the most educated regions, areas like Raleigh NC or Austin TX benefit from a large exposure to foreign competition; while for other highly-educated regions like Washington DC the total predicted effect is close to zero due to the low level of exposure. The opposite happens among the least educated areas. The negative conditional effect of import competition is exacerbated on areas like Reading PA or Greensboro NC due to a large increase in import penetration. On the other hand, the total predicted effect in areas like Las Vegas NV or Orlando FL is very close to zero even if the conditional predicted effect is negative.

8.2 Migration

Table 2 shows that the migration of college-educated workers accounts for most of the changes in the educational composition of commuting zones, rather than differences in graduation rates. Table 2 shows the estimated coefficients of the regression of migration flows of each population group with the full-control version of eq. (3), with net migration rates and the breakdown into im- and outmigration flows.

Figure 3: $\tilde{\beta}_{\Delta\mathrm{IP}}^{cz} = \hat{\beta}_{\Delta\mathrm{IP}} + \sum_{\gamma \in \Gamma} \hat{\beta}_{\Delta\mathrm{IP}\cdot\gamma}\gamma^{cz}$

Figure 4: $\Delta\hat{y}_{cz} = \left[\hat{\beta}_{\Delta\mathrm{IP}} + \sum_{\gamma \in \Gamma} \hat{\beta}_{\Delta\mathrm{IP}\cdot\gamma}\gamma^{cz}\right] \cdot \Delta\mathrm{IP}_{cz}$

Figure 5: $\tilde{\beta}^{cz}_{\Delta \text{IP}} = \hat{\beta}_{\Delta \text{IP}} + \sum_{\gamma \in \Gamma} \hat{\beta}_{\Delta \text{IP} \cdot \gamma} \gamma^{cz}$

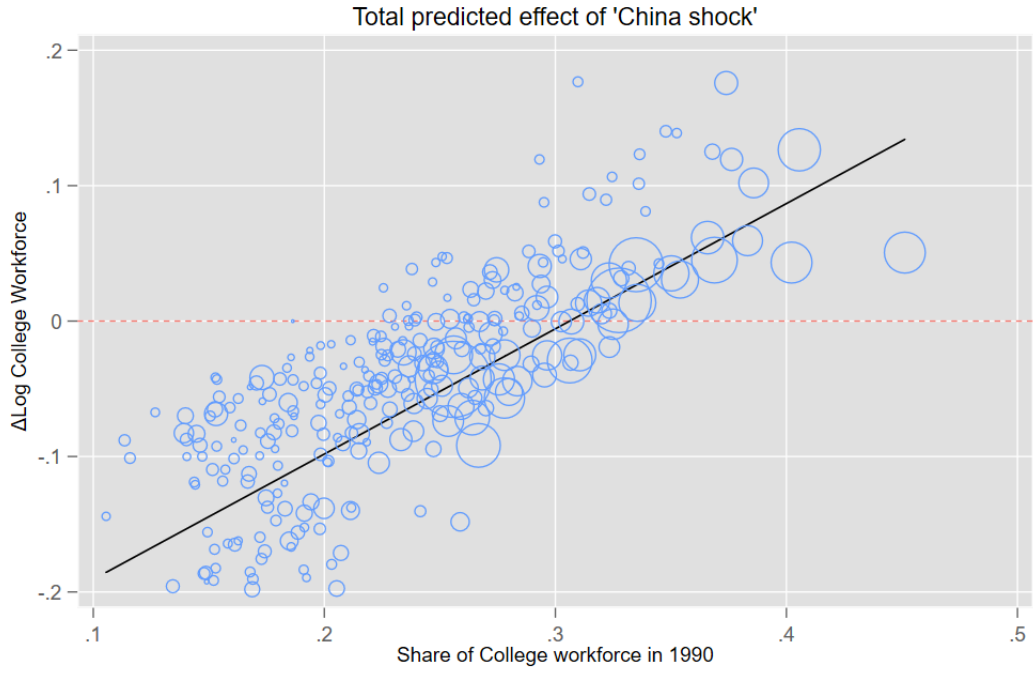Figure 6: $\Delta \hat{y}_{cz} = \left[\hat{\beta}_{\Delta \text{IP}} + \sum_{\gamma \in \Gamma} \hat{\beta}_{\Delta \text{IP} \cdot \gamma} \gamma^{cz} \right] \cdot \Delta \text{IP}_{cz}$
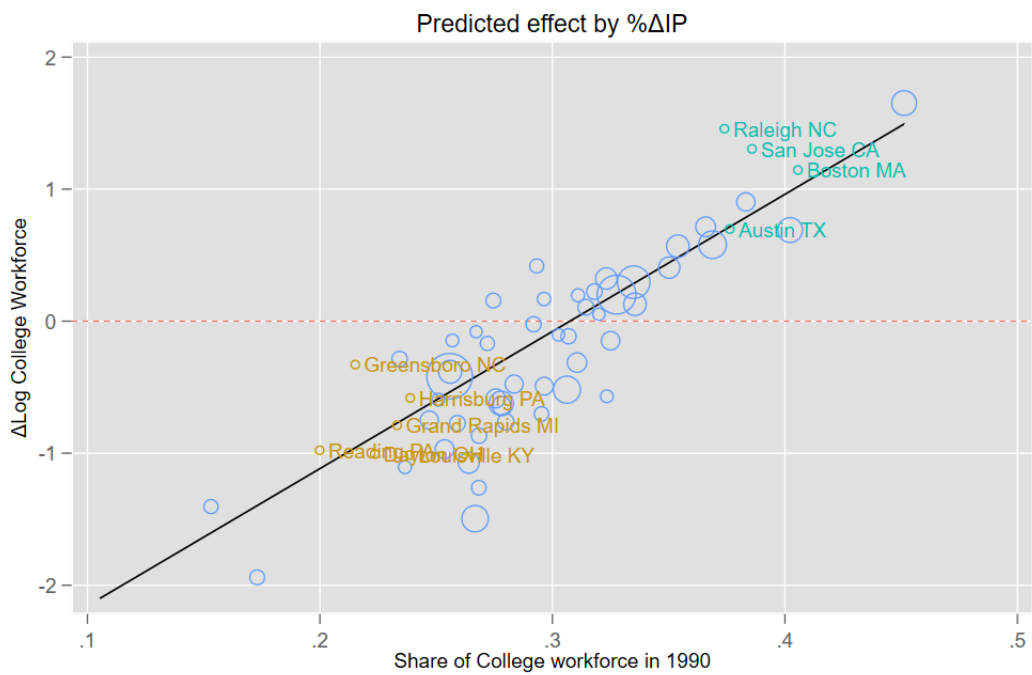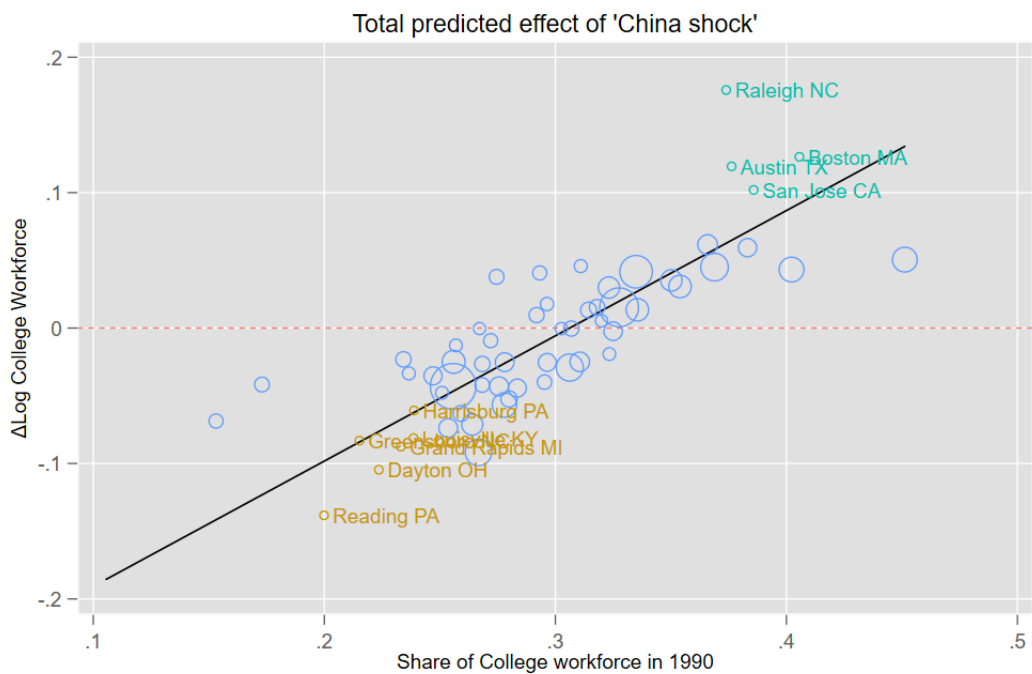
Table 2

	Immigration		Outmigration		Net Migration	
			Total Population			
$\Delta \text{IP}_{i,t}^{\text{CZ}}$	0.35***	-4.40**	0.25***	-1.58	0.10	-2.82**
	[0.12]	[1.96]	[0.07]	[1.29]	[0.09]	[1.22]
$\text{College}_{i,t-1}^{\text{CZ}}$	-0.01	-0.10*	0.04***	0.00	-0.05***	-0.10***
	[0.01]	[0.06]	[0.01]	[0.03]	[0.01]	[0.04]
$\Delta \text{IP}_{i,t}^{\text{CZ}} \cdot \text{College}_{i,t-1}^{\text{CZ}}$		17.31**		6.46		10.84**
		[7.29]		[4.71]		[4.62]
			College Educated			
$\Delta \text{IP}_{i,t}^{\text{CZ}}$	0.38**	-7.98***	0.18	-2.72	0.20	-5.26**
	[0.16]	[2.93]	[0.15]	[2.34]	[0.16]	[2.42]
$\text{College}_{i,t-1}^{\text{CZ}}$	-0.02	-0.21***	0.07***	0.00	-0.08***	-0.20***
	[0.03]	[0.08]	[0.01]	[0.06]	[0.02]	[0.06]
$\Delta \text{IP}_{i,t}^{\text{CZ}} \cdot \text{College}_{i,t-1}^{\text{CZ}}$		30.18***		11.19		18.99**
		[10.69]		[8.52]		[8.70]
			Young (25-35 y.o.) & College educated			
$\Delta \text{IP}_{i,t}^{\text{CZ}}$	0.21**	-5.29***	0.11	-1.30	0.10	-3.99**
	[0.09]	[1.65]	[0.12]	[1.67]	[0.13]	[1.65]
$\text{College}_{i,t-1}^{\text{CZ}}$	0.01	-0.09**	0.07***	0.04	-0.05***	-0.13***
	[0.01]	[0.04]	[0.01]	[0.04]	[0.02]	[0.03]
$\Delta \text{IP}_{i,t}^{\text{CZ}} \cdot \text{College}_{i,t-1}^{\text{CZ}}$		19.59***		5.88		13.71**
		[6.02]		[6.06]		[5.76]
			Non College Educated			
$\Delta \text{IP}_{i,t}^{\text{CZ}}$	0.27**	-2.00	0.18***	-0.38	0.09	-1.62
	[0.11]	[1.67]	[0.06]	[0.89]	[0.08]	[1.19]
$\text{College}_{i,t-1}^{\text{CZ}}$	-0.03**	-0.05	0.01*	0.00	-0.04***	-0.05
	[0.01]	[0.05]	[0.01]	[0.02]	[0.01]	[0.04]
$\Delta \text{IP}_{i,t}^{\text{CZ}} \cdot \text{College}_{i,t-1}^{\text{CZ}}$		8.66		1.95		6.71
		[6.22]		[3.31]		[4.48]
<u>Interacted Controls:</u>						
Mfg. Sector Controls	✓		✓		✓	
Demographics	✓		✓		✓	
Exports	✓		✓		✓	

NOTE - Controls in levels are included in every regression. Controls interacted with $\Delta \text{IP}_{i,t}^{\text{CZ}}$ are included as stated. All the regressions include the interaction of $\text{College}_{i,t-1}^{\text{CZ}}$ with a time dummy. Regressions are weighted by start-of-the-sample population. Robust standard errors are clusted at the state level. All the variables, except $\Delta \text{IP}_{i,t}^{\text{CZ}}$ and $\text{College}_{i,t-1}^{\text{CZ}}$, are population-weighted demeaned. * $p < .1$, ** $p < .05$, *** $p < .01$

The pattern of results is similar to the one in table 1. Even if the effect of the interaction between $\Delta\text{IP}_{i,t}^{\text{CZ}}$ and $\text{College}_{i,t-1}^{\text{CZ}}$ has a positive effect on the net migration rates of college and non-college educated workers, the magnitude is significantly larger for the former group, and only for college-educated workers the effect is statistically significant.

The second panel shows the migration rates of college-educated workers with age between 25 and 35 as a percentage of the college-educated workforce in the CZ at the beginning of the period. Comparing the magnitudes of the second and third panel shows the importance of the migration of college-educated workers immediately after graduation or in the early stages of their worklife. The coefficients of the interaction between $\Delta\text{IP}_{i,t}^{\text{CZ}}$ and $\text{College}_{i,t-1}^{\text{CZ}}$ for young-and-educated workers are more significant than for overall college-educated workers, and they account for roughly the 70% of the effect of the interaction on college-educated net migration rates.[27]

Finally, the breakdown of net migration flows into in- and outmigration shows the contribution of each flow to population growth. The total flows of workers are driven mainly by workers inflows. College-educated and, to a lower extent, non-college-educated workers move to areas where the 'China shock' coincides with a high prior level of college education. Concerning immigration, the estimated coefficients for the interaction are larger and highly significant for college-educated and young-and-educated workers, and marginally significant for non-college educated workers.

These results are consistent with the reallocation hypothesis. If those areas with a larger fraction of college-educated workers adapt better to a negative shock to the manufacturing sector, and they grow new skill-intensive industries, these regions will attract workers, especially college-educated ones.

The estimated coefficient for outmigration rates is only marginally significant for non-college-educated workers, but the sign is positive for every subpopulation group. The size of the estimator is similar to the one for immigration among non-college-educated workers and around one-third of its size among college-educated workers. This finding can be rationalized under the assumption that skilled regions facing a negative shock to their manufacturing sector undergo a more substantial sectoral reallocation. Even if this reallocation will foster new opportunities for incoming workers, it might also force current workers in the region to switch to new sectors or leave the local labor market.[28]

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[27] In comparison, college-educated workers with age between 25 and 35 are, on average, the 31% of the total college-educated population of the CZ.

[28] Monras (2018) documents similar results. Exploiting heterogeneous incidence of the Great Recession at the local level, he finds that most of the response of internal migration is accounted for by immigration rates

8.3 Wages and Skill Premium

Table 3 shows the results for changes in average weekly wages. The dependent variables are the growth rates of average weekly real wages for college-educated and non-college-educated workers and the change in college wage premium. As in table 1, column 3-5 includes the set of interactive controls sequentially.

The estimated coefficients for $\Delta\text{IP}_{i,t}^{\text{CZ}} \cdot \text{College}_{i,t-1}^{\text{CZ}}$ show that the effects of the 'China shock' are significantly heterogeneous concerning the growth rate of real wages for college-educated workers. Its effect breaks up into a negative intercept and a significantly positive slope. In other words, for regions with a low share of college-educated workforce, the effect of being exposed to import competition decreases real wages of skilled workers. On the other hand, among the most educated regions, the predicted effect turns positive, and a higher degree of exposure to import penetration means higher real wages for college-educated workers. Concerning changes in real wages for non-college educated workers, there is not any significant heterogeneity in the effects. As a results of this, consequences on college wage premium are entirely driven by the changes in real wages of college-educated workers.

These results illustrates the contribution of rising import competition to the second dimension of regional divergence. Skilled regions adapt to the trade shock and they react to the negative shock in manufacturing by growing more skill intensive sectors. Under the hypothesis of a skilled biased sectoral change, the coincidence of trade exposure and college education will have a positive impact on wages for skilled wages, while it will be neutral in term of wages for non college-educated workers.[29]

Column 3 includes the interacted controls with Census regions, and it already shows the pattern of results: in those regions where the trade shock coincides with a high level of college education, college wage premium rises due to hike in wages for college-educated workers. As in table 1, the inclusion of the interaction of local manufacturing characteristics with $\Delta\text{IP}_{i,t}^{\text{CZ}}$ as controls amplifies the estimated coefficient of $\Delta\text{IP}_{i,t}^{\text{CZ}} \cdot \text{College}_{i,t-1}^{\text{CZ}}$ on the growth rate of real college wages. The inclusion of demographic controls and the exposure to exports does not significantly change the magnitude of the coefficients.

Comparative results

The effects are significant comparing regions with different college intensity, but also when comparing regions with similar college intensity but different exposure to trade. To provide a more meaningful interpretation of the results in table 3, I reproduce the same inter-regional comparisons as in the previous section. Taking two regions with different positions

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[29]Table 5 breaks down growth rates of wages by education and manufacturing and non-manufacturing. Results in the table show that changes in wages for college-educated workers are mainly driven by changes of college-educated workers in the non-manufacturing sector.

Table 3

	(1)	(2)	(3)	(4)	(5)
	College workers - Log Real Weekly Wage change				
$\Delta\text{IP}^{\text{CZ}}_{i,t}$	-0.08	-1.91***	-2.57**	-2.53**	-2.38**
	[0.08]	[0.67]	[1.05]	[1.15]	[1.19]
$\text{College}^{\text{CZ}}_{i,t-1}$	0.30***	-0.03	-0.61	-0.48	-0.44
	[0.08]	[0.28]	[0.40]	[0.48]	[0.49]
$\Delta\text{IP}^{\text{CZ}}_{i,t}\cdot\text{College}^{\text{CZ}}_{i,t-1}$		6.49***	9.00**	9.64**	9.13**
		[2.52]	[3.58]	[4.23]	[4.37]
	Non College workers - Log Real Weekly Wage change				
$\Delta\text{IP}^{\text{CZ}}_{i,t}$	-0.05	0.89	0.61	0.87	1.20*
	[0.09]	[0.70]	[0.56]	[0.64]	[0.67]
$\text{College}^{\text{CZ}}_{i,t-1}$	-0.29***	0.37	-0.04	0.09	0.2
	[0.06]	[0.32]	[0.27]	[0.33]	[0.31]
$\Delta\text{IP}^{\text{CZ}}_{i,t}\cdot\text{College}^{\text{CZ}}_{i,t-1}$		-4.27	-2.85	-3.68	-4.88
		[2.87]	[2.06]	[2.51]	[2.86]
	College Premium - Weekly Wage				
$\Delta\text{IP}^{\text{CZ}}_{i,t}$	-0.03	-2.80***	-3.18***	-3.40***	-3.58***
	[0.11]	[0.88]	[0.95]	[1.19]	[1.22]
$\text{College}^{\text{CZ}}_{i,t-1}$	0.59***	-0.4	-0.57	-0.57	-0.64
	[0.08]	[0.33]	[0.35]	[0.45]	[0.46]
$\Delta\text{IP}^{\text{CZ}}_{i,t}\cdot\text{College}^{\text{CZ}}_{i,t-1}$		10.76***	11.85***	13.33***	14.01***
		[3.08]	[3.26]	[4.38]	[4.41]
Interacted Controls:					
Mfg. Sector Controls			✓	✓	✓
Demographics				✓	✓
Exports					✓
Observations	640	640	640	640	640

NOTE - Controls in levels are included in every regression. Controls interacted with $\Delta\text{IP}^{\text{CZ}}_{i,t}$ are included as stated. All the regressions include the interaction of $\text{College}^{\text{CZ}}_{i,t-1}$ with a time dummy. Regressions are weighted by start-of-the-sample population. Robust standard errors are clustered at the state level. All the variables, except $\Delta\text{IP}^{\text{CZ}}_{i,t}$ and $\text{College}^{\text{CZ}}_{i,t-1}$, are population-weighted demeaned. * $p < .1$, ** $p < .05$, *** $p < .01$

Figure 7: $\tilde{\beta}^{cz}_{\Delta\mathrm{IP}} = \hat{\beta}_{\Delta\mathrm{IP}} + \sum_{\gamma\in\Gamma}\hat{\beta}_{\Delta\mathrm{IP}\cdot\gamma}\gamma^{cz}$

Figure 8: $\Delta\hat{y}_{cz} = \left[\hat{\beta}_{\Delta\mathrm{IP}} + \sum_{\gamma\in\Gamma}\hat{\beta}_{\Delta\mathrm{IP}\cdot\gamma}\gamma^{cz}\right]\cdot\Delta\mathrm{IP}_{cz}$

Figure 9: $\tilde{\beta}_{\Delta\mathrm{IP}}^{cz} = \hat{\beta}_{\Delta\mathrm{IP}} + \sum_{\gamma\in\Gamma} \hat{\beta}_{\Delta\mathrm{IP}\cdot\gamma}\gamma^{cz}$
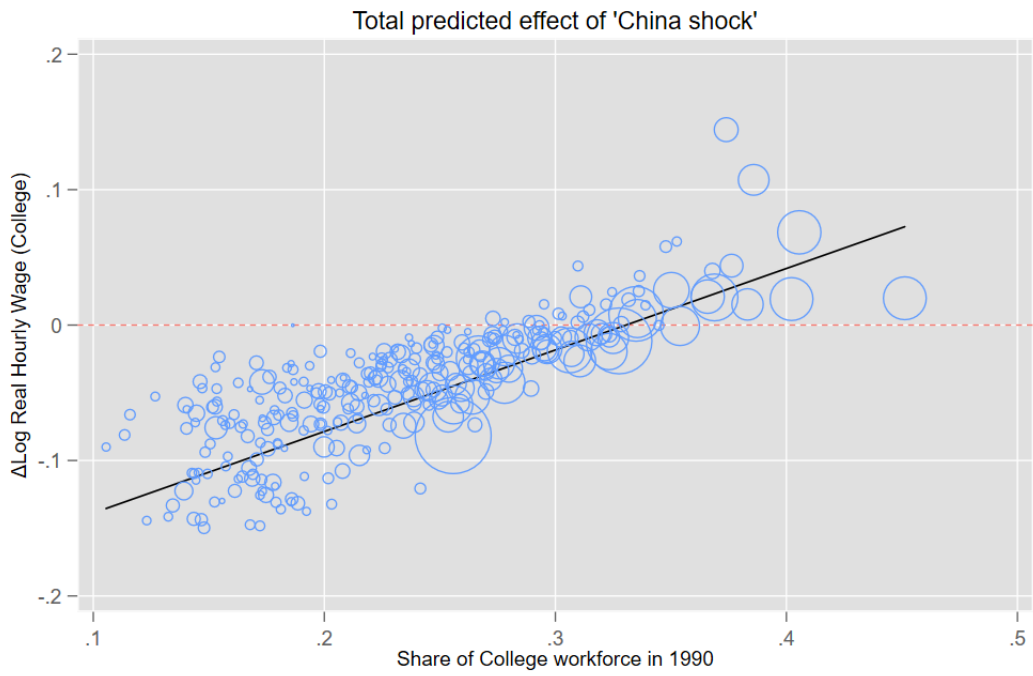

Figure 10: $\Delta\hat{y}_{cz} = \left[\hat{\beta}_{\Delta\mathrm{IP}} + \sum_{\gamma\in\Gamma} \hat{\beta}_{\Delta\mathrm{IP}\cdot\gamma}\gamma^{cz}\right]\cdot\Delta\mathrm{IP}_{cz}$
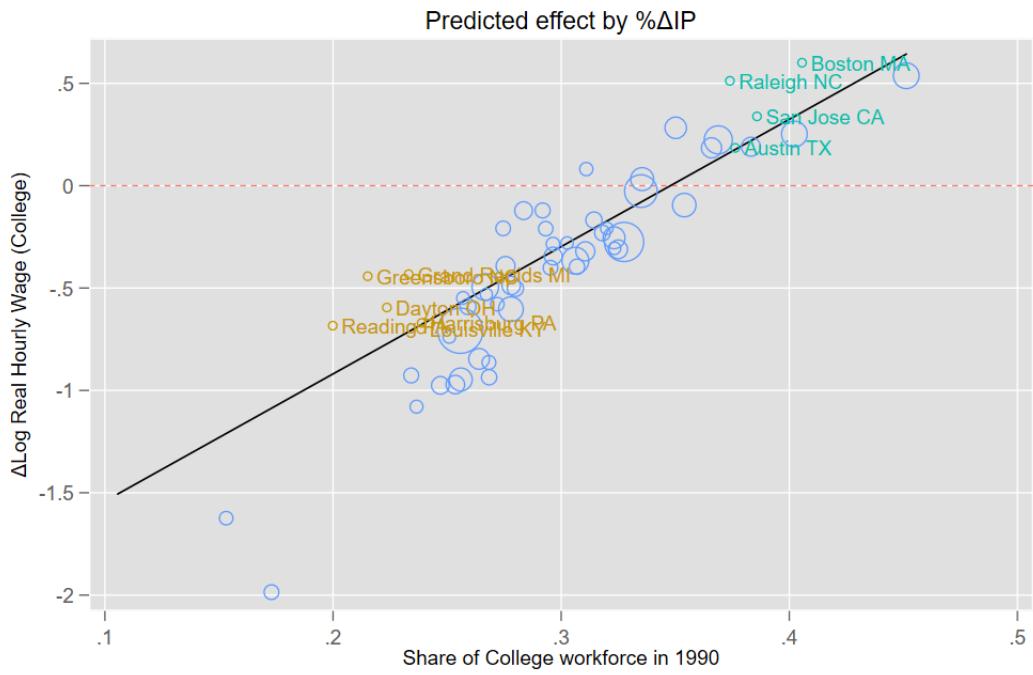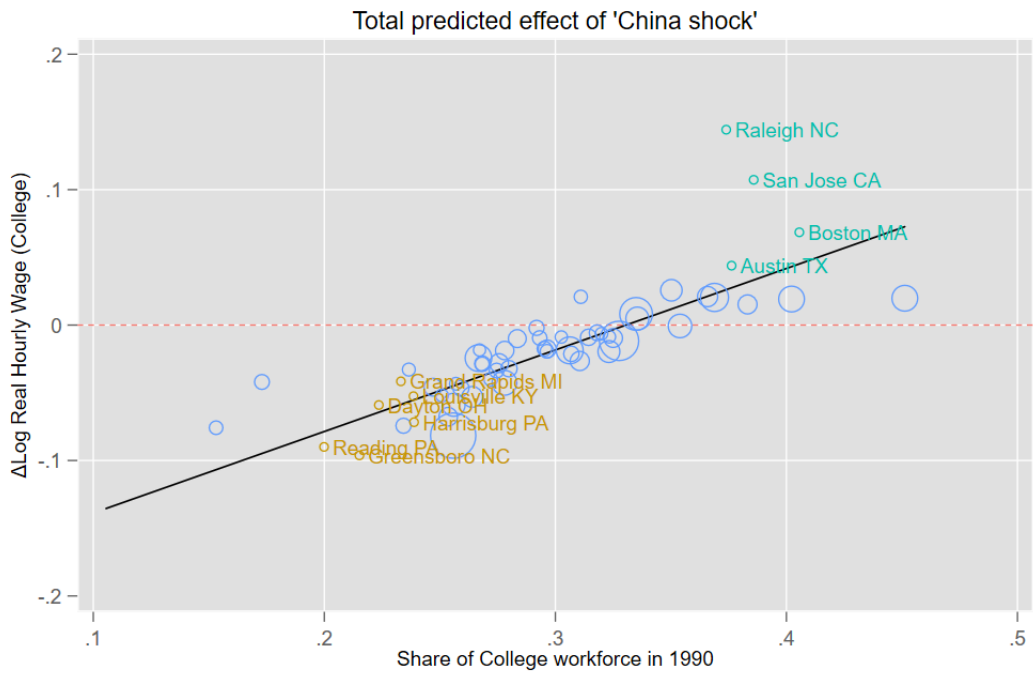
in the ranking of college education in 1990 (75th versus 25th percentile), and conditioning a to median level of exposure to trade competition, real wages for college-educated workers grow a 5.34% faster in the skill-intensive area per decade, accounting for 0.63 standard deviations. Also, the college wage premium increases 5.44 percentage points more than in the low-educated region, equal to 0.67 standard deviations.

Differential effects are also significant among highly-educated regions. Taking two areas in the 75th educational percentile, a commuting zone exposed to the 75th percentile of import competition has a 1.56% faster growth of real college wages per decade than one at the 25th percentile of exposure. This is 0.21 standard deviations. The wage premium grows 2.61 percentage points per decade, or 0.39 standard deviations, in the more exposed region due to the effect of import competition.

The comparisons among low educated regions draw the opposite sign. Low educated areas facing a large growth of import competition have a decrease of 4.12% in real college wages, or 0.45 standard deviations, and a relative decline of 1.78 percentage points in the college premium per decade than another low-educated but little-exposed region.

8.4   Structural change, STEM occupations, and Innovation

Table 4 shows how commuting zones react differently to the rise of import competition regarding structural change and innovation-related outcomes. The dependent variable in the top panel is the change in log employment in manufacturing. The second panel shows the change in log employment in STEM-intensive industries. Finally, the third panel shows the change in patents per capita.

The top panel shows that skill-intensive regions undergo a faster structural transformation following the negative shock to the manufacturing sector. Even if the average effect of the 'China shock' on manufacturing employment is negative, the magnitude of the effect is larger among regions with a larger share of college-educated workforce. On the other hand, panel 2 shows that the loss of manufacturing employment in those regions is replaced by a significant growth of employment in industries that intensively employ STEM-related occupations.

Consistent with the discussion above, the rise of import competition also have significantly heterogeneous effects on the number of patents per capita. Higher exposure to trade does not change the number of patents per capita on the average commuting zones, but it has a positive effect among regions with a high share of college-educated workforce, while it decreases the relative number of patents per capita among regions with low educational attainment.

These findings provide evidence that college-educated regions react to the negative shock to the manufacturing sectors by growing industries that employ college-educated workers,

Table 4

	(1)	(2)	(3)	(4)	(5)
			Log workers in manufacturing sector (change)		
$\Delta\text{IP}_{i,t}^{\text{CZ}}$	-0.61***	0.22	0.11	1.28	1.04
	[0.09]	[0.40]	[0.27]	[1.44]	[2.63]
$\text{College}_{i,t-1}^{\text{CZ}}$	-0.05***	0.00	0.00	0.02	0.02
	[0.01]	[0.01]	[0.01]	[0.03]	[0.06]
$\Delta\text{IP}_{i,t}^{\text{CZ}} \cdot \text{College}_{i,t-1}^{\text{CZ}}$		-2.88***	-2.85***	-7.99**	-7.21**
		[0.74]	[0.68]	[3.93]	[3.74]
			Log workers in STEM-intensive sector (change)		
$\Delta\text{IP}_{i,t}^{\text{CZ}}$	0.31	-2.92***	-3.59***	-7.30***	-7.66***
	[0.26]	[0.86]	[1.12]	[0.95]	[1.30]
$\text{College}_{i,t-1}^{\text{CZ}}$	-0.02	-0.07**	-0.07*	-0.14***	-0.15***
	[0.03]	[0.03]	[0.04]	[0.03]	[0.03]
$\Delta\text{IP}_{i,t}^{\text{CZ}} \cdot \text{College}_{i,t-1}^{\text{CZ}}$		10.68***	10.84***	25.79***	26.98***
		[2.39]	[3.11]	[4.39]	[5.00]
			Patents per capita (change x 100)		
$\Delta\text{IP}_{i,t}^{\text{CZ}}$	-0.01	-0.18	-0.32***	-0.69**	-0.86**
	[0.04]	[0.15]	[0.10]	[0.27]	[0.35]
$\text{College}_{i,t-1}^{\text{CZ}}$	0.00	-0.01***	-0.01***	-0.02***	-0.02***
	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]
$\Delta\text{IP}_{i,t}^{\text{CZ}} \cdot \text{College}_{i,t-1}^{\text{CZ}}$		0.71***	0.74***	2.42***	2.97***
		[0.24]	[0.29]	[0.89]	[0.94]
Interacted Controls:					
Mfg. Sector Controls			✓	✓	✓
Demographics				✓	✓
Exports					✓

NOTE - Controls in levels are included in every regression. Controls interacted with $\Delta\text{IP}_{i,t}^{\text{CZ}}$ are included as stated. All the regressions include the interaction of $\text{College}_{i,t-1}^{\text{CZ}}$ with a time dummy. Regressions are weighted by start-of-the-sample population. Robust standard errors are clustered at the state level. All the variables, except $\Delta\text{IP}_{i,t}^{\text{CZ}}$ and $\text{College}_{i,t-1}^{\text{CZ}}$, are population-weighted demeaned. * $p < .1$, ** $p < .05$, *** $p < .01$

and even more intensively, innovative sectors with a large share of STEM-intensive occupations.

9   Conclusions

Over the last decades, regions in the United States have been diverging. More skill-intensive areas have experienced a higher wage and skill premium growth at the same time that they became even more skill-intensive. This process deepened inequality both between and within urban areas, concentrating educated and high-earning workers into few cities. In this paper, I show that the substantial decline of manufacturing industries following the sharp rise of Chinese exports, and how local economies adapted to the loss of employment in those sectors, contributed significantly to the divergence among metropolitan areas in the US.

Empirically, I test the consequences on US local labor markets of the sharp rise of Chinese manufacturing imports during the period 1990-2007 and its contribution to the process of skill sorting and wage dispersion among metropolitan areas. I find that this contribution happens through the heterogeneity of the effect of import competition on local labor outcomes.

Conditional on being exposed to the same degree of trade competition, effects are different depending on the share of college-educated workforce in the region at the time of the shock. Adverse effects of the shock on manufacturing concentrate on exposed regions with a low share of college-educated workforce. On the other hand, among areas with a high skill intensity, a higher exposure to trade implies a rise in real college wages, the growth of the college-educated population and specialization in skill-intensive sectors. These findings are particularly relevant considering that the average effect of trade competition on those variables, as in the results that can be obtained with a standard analysis as in Autor et al. (2013), are not significantly different from zero.

Namely, metropolitan areas such as San Jose, CA, Raleigh, NC or Austin, TX (with large and highly exposed manufacturing sectors, and a large share of college-educated workforce by 1990) will do better not only than cities in the Rust Belt such as Reading, PA or Dayton, OH (large and exposed manufacturing and low share of college education), but also than cities like Washington, DC (with similarly large college-educated population but negligible exposure to trade). On the other hand, those regions in the Rust Belt will do worse than other areas with a similarly low share of college-educated population but lower exposure to import competition such as Las Vegas, NV or Jacksonville, FL.

Differential effects are sizable. I find that among regions exposed to a rise of $1700 per worker in Chinese imports per decade (median value), a 6.6% higher share of workers with a college degree (1 standard deviation) means a growth of college-educated population of 10.11% faster per decade (equivalent to 0.52 standard deviations), average real wages

for college-educated workers grow a 3.78% more per decade (0.45 standard deviations) and college wage premium becomes 3.86 percentage points higher per decade (0.47 standard deviations) due to the effect of Chinese import competition.

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Table 5

	(1)	(2)	(3)	(4)	(5)
	College workers - Log Real Weekly Wage change - Manufacturing				
$\Delta \text{IP}_{i,t}^{\text{CZ}}$	0.02	-0.32	-0.67	-0.36	-0.07
	[0.12]	[1.04]	[1.32]	[1.77]	[1.82]
$\text{College}_{i,t-1}^{\text{CZ}}$	0.37***	0.28	-0.15	0.01	0.07
	[0.08]	[0.36]	[0.57]	[0.74]	[0.75]
$\Delta \text{IP}_{i,t}^{\text{CZ}} \cdot \text{College}_{i,t-1}^{\text{CZ}}$		1.18	3.14	2.24	1.46
		[3.89]	[4.79]	[7.08]	[7.21]
	Non College workers - Log Real Weekly Wage change - Manufacturing				
$\Delta \text{IP}_{i,t}^{\text{CZ}}$	0.03	0.17	0.38	0.42	0.73
	[0.11]	[0.63]	[0.77]	[0.92]	[0.93]
$\text{College}_{i,t-1}^{\text{CZ}}$	-0.09	0.09	-0.13	-0.05	0.06
	[0.09]	[0.27]	[0.30]	[0.39]	[0.37]
$\Delta \text{IP}_{i,t}^{\text{CZ}} \cdot \text{College}_{i,t-1}^{\text{CZ}}$		-1.23	-1.68	-1.12	-2.27
		[2.36]	[2.80]	[3.62]	[3.60]
	College workers - Log Real Weekly Wage change - Non Manufacturing				
$\Delta \text{IP}_{i,t}^{\text{CZ}}$	-0.12	-2.00**	-2.78***	-2.87**	-2.77**
	[0.10]	[0.79]	[1.05]	[1.33]	[1.38]
$\text{College}_{i,t-1}^{\text{CZ}}$	0.33***	-0.07	-0.69*	-0.62	-0.58
	[0.10]	[0.31]	[0.40]	[0.55]	[0.56]
$\Delta \text{IP}_{i,t}^{\text{CZ}} \cdot \text{College}_{i,t-1}^{\text{CZ}}$		6.58**	9.44***	10.58**	10.17**
		[2.94]	[3.62]	[4.98]	[5.15]
	Non College workers - Log Real Weekly Wage change - Non Manufacturing				
$\Delta \text{IP}_{i,t}^{\text{CZ}}$	-0.12	1.30*	0.91	1.09	1.39*
	[0.09]	[0.79]	[0.65]	[0.73]	[0.76]
$\text{College}_{i,t-1}^{\text{CZ}}$	-0.26***	0.54	0.11	0.2	0.3
	[0.06]	[0.35]	[0.30]	[0.34]	[0.34]
$\Delta \text{IP}_{i,t}^{\text{CZ}} \cdot \text{College}_{i,t-1}^{\text{CZ}}$		-5.91**	-4.16*	-4.80*	-5.89**
		[2.76]	[2.32]	[2.79]	[2.86]
<u>Interacted Controls:</u>					
Mfg. Sector Controls			✓	✓	✓
Demographics				✓	✓
Exports					✓
Observations	640	640	640	640	640

NOTE - Controls in levels are included in every regression. Controls interacted with $\Delta \text{IP}_{i,t}^{\text{CZ}}$ are included as stated. All the regressions include the interaction of $\text{College}_{i,t-1}^{\text{CZ}}$ with a time dummy. Regressions are weighted by start-of-the-sample population. Robust standard errors are clustered at the state level. All the variables, except $\Delta \text{IP}_{i,t}^{\text{CZ}}$ and $\text{College}_{i,t-1}^{\text{CZ}}$, are population-weighted demeaned. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 6

	(1)	(2)	(3)	(4)	(5)
			$\Delta\text{IP}^{\text{CZ}}_{i,t}$		
$\Delta\text{IP}^{\text{Ot}}_{i,t}$	0.677***	0.608***	0.772***	3.400*	2.225
	[0.0652]	[0.175]	[0.227]	[2.003]	[1.810]
$\text{College}^{\text{CZ}}_{i,1970}$		0.0454	0.11	-0.186	-0.0774
		[0.116]	[0.111]	[0.171]	[0.155]
$\Delta\text{IP}^{\text{Ot}}_{i,t} \cdot \text{College}^{\text{CZ}}_{i,1970}$		-0.0627	-1.43	3.084	2.111
		[1.321]	[1.720]	[2.835]	[2.621]
F-Statistic	104.47	107.93	160.33	174.6	311.66
SW F-statistic	104.47	81.86	132.47	96.2	82.81
			$\text{College}^{\text{CZ}}_{i,t-1}$		
$\Delta\text{IP}^{\text{Ot}}_{i,t}$		0.0374	-0.028	1.947**	1.249
		[0.0708]	[0.0858]	[0.803]	[0.817]
$\text{College}^{\text{CZ}}_{i,1970}$		0.865***	0.827***	0.801***	0.858***
		[0.116]	[0.114]	[0.134]	[0.135]
$\Delta\text{IP}^{\text{Ot}}_{i,t} \cdot \text{College}^{\text{CZ}}_{i,1970}$		0.336	0.847	0.813	0.156
		[0.517]	[0.671]	[0.836]	[0.883]
F-Statistic		167.06	165.4	169.72	139.43
SW F-statistic		70.15	100.89	96.33	91.81
			$\Delta\text{IP}^{\text{CZ}}_{i,t} \cdot \text{College}^{\text{CZ}}_{i,t-1}$		
$\Delta\text{IP}^{\text{Ot}}_{i,t}$		-0.0356	-0.00708	0.742	0.244
		[0.0410]	[0.0709]	[0.646]	[0.533]
$\text{College}^{\text{CZ}}_{i,1970}$		-0.0605**	-0.0461	-0.113*	-0.0654
		[0.0257]	[0.0311]	[0.0578]	[0.0486]
$\Delta\text{IP}^{\text{Ot}}_{i,t} \cdot \text{College}^{\text{CZ}}_{i,1970}$		1.618***	1.384**	2.407**	1.974**
		[0.357]	[0.591]	[0.958]	[0.870]
F-Statistic		94.06	117.66	144.67	108.88
SW F-statistic		302.65	204.45	91.01	84.23
Observations	640	640	640	640	640
Interacted Controls:					
Mfg. sector			✓	✓	✓
Demographics				✓	✓
Exports					✓

NOTE - Controls in levels are included in every regression. Controls interacted with $\Delta\text{IP}^{\text{CZ}}_{i,t}$ are included as stated. All the regressions include the interaction of $\text{College}^{\text{CZ}}_{i,t-1}$ with a time dummy. Regressions are weighted by start-of-the-sample population. Robust standard errors are clustered at the state level. All the variables, except $\Delta\text{IP}^{\text{CZ}}_{i,t}$ and $\text{College}^{\text{CZ}}_{i,t-1}$, are population-weighted demeaned. * $p < .1$, ** $p < .05$, *** $p < .01$
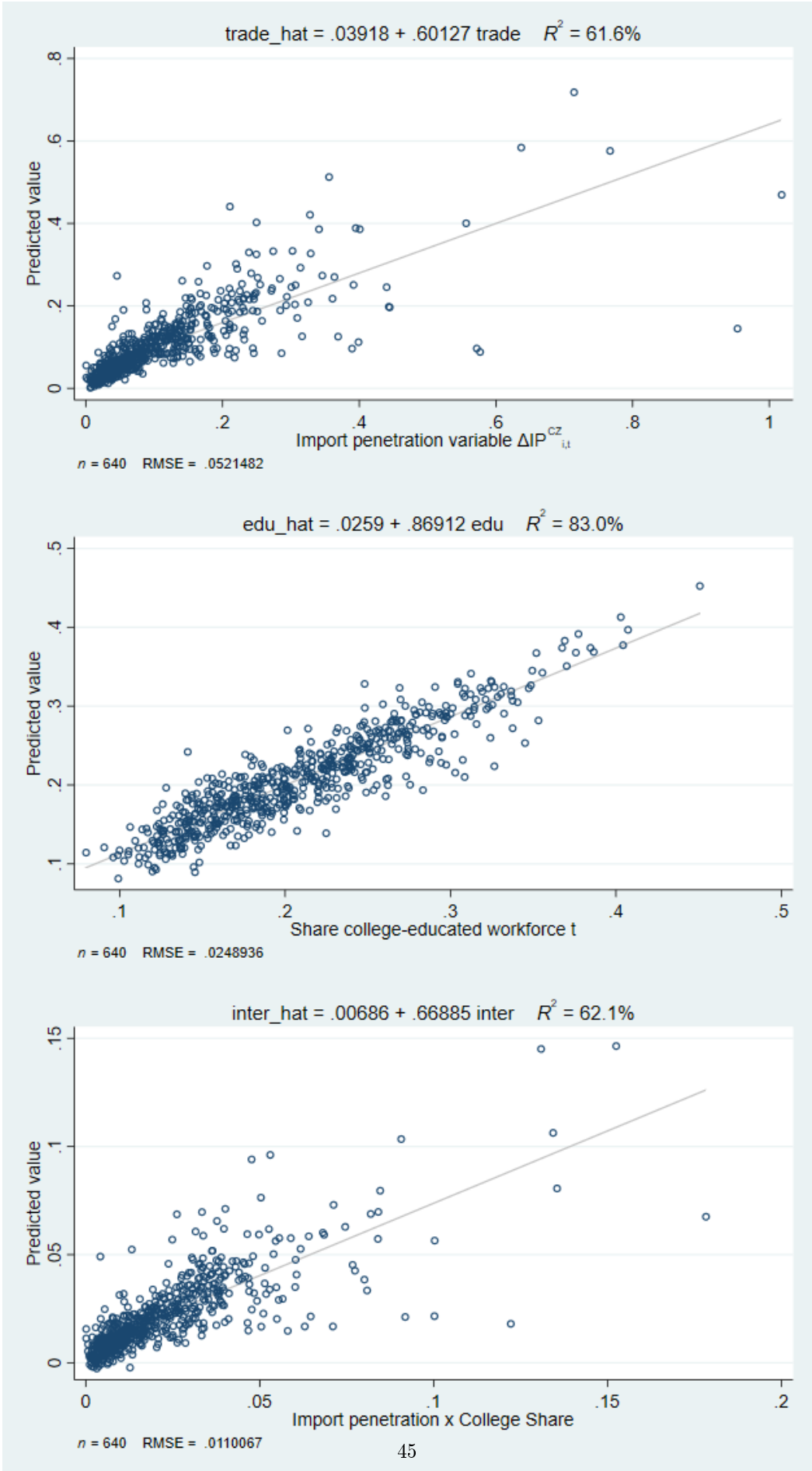
Figure 11: First stage for main variables

A Derivation of equilibrium office space allocation

$$
\begin{aligned}
P_M \cdot Y_M &= P_M \cdot \mathbb{M} \cdot O_M^\alpha L_M^{1-\alpha} \\
r_M &= \alpha \cdot P_M \cdot \mathbb{M} \cdot O_M^{\alpha-1} L_M^{1-\alpha}
\end{aligned}
$$

$$
\begin{aligned}
Y_A &= O_A^\alpha \cdot \left(\psi \cdot L_A^\sigma + (1-\psi)\, \mathbb{X} \cdot H^\sigma\right)^{\frac{1-\alpha}{\sigma}} \\
r_A &= \alpha \cdot O_A^{\alpha-1} \cdot \left(\psi \cdot L_A^\sigma + (1-\psi)\, \mathbb{X} \cdot H^\sigma\right)^{\frac{1-\alpha}{\sigma}}
\end{aligned}
$$

$$
\begin{aligned}
\alpha P_M \mathbb{M} O_M^{\alpha-1} L_M^{1-\alpha} &= \alpha O_A^{\alpha-1} \left(\psi L_A^\sigma + (1-\psi)\, \mathbb{X} H^\sigma\right)^{\frac{1-\alpha}{\sigma}} \\
\frac{O_A}{O_M} &= \frac{O_A}{\overline{O} - O_A} = (P_M \mathbb{M})^{\frac{1}{1-\alpha}} \cdot \frac{\left(\psi L_A^\sigma + (1-\psi)\, \mathbb{X} H^\sigma\right)^{\frac{1}{\sigma}}}{L_M}
\end{aligned}
$$

$$
\frac{\partial \ln O_A}{\partial \ln P_M} = -\frac{1}{1-\alpha} \frac{O_M}{\overline{O}}
$$

B Derivation of equilibrium unskilled labor

$$
\begin{aligned}
P_M \cdot Y_M &= P_M \cdot \mathbb{M} \cdot O_M^\alpha L_M^{1-\alpha} \\
w_M &= (1-\alpha) \cdot P_M \cdot \mathbb{M} \cdot O_M^\alpha \cdot L_M^{-\alpha}
\end{aligned}
$$

$$
\begin{aligned}
Y_A &= O_A^\alpha \cdot \left(\psi \cdot L_A^\sigma + (1-\psi)\, \mathbb{X} \cdot H^\sigma\right)^{\frac{1-\alpha}{\sigma}} \\
w_A &= (1-\alpha) \cdot O_A^\alpha \cdot \left(\psi \cdot L_A^\sigma + (1-\psi)\, \mathbb{X} \cdot H^\sigma\right)^{\frac{1-\alpha}{\sigma}-1} \cdot \psi \cdot L_A^{\sigma-1}
\end{aligned}
$$

$$
\begin{aligned}
P_M \cdot \mathbb{M} \cdot O_M^\alpha \cdot L_M^{-\alpha} &= O_A^\alpha \cdot \left(\psi \cdot L_A^\sigma + (1-\psi)\, \mathbb{X} \cdot H^\sigma\right)^{\frac{1-\alpha}{\sigma}-1} \cdot \psi \cdot L_A^{\sigma-1} \\
\frac{L_A^{1-\sigma}}{L_M^\alpha} &= \left(\frac{O_A}{O_M}\right)^\alpha \cdot \left(\psi \cdot L_A^\sigma + (1-\psi)\, \mathbb{X} \cdot H^\sigma\right)^{\frac{1-\alpha}{\sigma}-1} \frac{1}{P_M \cdot \mathbb{M}}
\end{aligned}
$$

Plugging from equilibrium values of office space

$$L_A^{1-\sigma} = (P_M \mathbb{M})^{-\frac{1}{1-\alpha}} \cdot (\psi \cdot L_A^\sigma + (1-\psi)\, \mathbb{X} \cdot H^\sigma)^{\frac{1-\sigma}{\sigma}}$$

$$\frac{\partial \ln L_A}{\partial \ln P_M} = -\frac{1}{(1-\alpha)(1-\sigma)}\left[1 + \frac{1-\psi}{\psi}\left(\frac{L_A}{\mathbb{X}H}\right)^\sigma\right]$$

C   Derivation of skilled wages

$$w_H = O_A^\alpha \frac{1-\alpha}{\sigma}\left(\psi L_A^\sigma + (1-\psi)\,\mathbb{X}H^\sigma\right)^{\frac{1-\alpha-\sigma}{\sigma}}(1-\psi)\,\mathbb{X}\sigma H^{\sigma-1}$$

$$\ln w_H = \alpha \ln O_A + \ln(1-\psi) + \frac{1-\alpha-\sigma}{\sigma}\ln\left(\psi L_A^\sigma + (1-\psi)\,\mathbb{X}H^\sigma\right) + \ln \mathbb{X} - (1-\sigma)\ln H$$

$$\frac{\partial \ln w_H}{\partial \ln P} = \alpha \frac{\ln O_A}{\partial \ln P} + \left[(1-\alpha-\sigma)\frac{\psi L_A^\sigma}{\psi L_A^\sigma + (1-\psi)\,\mathbb{X}H^\sigma} + \frac{\partial \ln \mathbb{X}}{\partial \ln L_A}\right] \cdot \frac{\partial \ln L_A}{\partial \ln P}$$