IMPORT COMPETITION, REGIONAL
DIVERGENCE, AND THE RISE OF THE
SKILLED CITY

2021

BANCO DE ESPAÑA
Eurosistema

Documentos de Trabajo
N.º 2115

Javier Quintana

IMPORT COMPETITION, REGIONAL DIVERGENCE, AND THE RISE OF THE SKILLED CITY

IMPORT COMPETITION, REGIONAL DIVERGENCE, AND THE RISE OF THE SKILLED CITY

Javier Quintana [*]

BANCO DE ESPAÑA

Abstract

This paper analyzes the contribution of import competition to the regional divergence among US metropolitan areas over recent decades. I document that the sharp rise in imports of Chinese manufacturing goods had a significant effect on the spatial skill polarization and the divergence of college wage premium among local labor markets. The effects of the China trade shock were systematically different depending on the skill intensity of local services. Among regions with skill-intensive services, a higher exposure to import competition in manufacturing increased the number and wages of college-educated workers. The negative effects of the China shock concentrated in exposed regions with a low density of college-educated workers. The heterogeneous effects of import competition explain one third of the spatial skill polarization and one fourth of the divergence in college wage premium. I show that the contribution of the trade shock operates through the reallocation of workers across sectors and regions. Using a novel measure of "labor market exposure to the China shock", I document that service industries expand when local manufacturers face import competition. High human capital regions exposed to the China shock undergo a faster transition from manufacturing to skill-intensive service industries and attract college-educated workers from other locations.

Resumen

Este artículo analiza la contribución de la competencia de importaciones a la divergencia regional entre áreas metropolitanas de Estados Unidos. Se acredita que el fuerte aumento de las importaciones de bienes manufactureros de China tuvo un impacto significativo en la polarización geográfica en términos de talento y en la divergencia de la prima salarial de educación entre los mercados de trabajo locales. Los efectos del *shock* comercial chino fueron significativamente distintos dependiendo de la intensidad en mano de obra cualificada de los sectores de servicios locales. Entre las regiones con servicios intensivos en cualificación, una mayor exposición a las importaciones de manufacturas supuso un aumento tanto del número como de los salarios reales de los trabajadores cualificados. Los efectos negativos del *shock* se concentraron en las regiones expuestas y con una baja densidad de trabajadores cualificados. La heterogeneidad de los efectos de la competencia de importaciones explica un tercio de la polarización de trabajadores cualificados y un cuarto de la divergencia de la prima salarial. Se muestra que la contribución del *shock* de comercio internacional opera a través de la recolocación de trabajadores entre sectores y regiones. Usando una nueva medida de «exposición al *shock* a través del mercado laboral», se documenta que las industrias de servicios se expanden cuando las manufacturas locales se enfrentan a una mayor competencia internacional. Las regiones con alto nivel de capital humano expuestas al *shock* de importaciones chinas realizan una transición más rápida desde industrias manufactureras hacia servicios de alta cualificación y atraen a trabajadores cualificados de otras regiones.

Palabras clave: comercio internacional, competencia de importaciones, desigualdades regionales, polarización de talento, movilidad de factores.

Códigos JEL: F14, F16, F66, I24, J24, J61, R12.

1. Introduction

Over recent decades, cities in the United States have grown apart from each other. While some metropolitan areas thrived, others have experienced a secular decline. In particular, areas with a higher density of college-educated workers have displayed a superior performance over a whole range of urban and economic growth measures. Two of the most salient features of the Great Divergence are the spatial skill polarization and the divergence of the college wage premium across local labor markets (Moretti (2012)). Most educated metropolitan areas have increased their skill advantage over the last decades. Workers with a college degree are more likely to move to cities with a high density of college-educated population today than they used to be. At the same time, real wages for workers with a college degree have stopped converging across local labor markets, as opposed to the convergence of real wages for workers without college education. College-educated workers in skill-abundant cities have experienced a more rapid wage growth than their peers in less educated areas. The sorting of educated and high-earning workers into few metropolitan areas have deepened inequalities within and between locations. The relevance of this spatial inequalities goes beyond economic or labor outcomes: a large literature has drawn attention to how spatial polarization has first-order social, political, and cultural implications.

Contemporaneously, the United States experienced an unprecedented increase in imports of manufacturing goods following China's access to the world market economy. An extensive literature documents that the increase of Chinese imports had a significantly negative impact on manufacturing employment (Autor et al. (2013) (hereafter ADH), Pierce and Schott (2016)). Geographically, the drop in manufacturing employment was more severe in labor markets specialized in industries most exposed to Chinese competition. The consequences of the China shock were not limited to manufacturing-related outcomes. A vast literature documents that local labor markets with a larger employment share in exposed industries had different outcomes in a wide range of topics.[1] However, according to this analysis, the China shock did not have any significant effect on the spatial skill polarization or the divergence of

---

[1] An incredibly rich literature reports the consequences of the China shock on a wide variety of outcomes. On innovation (Dorn et al. (2016), Bloom et al. (2016)), political outcomes (Autor et al. (2016), Colantone and Stanig (2018)), provision of public goods (Feler and Senses (2017)), health (Colantone et al. (2015),Adda and Fawaz (2019)), pollution (Rohlf (2018)) or marriage market (Dorn et al. (2017)). My contribution, instead, focuses on standard dependent variables -wages and workforce size- but heterogeneous effects of the China shock

skill premium. Areas with a larger share of employment in industries competing with Chinese manufacturers did not experience, on average, different changes in terms of population or returns to skills than areas with lower exposure to import competition. I demonstrate that this finding masks systematic differences in the effects of the China shock according to the skill intensity in the local non-manufacturing sector.

In this paper, I show that the rise of import competition played a relevant role on the divergence among US metropolitan areas over the period between 1990 and 2007. Conditional to a similar level of exposure to the China shock, the effects on the size of local college-educated workforce and college wage premium differ according to the skill intensity of local service industries. Among cities with high human capital, a higher exposure to the China shock fosters an inflow of college-educated workers to the region and an increase of real wages for skilled workers. On the other hand, when import competition affects skill-scarce locations, the consequences are a drop in college-educated workforce and real wages for skilled workers.

I present evidence that the reallocation of labor from exposed manufacturing industries to the service sector explains these systematic differences. Competition in local labor markets is a key propagation channel of the trade shock from directly exposed manufacturing industries to the rest of the economy. Service industries expand when local manufacturing sectors are exposed to the China shock as long as the latter contract their labor demand. When the existing service industries in a location are highly skilled, they benefit from agglomeration externalities, and they shift up the demand for skilled workers in the region. Thus, when the China shock meets a high skill-intensity region, the final outcome is a stronger reallocation of labor from manufacturing to skill-intensive services and a positive inflow of skilled workers from other areas.

Namely, metropolitan areas such as San Jose, Raleigh or Austin (with large and highly exposed manufacturing sectors, and a large share of college-educated workforce by 1990) will perform better than cities in the Rust Belt such as Reading, Harrisburg or Dayton (with similarly large and exposed manufacturing sectors but with a low density of college-educated workers). In the former regions, the China shock reallocates resources from manufacturing industries to skill-intensive and fast-growing service industries present in the area. I show that due to the China shock, these skilled-and-exposed metropolitan areas will also display a superior performance than areas like Washington or New York (with a similar density of college-educated workers but negligible exposure to manufacturing import competition). On the other hand, those regions in the Rust Belt perform worse than other areas with a similarly

low share of college-educated population but lower exposure to import competition such as Las Vegas or Jacksonville. In these cases, the low skill-intensive local service sectors will not compensate the loses in the manufacturing industries.[2]

Empirically, I develop my analysis in two steps. First, following the spirit of ADH I analyze the impact of the change in import penetration on skill sorting and skill premium in urban commuting zones between 1990 and 2007.[3] The main dependent variables are decade changes in working-age population and changes in real wages by educational level. I extend ADH baseline regressions including the interaction between exposure to import competition and the initial share of college-educated workforce in the non-manufacturing sector. This will be my variable of interest, capturing the heterogeneity of effects of the trade shock according to the skill intensity of local services. The main threat to the identification of the heterogeneous effects will be the potential correlation of skill intensity in local services with other local characteristics. By construction, the interaction of those covariates and the change in import penetration will also correlate with my variable of interest. I address the issue by including a large set of controls interacting the China shock with local manufacturing characteristics, demographic variables, and the export potential of the local labor markets. These controls account for confounding sources of heterogeneity as well as unobserved differences in exposure to trade competition.

The contribution of the China shock to regional divergence is significant and economically sizable. I find that the heterogeneous effects of import competition explains above than one third and one fourth of the variation of the spatial skill polarization and the divergence of skill premium, respectively. Comparing cities with the median level of exposure to import competition, a commuting zone at the 75th percentile of skill-intensity will have a 13.1% faster growth of college-educated workforce and a 4.5% faster growth of real wages of college-educated workers per decade than one at the 25th percentile of skill-intensity. Moreover, comparing cities at the 75th percentile of skill-intensity, a city at the 75th percentile of exposure to the China shock will have a 12.6% faster growth of college-educated workforce and a 3.3% faster growth of real wages of college-educated workers per decade than one at the 25th percentile of exposure to import competition. Conversely, among cities at the 25th percentile of skill intensity, a city at the 75th percentile of exposure to the China shock

---

[2]Figure 4 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.

[3]Throughout the paper I use interchangeably the terms city, metropolitan area, and local labor market as equivalent terms for urban commuting zones. Section 2 provides the definition of this geographical unit (Tolbert and Sizer (1996))

will have a 5.6% relative drop of college-educated workforce and a 2.9% relative drop of real wages of college-educated workers per decade than one at the 25th percentile of exposure to import competition.

Second, I carry out the analysis of labor reallocation as the mechanism for trade-induced regional divergence. I introduce a novel measure of 'labor market exposure' to the China shock for service industries. This measure exploits occupational similarities between sectors, the geographical distribution of directly exposed industries, and the uneven geographical co-location of different manufacturing and non-manufacturing industries. It captures the changes in the local labor supply that a service industry faces following the contraction of employment demand of directly exposed manufacturing industries.

Armed with my measure of 'labor market exposure' to the China shock I quantify the cross-sector labor reallocation and I analyze whether local service industries benefit from the negative shock to the rest of local industries. Empirically, I regress growth rates of employment and wages of industry-commuting zone pairs on my measure of 'labor market exposure' to the China shock. This measure varies at the industry-commuting zone level, so it allows the inclusion of city-time and industry-time fixed effects. Thus, the analysis gets rid of potential city- or industry-specific trends, such as technological progress or aggregate demand effects. This setting compares the growth rate of employment and wages of the same industry across locations with distinct levels of exposure to the China shock. Finally, I can test whether the reallocation of labor favors the most skill-intensive industries.

This mechanism rationalizes the contribution of import competition to the spatial skill polarization and the divergence of skill premium. Skill-intensive industries leverage out the flow of workers leaving the local manufacturing sector. Skilled services in highly exposed locations have access to a larger pool of resources, they benefit from agglomeration externalities, offer higher wages, and they attract skilled workers from other regions. Empirically, I find that cities with higher a skill density undergo a faster transition from manufacturing to service industries. Conditional to the same level of exposure to the China shock, the contraction in manufacturing employment is larger in most educated local labor markets. In skilled-and-exposed regions, the growth of knowledge-intensive industries compensate the losses of manufacturing employment.

Related Literature

This paper relates to a number of literature strands. First, it contributes to the abundant literature about the effects on US local labor markets of the sharp rise of Chinese manufacturing exports. I document the role of the China shock in the divergence among US commuting zones in terms of spatial skill polarization and dispersion of skill premium. Autor et al. (2013) exploit initial differences in industry specialization to account for exposure to Chinese import competition. Local labor markets with a larger share of employment in exposed industries experienced a sharper contraction of manufacturing employment. Nonetheless, their analysis does not find any significant effect of the China shock on population counts, density of college-educated workers, or skill premium. I show that the average zero effect masks systematic differences in the effect of import competition on those variables. First, the novel heterogeneity analysis in my paper establishes that import competition has positive effects among the most skill-abundant labor markets and that the negative impact is concentrated in skill-scarce labor markets. This implies that the non-significant effects estimated in ADH are the average of highly heterogeneous consequences of exposure to import competition.

Similar to my paper, Bloom et al. (2019) analyze the interaction between the contraction of manufacturing employment and the expansion of service industries. Using firm-level data, they document the reorganization of labor from manufacturing to offshore-related activities. They find that this process occurs predominantly in high human capital areas and multinational firms. My paper reports consistent findings on the cross sector reorganization of labor and I document the implications in terms on population changes and wage inequalities at local level. I exploit similarities in occupational requirements to identify labor reallocation between industries. Additionally, I discuss the econometric challenges on the identification of heterogeneous effects due to the correlation of human capital density and other local characteristics.

Other recent papers provide a structural estimation of the effects of trade competition on local labor markets. Caliendo et al. (2019) estimate reallocation elasticities across sectors and locations. However, they do not consider the skill intensity of sectors or individuals, so they cannot address skill sorting or skill premium divergence. Burstein et al. (2019) analyze the contribution of technical change and trade to differences between occupations, although they do not have a geographical component in their work.

My work also contributes to the literature on inter-sectoral linkages and the transmission of shocks. My paper highlights the competition on local labor markets as propagation mechanism of industry-specific shocks. This channel complements other common approaches in the literature focusing on input-output relationships or general equilibrium price and demand effects. Acemoglu et al. (2016) analyzes the transmission of the China shock from directly exposed industries to upstream suppliers and downstream client industries exploiting national-wide input-output relationships. Adao et al. (2019a) consider the reallocation of homogeneous labor from manufacturing to an homogeneous non-manufacturing sector following changes in aggregate demand. My analysis quantifies the propagation of the shock to industry-commuting zone pairs that differ in skills as well as intensity in shock exposure. Also, I exploit the similarity in occupational requirements to identify the transmission of the shock.

Finally, this paper relates to the literature of inter-sectoral reallocation of labor. The closest reference is Curuk and Vannoorenberghe (2017). They exploit occupational similarities and geographical co-location of industries to estimate industry-level responsiveness to aggregate shock. I contribute to this literature accounting for the effect of differential agglomeration effects according to industries' skill intensity and differential migration propensity according to workers' level of education.

My paper also relates to the long standing literature on skill premia, and more precisely to the geographical component of wage differentials. I show that skill-abundant regions will benefit from the negative shock to the local manufacturing sector, as they will undergo a positive and skill-oriented sectoral transformation. The sectoral change shifts the relative labor demand in skill-abundant cities in favor of college-educated workers. This approach complements the usual focus on skill-biased technological change as the main driver of skill premium. Autor and Dorn (2013) find 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) examine the faster PC adoption in skill-abundant metropolitan areas and the subsequent increase in skill premium. Eckert et al. (2019) document the contribution of falling communication cost to the rise of skill services in large cities. These approaches rely on changes that have industry-specific effects, but without geographical variation within industries. My analysis complements this strand of the literature. Using my 'labor market' measure of exposure to the China shock, I can compare the growth of the same industry across different locations. This setting allows me to con-

trol for industry-specific exposure to automation, technical change, or falling communication costs. I show that in the comparison of industry-commuting zone pairs, skill-intensive industries located in highly exposed regions experience a faster employment growth.

My work also relates to the literature concerning the sorting of college-educated workers. I show that skill-abundant regions with a high exposure to the China shock increase their skill advantage because of trade competition. Hornbeck and Moretti (2018) solves a similar spatial equilibrium where college-educated workers migrate following TFP changes in manufacturing. In my paper I show that migration flows arise only from the interaction of the shock on manufacturing and the characteristics of the service sector. Skilled-and-exposed regions increase simultaneously the supply and real wages of college-educated workers in non-manufacturing industries. I find that population changes are entirely driven by college-educated workforce, while the number of workers without a college degree does not respond to the exposure to the China shock. This finding is consistent with the literature reporting that propensity to migrate increases with education (Wozniak (2010), Malamud and Wozniak (2012), Notowidigdo (2019)). Similar to Monras (2018), I find that positive immigration flows to regions experiencing a positive transformation are more important than outmigration flows from declining areas.

The structure of the paper is as follows. Section 2 presents the data and sample of the analysis. Section 3 discusses the econometrical approach. Section 4 documents the contribution of import competition to spatial skill polarization and divergence of skill premium. Section 5 introduces the measure of 'labor market' exposure and quantifies the labor reallocation across sectors. Section 6 provides concluding remarks. More details on the data and the model are in Appendix A and Appendix B respectively.

2.   Data and Sample

This section describes the sample and data sources employed in the empirical analysis of the paper. There are two main empirical settings in the paper. In the first one, the level of analysis is the local labor market. In the second one, the units of analysis are pairs of industries and local labor markets.

The geographical unit in both parts is the commuting zone (CZ), as defined by Tolbert and Sizer (1996).These commuting zones are clusters of US counties that repli-

cate local labor markets. I restrict my sample to the 321 urban commuting zones overlapping with Metropolitan Statistical Areas in contiguous continental US.[4]

2.1 Commuting Zone Level Analysis

The first econometric setting analyzes changes in outcomes of commuting zones. Following the previous literature (Autor et al. (2013), Acemoglu et al. (2016)), the sample consists of two ten-year equivalent differences in the outcomes of interest. For each commuting zone, I include two differences for the periods 1990-2000 and 2000-2007.

The primary source for data at the commuting zone level are the Census Integrated Public Use Micro Samples (Census IPUMS) for the years 1970, 1980, 1990 and 2000, and the American Community Survey (ACS) for the period 2006-2008 (Ruggles et al. (2016)). From this sources, I get data on the level of education, age, gender, wages, type of worker and employer, number of weeks and hours of work, industry and occupation, place of work and birth, and rental prices. Using this data, I construct the main dependent variables of the analysis, the skill intensity of local industries, and additional controls.[5] I compute changes in the workforce size by educational level and changes in real wages[6] and college wage premium. I restrict the sample to individuals between 25 and 60 y.o., and I compute wages excluding self-employed workers, public employees, individuals with missing wages or weeks, or who worked less than 26 weeks in the previous year. I supplement the data with additional controls at the commuting zone from Autor et al. (2013).[7]

Finally, I use the measure of import penetration from Acemoglu et al. (2016). Section 3.1 discusses in detail the construction of the variable, the instrumental counterpart, and potential mismeasurement issues.

2.2 Industry-Commuting Zone Level Analysis

The second setting examines changes in wages and the employment of pairs of industries and commuting zones. The sample consists, as well, in two stacked quasi-

---

[4]Excluding Alaska, Hawaii, and Puerto Rico

[5]These demographic controls include population, female labor participation, share of foreign-born, and share of young population. The manufacturing sector controls include average wage, share of college-educated workers in the sector and the share of employment in management occupations

[6]Appendix A details the construction of commuting zone-specific changes in real wages.

[7]This variables includes characteristics of local labor markets as offshorability and routine intensity of occupations.

decade changes in log employment for the periods 1990-2000 and 2000-2007. Data on employment in industry-commuting zone pairs comes from the 1990, 2000 and 2007 samples of the County Business Patterns (CBP) from the US Census.[8][9] The degree of industrial aggregation is the 4-digit SIC level.

The main dependent variable in this setting is my novel measure of 'labor market exposure' to the China shock that I introduce in Section 5.1. The construction of this data requires data on the intensity with which each industry employs an occupation. I use the Occupational Employment Statistics (OES) from the Bureau of Labor Statistics. This dataset provides the level of employment of 711 occupations (7-digit Standard Occupational Classification) for 368 SIC industries (135 manufacturing and 233 non-manufacturing industries).

I group the SOC occupational titles in the data into 60 occupational clusters. I cluster occupations using the data from the Careers Changers Matrix from O*Net database[10] (Farr and Shatkin (2004)). This dataset exploits similarities in the required experience and skills for a given job. It provides the list of occupations to which *workers from one occupation may transfer with minimal additional preparation.*

3. Import competition and Regional Divergence

In this section, I document several facts about the causal relationship between the rise of import competition and regional divergence. First, I analyze the contribution of the China shock to changes in college intensity among regions. I find that skill-intensive regions facing a higher import competition increase the density of college-educated workers. This change comes from immigration flows of college-educated workers, while I do not find significant evidence of crowding out of workers without a college degree. On the other hand, skill-scarce regions decrease their skill-density through a relative drop in the number of college-educated workers when they are exposed to import competition.

Second, the contribution of import competition to the divergence of skill premia follows a similar pattern. Among regions with a skill-intensive non-manufacturing sector, a higher level of import penetration increases the relative returns to skills.

---

[8]https://www.census.gov/programs-surveys/cbp.html

[9]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.

[10]https://www.onetcenter.org/dictionary/20.3/excel/career_changers_matrix.html

On the other hand, import competition reduces de wage gap between college and non-college workers in less educated areas. In this section, I show that this contribution operates through the change of real wages of college-educated workers in non-manufacturing industries. The effect of the China shock is not significant in terms of real wages in the manufacturing sector or for service workers without college education.

3.1   Econometric Specification

The following section discusses the identification strategy that I follow to analyze the causal effect of the rise of Chinese manufacturing imports on changes in college-education ratios and skill returns in US local labor markets. The econometric specification follows closely the spirit of ADH regressing changes in commuting zones' outcomes on the exposure to import competition, based on initial industrial specialization. The sample of the analysis are two stacked ten-year equivalent differences between 1990-2000 and 2000-2007. The geographical units are 321 urban commuting zones that include all the local labor markets overlapping with metropolitan areas.

My analysis extends the one in ADH by allowing the China shock to have systematically heterogeneous effects. The empirical setting allows the effects of the decade changes in import penetration to be different according to characteristics at the beginning of the period. In particular, the variable of interest in my analysis is the interaction between the exposure to Chinese manufacturing import competition and the skill intensity of local services.

Equation (1) displays the baseline specification for the regressions at the commuting zone level. It identifies the effect of the change in import penetration conditional on a given level of skill intensity of local services. $\Delta Y_{c,t}$ are ten year-equivalent changes in the outcomes of interest. $\Delta \mathrm{IP}_{c,t}$ is the change in import penetration faced by a commuting zone in the period between t and $t+1$, following the definition in Acemoglu et al. (2016) that I describe in the next section. $\mathrm{Skill}_{c,t-1}$ is the share of workers with a college degree in the non-manufacturing sector of the commuting zone at the beginning of the period. Finally, $\Gamma_{c,t-1}$ are additional characteristics of the commuting zone at the beginning of the period included as controls.[11]

$$\Delta Y_{c,t} = \beta_{\mathrm{I}} \cdot \Delta \mathrm{IP}_{c,t} + \beta_{\mathrm{IS}} \cdot \Delta \mathrm{IP}_{c,t} \cdot \mathrm{Skill}_{c,t-1} + \beta_{\Gamma} \cdot \Gamma_{c,t-1} + \beta_{\mathrm{I\Gamma}} \cdot \Delta \mathrm{IP}_{c,t} \cdot \Gamma_{c,t-1} + \epsilon_{c,t} \qquad (1)$$

---

[11] The set of variables includes as well the share of workers with a college degree in the non-manufacturing sector of the commuting zone at the beginning of the period.

In this setting, the effect of the China shock is the combination of an intercept, β_{I}, and a slope, β_{IS}, that moves along the values of skill intensity in local non-manufacturing sectors. A significant estimate $\widehat{\beta}_{\text{IS}}$ would imply that the effects of rising import penetration are statistically different for commuting zones with diverse levels of services' skill intensity. In other words, even conditional on a similar level of exposure to import competition, the predicted effects of trade competition would be different according to regions' density of skilled workers.

There are several threats to the validity of this approach. First, the potential endogeneity of trade flows and skill intensity. Second, unobserved differences in effective exposure to import competition. Finally, the existence of confounding sources of heterogeneous effects of the China shock.

3.1.1 Endogeneity and Instrumental Strategy

Import exposure

I define import penetration following Acemoglu et al. (2016) (hereafter AADHP). It consists of a shift-share procedure, apportioning the growth in Chinese imports in every manufacturing industry j according to the share of employment in the industry in the commuting zone, c, at the beginning of the period.

$$\Delta\text{IP}_{c,t} = \sum_j \frac{L_{c,j,t-1}}{L_{c,t-1}} \cdot \frac{\Delta M_{j,t}^{UC}}{Y_{j,91} + M_{j,91} - E_{j,91}} \tag{2}$$

where $\Delta M_{j,t}^{UC}$ denotes the change in US imports from China in sector j between $t-1$ and t. This value is normalized by the domestic absorption at the beginning of the period. $L_{c,j,t-1}$ represents the start-of-the-period employment in sector j in local market, and $L_{c,t-1}$ represents the total local employment. Thus, geographical variation in $\Delta\text{IP}_{c,t}$ comes entirely from differences in local industry structure at the beginning of the period.

The measure of commuting zone import exposure is likely to suffer from an endogeneity problem. To isolate the supply-driven component (e.g. productivity growth of Chinese producers and fall of tariffs and trading costs) from US local demand or productivity shocks, the instrumental variable applies the Bartik formula to the contemporaneous changes in exports from China to eight other developed economies normalized by local domestic absorption.

$$\Delta \text{IP}_{c,t}^{IV} = \sum_j \frac{L_{c,j,88}}{L_{c,88}} \cdot \frac{\Delta M_{j,t}^{OC}}{Y_{j,88} + M_{j,88} - E_{j,88}} \tag{3}$$

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

The second element of interest for the analysis is the skill intensity of local non-manufacturing industries. Following Acemoglu and Autor (2011), I use educational attainment as a proxy for skills. For each local labor market, I measure the share of workforce employed in non-manufacturing industries with at least a bachelor's degree at the beginning of each period. [12][13]

College density might be endogenous to other local underlying trends in relative wage changes or industrial composition. This is a threat to the causal inference of the analysis. If the skill intensity of non-manufacturing industries is endogenous to other local changes, the interaction between import penetration and skill intensity would be capturing other sources of heterogeneous effects. To address that issue, I instrument skill intensity at the beginning of each period with the share of non-manufacturing workforce with a college degree in 1970, introducing a two-decade lag.[14]

3.1.2 Confounding Sources of Heterogeneity

Another potential threat to the identification strategy is the existence of other sources of heterogeneity correlated with skill intensity. Given that the regressor of interest in my analysis is an interaction of $\Delta \text{IP}_{c,t}$, I need to control by other potential interactions of covariates correlated with $\text{Skill}_{c,t-1}$. Take as an example the case of larger

---

[12]I restrict the sample to individuals between 25 and 60 y.o., excluding self-employed workers, public employees, individuals with missing wages or weeks, or who worked less than 26 weeks in the previous year.

[13]The age restriction to workers older than 25 y.o. alleviates measurement concerns regarding individuals combining studies and part-time jobs.

[14]Including a two-decade lag also helps to mitigate the potential bias introduced by the contemporaneous process of skilled-bias technological change that started in the 1980s by using a predetermined instrumental variable. This strategy exploits the long-term persistence of the level of college education, 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.

commuting zones. This areas are typically more educated that smaller commuting zones. If larger cities were better at responding to adverse shocks, my variable interest could be capturing this heterogeneity source rather than properly the skill intensity of local services. Similarly, import penetration might have heterogeneous effects on the skill premium when the local manufacturing sector employs a larger share of college-educated workers.This would create an identification issue if skill intensity in manufacturing and non-manufacturing industries are positively correlated at the local level.

I deal with the issue including a set of interactive controls for local characteristics. These controls are the interaction of $\Delta \text{IP}_{c,t}$ with characteristics of the local manufacturing sector in a commuting zone at the beginning of the sample, $\Gamma_{c,t-1}$.

First, if the composition of local manufacturing industries is correlated with local services' skill intensity, the estimated effect for the interactive term $\Delta \text{IP}_{c,t} \cdot \text{Skill}_{c,t-1}$ would be biased[15]. If manufacturing industries in skill-intensive regions are particularly protected from trade due to their composition, the estimator would be biasing down the effect of the interaction.

I deal with the issue including a set of interactive controls of characteristics of local manufacturing industries. These controls are the interaction of $\Delta \text{IP}_{c,t}$ with characteristics of the local manufacturing sector in a commuting zone at the beginning of the sample, $\Gamma_{c,t-1}$. These characteristics of local manufacturing are the share of college-educated workers, the share of management, routine-intensive or offshorable occupations in the sector, and average wage as a proxy of productivity. The inclusion of these controls, both in levels as well as interacted with $\Delta \text{IP}_{c,t}$, controls for local characteristics as well as unobserved differences in exposure to import penetration.

The second set of controls deals with local demographic characteristics. I include as controls the log population, the share of foreign-born population, female employ-

---

[15]The definition of import exposure in AADHP implicitly assumes homogeneity within each manufacturing industry. In other words, every worker within an industry contributes to the same extent to the degree of import exposure of their area, regardless of the nature of the tasks they carry out in their jobs. The weighting factor for the imputation of the growth of imports in industry j to each commuting zone c is the share of employment that industry j has in the commuting zone, independently of the type of workers or occupations that the industry employs in the location.

This assumption is not innocuous if the variation within industries is correlated with other local characteristics such as the skill intensity in the local sector. As an example, let's take a manufacturing company that locates its headquarters in a given commuting zone and its production plant in a different one. Given the nature of their jobs, production workers in the latter location will be more severely affected by the rise of import competition as their jobs will likely be suppressed. On the other hand, executive and managing employees in the former site could potentially benefit from offshoring part of the production process (Grossman and Rossi-Hansberg (2008)). Still, according to the measure of import competition in AADHP, both commuting zones should experience the same changes following the China shock as long as they employ a similar number of workers in the industry.

ment participation, and the share of young workforce.[16] More educated cities are typically larger, younger, have a larger share of foreign-born population, and women participate more in the labor market. At the same time, the elasticity of labor supply (both in the intensive and the extensive margin) might be different for diverse urban sizes, for areas with a diverse share of foreign-born, female labor participation, or with a younger population.

Finally, I include the variable of exposure to exports from Feenstra et al. (2017). The access of China to the world market economy meant a massive supply shock, but it was also a positive shift in the demand for producers in the rest of the world. Those regions that were more exposed to Chinese import competition could also benefit from a larger exposure to the growth of exports through the import of cheaper intermediate inputs. The inclusion of this control rules out the potential effects of within-sector specialization.

As long as the interactive controls include the endogenous trade component ($\Delta\text{IP}_{c,t}$), I instrument these terms with the interaction of the instrumental variable for import penetration ($\Delta IP^{Ot}_{c,t+1}$) and the value of the covariate at the beginning of the sample ($\Gamma_{c,t-1}$).

3.1.3 Bartik Instrument and Pre-trends of Dependent Variables

A growing literature (Borusyak et al. (2018), Goldsmith-Pinkham et al. (2018), Adao et al. (2019b)) has raised concerns on the identification of Bartik-style instruments. These concerns are related with the potential endogeneity of local industrial composition. Even if the factors driving the change in imports of each industry are exogenous to US local conditions (China's internal reforms and tariff reductions), the initial industrial structure and the share of employment in exposed industries might be correlated with the outcome variables. Larger shares of employment in certain industrial sectors might be the consequence of endogenous unobserved characteristics. In that case, the allocation of the exogenous trade shock according to these potentially endogenous Bartik weights would bias the results.

To address that issue, I implement two of the proposed solutions in the aforementioned papers. First, I include the pre-trend of the dependent variables in the decade between 1980 and 1990.[17] Second, I include the share of employment in directly ex-

---

[16]Table 8 shows the correlations between local services' skill intensity and the groups of covariates

[17]The inclusion of the pre-tend of the outcome variable addresses also other concerns like the existence of pre-dated evolution of local labor markets due to skill-biased technical change.

posed industries interacted with a time trend.[18] These two elements control for existing pretends as well as unobserved characteristics of regions with high exposure to the China shock.[19]

4. Stylized Facts on Skill Sorting and Skill Premium

Table 1 shows the estimation of Equation (1) for changes in the share of college-educated workforce and the change in college wage premium. For each panel, column 1 replicates the baseline analysis in ADH, regressing the dependent variables on the measure of import penetration, without the inclusion of any interactive term. Columns 2-4 estimate the models with the heterogeneous effects of $\Delta IP_{i,t}$ including sequentially the sets of interactive controls discussed in the previous section.

Column 1 reflects the fact that the average contribution of the China shock to skill sorting and the divergence of skill premium is not significantly different from zero. Commuting zones with a larger share of employment in industries exposed to Chinese competition did not perform differently, on average, than commuting zones with little employment in those industries. This finding could mislead to state that import competition did not contribute to spatial skill polarization or the divergence of skill premium. Columns 2-4 show that this is not the case.

The estimation of models with heterogeneous effects of import competition delivers a clear pattern of divergence. The contribution of import competition becomes the combination of a negative and significant intercept ($\hat{\beta}_I$) and a positive and significant slope ($\hat{\beta}_{IS}$) on the interaction of import competition and local services' skill intensity. Considering the effect of the China shock among regions with unskilled service industries, it is negative because the positive effect does not compensate the initial negative intercept. On the other hand, among regions with skill-intensive non-manufacturing sectors, the effect of import competition becomes positive. The non-significant average effects masks systematic differences in the effect of import competition on commuting zones with diverse non-manufacturing skill intensity.

---

[18]Following Acemoglu et al. (2016), I define the directly exposed sector to encompass all manufacturing industries for which predicted import exposure rose by at least 2 percentage points between 1991 and 2011

[19]As a robustness check, I compute robust standard errors instead of standard errors clustered at state-level. Additionally, also as a robustness check, I include the interaction of a time trend with the share of employment in the five manufacturing industries with highest Rotemberg weights as defined in Goldsmith-Pinkham et al. (2018)

The absolute value of the ratio $\hat{\beta}_{\mathrm{I}}/\hat{\beta}_{\mathrm{IS}}$ denotes the level of services' skill intensity above which the effect of the China shock becomes positive in terms of college-education density or skill premia.[20] In all the specifications in which the estimated effects of the China shock are significantly heterogeneous,[21] this value falls close to $1/3$, approximately the population-weighted median of the share of college-educated workers in non-manufacturing in 1990. In other words, the half of commuting zones with more skill-intensive services industries in 1990 increased their college intensity and college wage premium due to being exposed to the China shock. The negative effects concentrate in the least educated half of the country.

Table 1: - Effect of Import Penetration on Skill Sorting and Skill Premium

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Share College-Educated Workforce				*College Premium*			
$\Delta\mathrm{IP}_{c,t}$	-0.01	-0.61**	-1.27***	-1.28***	0.03	-3.35***	-3.59**	-3.71**
	[0.02]	[0.25]	[0.43]	[0.44]	[0.11]	[0.99]	[1.67]	[1.66]
$\Delta\mathrm{IP}_{c,t}\cdot\mathrm{Skill}_{c,t-1}$		1.74**	3.82***	3.83***		10.42***	10.27**	10.78**
		[0.78]	[1.33]	[1.34]		[3.02]	[5.18]	[5.19]
Interacted Controls:								
Mfg. Sector Controls		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Exports				✓				✓
$\hat{\beta}_{\mathrm{I}}/\hat{\beta}_{\mathrm{IS}}$		35.1%	33.2%	33.4%		32.1%	35.0%	34.4%
SW F-Statistic								
$\Delta\mathrm{IP}_{c,t}$	60.70	30.13	27.96	25.22	51.63	31.53	36.24	38.36
$\Delta\mathrm{IP}_{c,t}\cdot\mathrm{Skill}_{c,t-1}$		28.69	26.61	23.98		29.96	33.61	34.86

NOTE - N=632 (321 Urban Commuting Zones $\times$ 2 time periods). Two stacked ten-year equivalent differences between 1990-2000 and 2000-2007. All the models include the full set of controls in levels described in the text. Columns 2-4 include sequentially the sets of interacted controls. Regressions include time trends interacted with Census regions fixed effects, $\mathrm{Skill}_{c,t-1}$, and the sum of employment in directly exposed industries. Regressions include the pre-trend between 1980 and 1990 of the dependent variable. Robust standard errors clustered at the state level. Models are weighted by start of the period commuting zone share of national population. * $p < .1$, ** $p < .05$, *** $p < .01$

---

[20]All the additional controls have been demeaned. The ratio shows the level of non-manufacturing skill intensity at which the effect of $\Delta\mathrm{IP}_{c,t}$ changes its sign for a region with average values of the rest of controls.
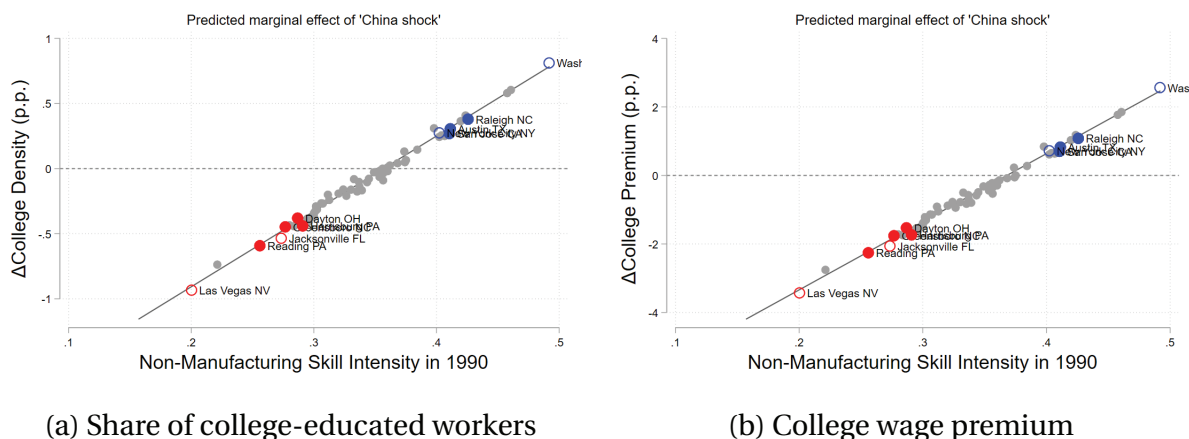
[21]I provide this statistic only in those cases in which the estimate $\widehat{\beta_{\mathrm{IS}}}$ is statistically significant at the 10%.

Graphical Representation

The previous results have an intuitive graphical representation. Figure 1a and fig. 1b plots the predicted marginal effects on the share of college-educated workforce and college premium in the 60 largest commuting zones, computed as in eq. (4). The figures plot the commuting zone-specific marginal effects against the initial levels of skill intensity in the local non-manufacturing sector. The figures illustrate that the zero average contribution of the China shock to spatial skill polarization and divergence in college wage premium is the consequence of a positive effect among regions at the top of the skill-intensity distribution and a negative one among those at the bottom of the distribution.

Figure 1: Predicted marginal effects of import competition by commuting zone

$$\tilde{\beta}^c_{\Delta IP} = \hat{\beta}_I + \hat{\beta}_{IS} \cdot \text{Skill}_{c,t-1} \qquad (4)$$

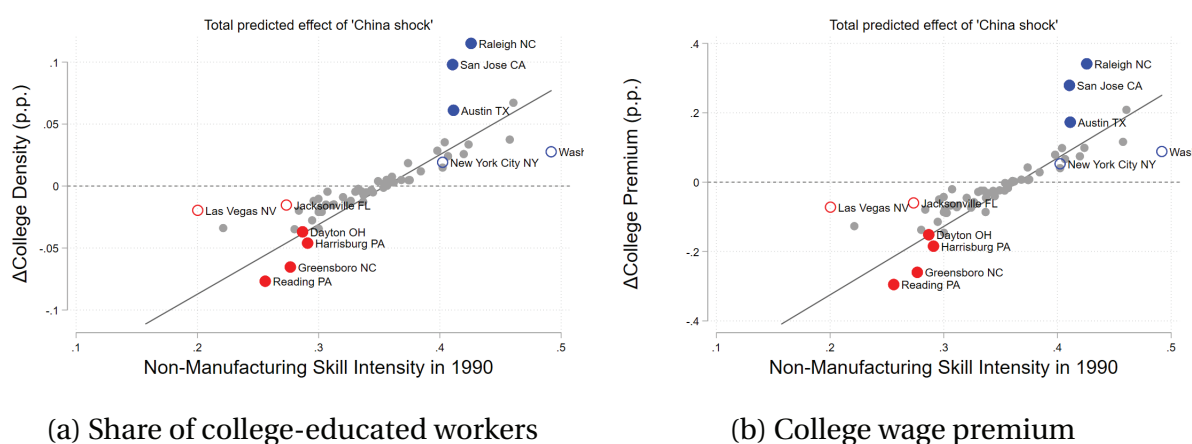(a) Share of college-educated workers   (b) College wage premium

On top of that, I compute the total predicted effect of the China shock as the product of the commuting zone-specific estimated marginal effects above and the level of import penetration of each commuting zone.

$$\Delta \tilde{y}_{cz} = \left[\hat{\beta}_I + \hat{\beta}_{IS} \cdot \text{Skill}_{c,t-1} \right] \cdot \Delta IP_{c,t} \qquad (5)$$

Figure 2a and fig. 2b show the estimated effects for the 60 largest commuting zones. The two pairs of figures illustrate the contribution of import competition to regional diverge. First, conditional on a similar level of exposure to import competition, the estimated marginal effects creates a wedge between the most and the least

educated areas. 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, Austin or San Jose benefit from a large exposure to foreign competition. Other similarly highly-educated area like Washington or New York experience little changes due to the low level of exposure. The opposite happens among the least educated areas. The negative marginal effect of import competition is exacerbated on areas like Reading or Greensboro due to a large increase in import penetration. On the other hand, the total predicted effect in areas like Las Vegas or Jacksonville is very close to zero due to the low exposure to China shock.

Figure 2: Predicted total effects of import competition by commuting zone

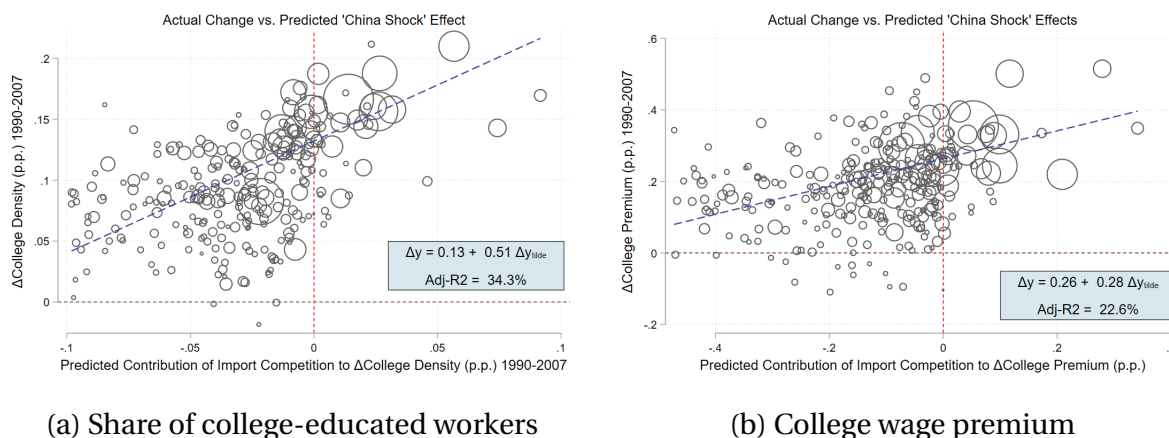(a) Share of college-educated workers   (b) College wage premium

4.1   Contribution of Import Penetration to Regional Divergence

This section computes how much does import penetration explain of the total variation in changes of the share of college-educated workforce and the college wage premium between 1990 and 2007. I compare the actual change in each commuting zone of the two features of regional divergence with the predicted effects of import competition on them, as computed in Equation (5).

Figure 3a plots the observations for the change of the share of college-educated workforce and the predicted causal effect of import competition, conditional on the skill intensity of local non-manufacturing industries. The size of each observation corresponds with the start-of-the-period population. The adjusted-R^2 of the regression is 0.34. In other words, import competition, taking into account the heterogeneity of effects due to local services' skill intensity, explains around one third of the variation in the college density of local labor markets between 1990 and 2007.

Figure 3b shows the same graph for the case of the divergence in college wage premium. The predicted contribution of import competition, conditional on local skill intensity, accounts for slightly more than one fifth of the variation on the returns to skills among local labor markets.[22]

Figure 3: Actual changes and predicted contribution of import competition.

(a) Share of college-educated workers

(b) College wage premium

In the following subsections I analyze through which particular demographics does import competition affect the share of college-educated workers. Similarly, I document which are the salaries that drive the trade-induced changes in college wage premium. Additionally, to provide a meaningful economic interpretation of the estimates, I compute interquartile comparatives in the predicted effects of the China shock exploiting differences in skill-intensity and degree of exposure.

4.2   Import Competition and Demographic Changes

Table 2 shows the effects of rising import competition on demographic changes in urban commuting zones. The three panels show the log changes of working-age population at aggregate level and by level of education. Each panel replicates the scheme of Table 1; Column 1 reproduces the analysis in ADH and columns 2-4 analyze the heterogeneous effects of $\Delta \text{IP}_{c,t}$ according to local skill-intensity of non-manufacturing industries. Similarly to the case in Table 1, the average effect of import competition on population changes is not significantly different from zero for any group. The specialization of local employment in exposed industries does not create

---

[22]The predicted effects of import competition, without accounting for the effect heterogeneity due to skill intensity, account respectively only for the 3.33% and 1.01% of the variation of actual changes

demographic changes per se. Again, the analysis of heterogeneous effects sheds light on the actual effect of import competition on population counts and how the average effect masks systematic differences in the consequence of the China shock.

The results in Table 2 show that changes in the share of workforce with a college degree shown in Table 1 are entirely driven by the change of college-educated population. When import competition meets a region with skill-intensive service industries, the consequence is a growth of the college-educated workforce. The effects are clearly significant only for this population group. Looking at the log change of workforce without a college degree, the effects are smaller and only marginally significant in the least restrictive specification. For this group, the effect of import competition is not significant neither on average nor accounting for heterogeneous effects. Nonetheless, it is noteworthy that there is not a crowding out effect of workers without college education. In other words, among the most skill-intensive half of commuting zones, a higher level of exposure increases the number of working-age college-educated individuals, while the population of workers without a college-degree seems to remain unaffected by the trade shock. The combination of these two facts gives the increase in the density of college-educated workers found in Table 1.

Comparative Effects

To provide a more meaningful economic interpretation of the estimated coefficients of table 2, I compute three different interquartile comparisons. Exploiting local differences in terms of manufacturing exposure to the China shock and in the share of college-educated workforce in local non-manufacturing industries, I compare 1) regions with similar exposure to import competition and differences in skill intensity, 2) skill-intensive commuting zones with differences in exposure to the China shock, and 3) skill-scarce commuting zones with different levels of import penetration.[23] [24]

---

[23]Figure 4 plots the ranking of college education in non-manufacturing in 1990 and the ranking of of import penetration in the period 1990-20007 for the 60 urban commuting zones.

[24]The formula of the comparison are:

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

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

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

Table 2: - Effect of Import Penetration on Working-age Population

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Log Population 25-60 y.o.				*Log College Workforce*				*Log Non College Workforce*			
$\Delta IP_{c,t}$	-0.09	-2.94**	-2.89	-2.98	-0.04	-4.30**	-6.54**	-6.72**	-0.06	-2.34*	-1.56	-1.64
	[0.10]	[1.23]	[1.95]	[2.02]	[0.16]	[1.70]	[2.61]	[2.72]	[0.10]	[1.25]	[1.99]	[2.06]
$\Delta IP_{c,t} \cdot Skill_{c,t-1}$		9.20**	8.04	8.44		13.42**	19.45**	20.17**		7.48*	4.02	4.39
		[3.87]	[6.10]	[6.35]		[5.37]	[8.08]	[8.45]		[3.90]	[6.20]	[6.44]
Interacted Controls:												
Mfg. Sector Controls		✓	✓	✓		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓			✓	✓
Exports				✓				✓				✓
$\hat{\beta}_I / \hat{\beta}_{IS}$		35.1%	-	-		32.0%	33.6%	33.3%		31.3%	-	-
SW F-Statistic												
$\Delta IP_{c,t}$	74.83	28.04	28.70	25.69	60.70	30.13	27.96	25.22	79.59	27.35	30.00	26.95
$\Delta IP_{c,t} \cdot Skill_{c,t-1}$		26.85	28.02	25.04		28.69	26.61	23.98		26.04	29.28	26.22

NOTE - N=632 (321 Urban Commuting Zones $\times$ 2 time periods). Two stacked ten-year equivalent differences between 1990-2000 and 2000-2007. All the models include the full set of controls in levels described in the text. Columns 2-4 include sequentially the sets of interacted controls. Regressions include time trends interacted with Census regions fixed effects, $Skill_{c,t-1}$, and the sum of employment in directly exposed industries. Regressions include the pre-trend between 1980 and 1990 of the dependent variable. Robust standard errors clustered at the state level. Models are weighted by start of the period commuting zone share of national population. * $p < .1$, ** $p < .05$, *** $p < .01$

First, comparing commuting zones with the median level of exposure to the China shock, a region at the 75th percentile of services skill intensity will experience a 12.5 log points faster growth of college-educated population per decade than a region at the 25th percentile (equivalent to 1.1 standard deviations).[25] Second, comparing two commuting zones at the 75th percentile of non-manufacturing skill-intensity, a commuting zone at the 75th percentile of exposure to the China shock will have a 8.2 log points faster growth of college-educated population per decade than a region at the 25th percentile of exposure (equivalent to 0.73 standard deviations). Finally, comparing regions at the 25th percentile of services skill-intensity, a commuting zone with a level of import penetration equal to the 75th percentile of import exposure will experience a 6.9 log points faster drop in college-educated population per decade than a region at the 25th percentile of exposure (equivalent to 0.62 standard deviations).

4.2.1 Migration Flows

Table 3 shows the results of the regression of migration flows on import competition and its interaction with local services' skill intensity. Each panel shows the net and gross migration flows of workers by level of education. Migration flows are computed as the ratio over the population of reference in the commuting zone at the beginning of the period. With this definition, the magnitudes in Table 3 are comparable with the population growth rates estimates in table Table 2.

The results in table 3 deliver two messages. First, almost all of the changes in college-educated workforce from table 2 are due to migration of workers. This finding rules out other potential channels such as endogenous changes in graduation rates in favor of actual movement of factors across regions.

Second, the net migration flows of college-educated workers to skilled-and-exposed labor markets are almost entirely driven by positive immigration flows rather than lower outmigration rates. In other words, the China shock induces demographic adjustments by changing the destination, rather than the origin, of college-educated migrants.[26] This finding underlines the importance of taking into account the transformation of local labor markets after the shock to understand the contribution of the China shock to regional divergence in the US. It is more important to know which regions will actually benefit from the shock (the skilled-and-exposed commuting zones will receive an inflow of college-educated workers) than just what regions are directly

---

[25]I use the estimates from Column 4, which include the full set of controls

[26]Monras (2018) finds similar patterns in the context of the housing bubble burst around the years 2006-2008

affected by the shock (import competition does not induce workers to leave more exposed commuting zones)

Table 3: - Effect of Import Penetration on Migration Flows

	Net Migration	Immigration	Outmigration	Net Migration	Immigration	Outmigration
	(1)	(2)	(3)	(1)	(2)	(3)
	College-Educated Population			Non College-Educated Population		
$\Delta \text{IP}_{c,t}$	-5.01**	-7.00***	-2.00	-0.81	-1.01	-0.21
	[2.03]	[2.56]	[1.90]	[0.79]	[1.04]	[0.49]
$\Delta \text{IP}_{c,t} \cdot \text{Skill}_{c,t-1}$	19.21***	25.71***	6.50	3.87	4.61	0.74
	[6.69]	[8.61]	[6.42]	[2.74]	[3.62]	[1.68]
Interacted Controls:						
Mfg. Sector Controls	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Exports	✓	✓	✓	✓	✓	✓

NOTE - N=632 (321 Urban Commuting Zones × 2 time periods). Two stacked ten-year equivalent differences between 1990-2000 and 2000-2007. All the models include the full set of controls in levels described in the text. Columns 2-4 include sequentially the sets of interacted controls. Regressions include time trends interacted with Census regions fixed effects, $\text{Skill}_{c,t-1}$, and the sum of employment in directly exposed industries. Regressions include the pre-trend between 1980 and 1990 of the dependent variable. Robust standard errors clustered at the state level. Models are weighted by start of the period commuting zone share of national population. $^*\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$

4.3   Import Competition and College Wage Premium

In this section I analyze the contribution of the China shock to the geographical divergence of returns to skills. Table 1 shows that among the most skill-intensive regions, the exposure to manufacturing import competition increases the skill premium; while among the least skill-intensive ones, the trade shock reduces the wage difference between college-educated and non-college-educated workers. In this section I analyze which changes in wages actually drive the movements of the college wage premium.

Table 4 introduces the estimation of the regression of the changes of average real weekly wages in the commuting zone, as well as real wages for workers with different educational attainment. For each panel, the table reproduces the scheme in table 1 and table 2. Column 1 regresses the dependent variable on the change in import penetration, without any interactive term. Columns 2-4 takes into account the heterogeneous effects according to local services' skill intensity, sequentially including different sets of interactive controls.

The effect of manufacturing import competition on the salary of college-educated workers is significantly different for commuting zones for diverse levels of skill intensity in local non-manufacturing industries. Similar to the case in table 2, the interaction of import penetration and local skill-intensity has a positive effect. Approximately, for the best-educated half of the US, the net effect of import competition on real wages of college workers is positive. On the other hand, among the least educated commuting zones, the benefits from the interaction $\Delta IP_{c,t} \cdot Skill_{c,t-1}$ do not offset the initial negative impact of $\Delta IP_{c,t}$. The effect on real wages for workers without a college-education are not significant under any specification. Then, I cannot reject the hypothesis that the effects of import competition on salaries for unskilled workers are the same across the country.

Then, from table 4, the China shock contributed to the dispersion of college-wage premium across commuting zones in the US only through its contribution to the divergence of real wages of college-educated workers. Conditioning two local labor markets to the same level of exposure to import competition, the effect is a growth of real college wages if the commuting zone has a skill intensive non manufacturing sector, while there will be a drop in real college wages if the commuting zone is skill-scarce.

Comparative Effects

The consequences of the rise in import competition on the divergence of the college wage premium are statistically significant, but also economically sizable. Below I provide the interquartile comparisons of the effect on real wages of college-educated workers.

Comparing to commuting zones at the median level of import competition, an area at the 75th percentile of non-manufacturing skill-intensity will have a 6.2 log points faster decade growth of real wages for college-educated workers than one at the 25th percentile of skill intensity (this is equivalent to 0.91 standard deviations). Comparing to regions at the 75th percentile of services' skill intensity, in a commuting zone at the 75th percentile of exposure to import competition real wages of college-educated workers will grow 3.5 log points faster per decade than if the commuting zone was at the 25th percentile of exposure to the China shock (equivalent to 0.52 standard deviations). Finally among commuting zones at the 25th percentile of skill-intensity, having an exposure equal to the 75th percentile of the distribution implies

Table 4: - Effect of Import Penetration on Real Wages

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Average Log Real Weekly Wage				*College workers - Log Real Wage*				*Non-College workers - Log Real Wage*			
$\Delta \mathrm{IP}_{c,t}$	-0.13**	-0.60	-1.61**	-1.50*	-0.09	-2.55**	-3.43**	-3.43**	-0.12	0.56	-0.10	0.03
	[0.07]	[0.83]	[0.81]	[0.82]	[0.08]	[1.10]	[1.57]	[1.60]	[0.08]	[0.77]	[0.81]	[0.85]
$\Delta \mathrm{IP}_{c,t} \cdot \mathrm{Skill}_{c,t-1}$		1.72	4.58*	4.13*		8.10**	10.06**	10.08**		-1.75	0.32	-0.23
		[2.57]	[2.41]	[2.44]		[3.30]	[4.80]	[4.91]		[2.44]	[2.51]	[2.63]
Interacted Controls:												
Mfg. Sector Controls		✓	✓	✓		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓			✓	✓
Exports				✓				✓				✓
$\hat{\beta}_{\mathrm{I}}/\hat{\beta}_{\mathrm{IS}}$		-	35.2%	36.3%		31.5%	34.1%	34.0%		-	-	-
SW F-Statistic												
$\Delta \mathrm{IP}_{c,t}$	51.64	30.74	34.41	35.10	54.16	30.97	34.95	34.97	52.81	30.70	34.26	35.25
$\Delta \mathrm{IP}_{c,t} \cdot \mathrm{Skill}_{c,t-1}$		29.43	31.97	31.96		29.60	32.19	31.59		29.43	31.90	32.13

NOTE - N=632 (321 Urban Commuting Zones $\times$ 2 time periods). Two stacked ten-year equivalent differences between 1990-2000 and 2000-2007. All the models include the full set of controls in levels described in the text. Columns 2-4 include sequentially the sets of interacted controls. Regressions include time trends interacted with Census regions fixed effects, $\mathrm{Skill}_{c,t-1}$, and the sum of employment in directly exposed industries. Regressions include the pre-trend between 1980 and 1990 of the dependent variable. Robust standard errors clustered at the state level. Models are weighted by start of the period commuting zone share of national population. * $p < .1$, ** $p < .05$, *** $p < .01$

a 4 log points faster drop of real college wages per decade that being at the 25th percentile of exposure to the trade shock (equivalent to 0.59 standard deviations).

4.3.1 College Wages by Sector

Table 5 provides additional insights on the contribution of the China shock to the skill premium and college wages divergence. The dependent variables are the log change of real wages of college educated workers in the manufacturing and the non-manufacturing sector. The estimates show that rising import competition in manufacturing has an effect on the wages of college-educated workers in non-manufacturing industries. The sign of this effects depends on the skill-intensity of the local non-manufacturing industries. The baseline effect of $\Delta IP_{c,t}$ is negative, but this might be partially compensated or fully reversed by the positive effect of the interaction $\Delta IP_{c,t} \cdot Skill_{c,t-1}$.

This finding hints to the importance of the interplay between the negative shock to the manufacturing sector and the characteristics of the non-manufacturing part of local economies. The effect on manufacturing wages of the China shock does not depend on the skill composition of local services. Instead, the geographical divergence in the skill premium happens through the divergence of the salaries of college-educated workers in the sector that is not directly exposed to trade competition.

5. Labor Reallocation across Sectors

The previous section showed that one of the consequences of import competition faced by local manufacturers in skill-abundant commuting zones is a simultaneous increase in both the number and real wages of college-educated workers. Moreover, there is evidence of these changes taking part in local service industries, which are not direct competitors to Chinese manufacturing exporters.

This fact implies that in order to understand the consequence of rising import competition in local labor markets, it is necessary to explore the mechanism through which the effects go beyond the directly exposed manufacturing sectors. In order to rationalize the previous findings, any such mechanism must show that a negative shock in manufacturing induces a positive demand shift of college-educated workers in non-manufacturing industries. Moreover, this should be the case only when local services are specialized in industries with a relatively high skilled labor component.

Table 5: - Effect of Import Penetration on Real Wages of College-Educated Workers

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	College workers - Manufacturing				*College workers - Non-Manufacturing*			
$\Delta\text{IP}_{c,t}$	0.00	0.25	1.26	1.10	-0.13	-2.83**	-4.19**	-4.17**
	[0.13]	[1.46]	[2.55]	[2.56]	[0.10]	[1.12]	[1.81]	[1.87]
$\Delta\text{IP}_{c,t} \cdot \text{Skill}_{c,t-1}$		0.36	-3.25	-2.62		8.65***	12.31**	12.24**
		[4.52]	[8.17]	[8.19]		[3.35]	[5.49]	[5.72]
Interacted Controls:								
Mfg. Sector Controls		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Exports				✓				✓
$\hat{\beta}_\text{I}/\hat{\beta}_\text{IS}$		-	-	-		32.7%	34.0%	34.1%

NOTE - N=632 (321 Urban Commuting Zones × 2 time periods). Two stacked ten-year equivalent differences between 1990-2000 and 2000-2007. All the models include the full set of controls in levels described in the text. Columns 2-4 include sequentially the sets of interacted controls. Regressions include time trends interacted with Census regions fixed effects, $\text{Skill}_{c,t-1}$, and the sum of employment in directly exposed industries. Regressions include the pre-trend between 1980 and 1990 of the dependent variable. Robust standard errors clustered at the state level. Models are weighted by start of the period commuting zone share of national population. * $p < .1$, ** $p < .05$, *** $p < .01$

Finally, this process must be reinforced by the inflow to the area of college-educated workers attracted by the rise in real wages.

In this section I show that the reallocation of labor from directly exposed manufacturing industries to the non-manufacturing sector is a relevant force behind the findings in Section 4. The key ingredients of the mechanism are two. First, workers can move from across different sectors as long as they perform a similar occupation that the one in which they were employed. This implies that the labor reallocation will happen among manufacturing and service industries employing similar set of occupations. Second, sectors employing a large fraction of skilled workers benefit from agglomeration forces. Therefore, skill-intensive local services increase their productivity when they receive workers from other sectors or regions.

Following an increase in import competition, there is a contraction in employment in directly exposed industries. Instead, the consequences for service industries located in the same area are different. These industries can expand due to the availability of a larger pool of labor –and potentially other production factors-previously employed in the local manufacturing sector. Therefore, the type of non-manufacturing industries operating in a commuting zone at the time that local man-

ufacturers face import competition will be key to the overall changes in local labor market.

When this reallocation of employment affects skill-intensive service industries, the increase in size goes in parallel with an increase in the productivity of the sector. Consistent with the large literature on agglomeration effects[27], when the local non-manufacturing sector is densely populated by skill-intensive industries, the reallocation of employment is accompanied by an increase in wages.

Thus, for commuting zones with skill-intensive non-manufacturing industries, the manufacturing decline following the China shock brings a positive shift in the labor demand of skilled services. On the other hand, in regions crowded of low skill-intensity service industries, the non-manufacturing sector does not benefit from the sectoral shift and will not be able to compensate the drop in wages and employment in manufacturing.

I test this reallocation effect in two steps. First, I introduce a variable that measure the impact that manufacturing import competition has on non-manufacturing industries. This variable takes into account the degree to which a local labor market is exposed to the shock and the similarities among sectors in terms of the set of occupations they employ. Second, I look at the growth rates of wages and employment of each industry-commuting zone pairs and test whether non-manufacturing industries expand faster if they are located in local labor markets with a higher manufacturing import penetration.

5.1 Labor Market Exposure to the China shock

In this section I introduce my novel measure of 'labor market exposure' to the China shock. This variable captures how non-manufacturing industries are exposed to the import competition faced by manufacturing sectors through the local labor market. Industries in the non-manufacturing sector benefit from the decline in labor demand of those industries competing directly with Chinese imports. In particular, this effect will be stronger when two industries employ a more similar set of occupations.

I construct the variable of 'labor market' import penetration $(\Delta \mathrm{LP}_{i,c,t})$ exploiting the geographical distribution of directly exposed industries, the uneven geograph-

---

[27]Combes and Gobillon (2015) provides an extensive review of the empirical evidence and the microfundations of positive productivity effects of the agglomeration of industry employment in a location. Among other authors, Elvery (2010) and Florida et al. (2011) document that these agglomeration externalities are stronger for skill-intensive industries and college-educated workers

ical co-location of different manufacturing and non-manufacturing industries, and occupational similarities between sectors.

The measure of labor market import penetration follows a double shift-share strategy. First, it computes the exposure of each occupation in a region to import penetration according to the industries in which it is most intensively employed in the area. Second, it computes the indirect exposure of non-manufacturing industries according to how intensively they employ each occupation.

$$\Delta\text{LP}_{i,c,t} = \underbrace{\Sigma_j \frac{L_{ijt}}{L_{it}}}_{\text{B}} \cdot \underbrace{\Sigma_{h\in\text{mfg}} \frac{L_{hjct}}{L_{jct}}\Delta\text{IP}_{ht+1}}_{\text{A}} \tag{6}$$

Term A in eq. (6) shows the change of import penetration that an occupation j faces in a commuting zone c. This is the weighted sum of the change in import penetration of each manufacturing industry h (this term is industry-specific, and does not change across locations), weighted by the importance that each industry has for a given occupation in the city.[28] This term has geographical variation as long as some local labor markets are more specialized in exposed industries.

Term B in eq. (6) captures the 'labor market' exposure to import penetration of an industry i according to the type of occupations that it employs. It weights the exposure to the China shock of each occupation j in a commuting zone c by the weight that the occupation has in the employment of non-manufacturing industry i.

The variation of the 'labor market' import penetration measure is at the industry-commuting zone level. Comparing the same industry across different locations, the source of variation comes from the fact that some commuting zones employs a larger share of the workforce in directly exposed industries. Within commuting zones, non-manufacturing industries differ in the level of exposure due to differences in the occupational requirements with the directly exposed industries

5.2 Labor Reallocation and Sectoral Transformation

In this section, I test whether the labor reallocation is an empirically relevant channel for the propagation of the import competition shock from directly exposed manufacturing industries to the non-manufacturing sector. Armed with the novel measure of 'labor market' exposure to the China shock introduced in Section 5.1, I regress the log

---

[28]Due to data limitations, I assume that the occupational requirements of each narrowly-defined industry is the same in every commuting zone.

change of employment and wages in service industries in different commuting zones
on their indirect labor supply shock.

$$\Delta \ln X_{ict} = \beta \cdot \Delta LP_{i,c,t} + \gamma_{ct} + \gamma_{it} + \varepsilon_{ict} \qquad (7)$$

The variation within and between commuting zones of the 'labor market expo-
sure' to the China shock allows to include industry-time and commuting zone-time
fixed effects. In this setting, the estimate β provides a comparison of the employ-
ment growth rate of the same industry located in areas with different levels of import
penetration. Therefore, this analysis gets rid of contemporaneous covariates such as
technological changes, aggregate demand, or other potential factors operating at the
industry level.

$$\Delta \ln X_{ict} = \Sigma_{k \in H,M,L} \left[\beta_k \cdot \Delta LP_{i,c,t} \cdot \mathbb{I}_k \right] + \gamma_{ct} + \gamma_{it} + \varepsilon_{ict} \qquad (8)$$

Besides, I estimate the specification in eq. (7) allowing for differential estimates
for service industries by terciles of skill intensity. In this setting, I compare how in-
dustries with different levels of skill intensity react to the trade-induced labor supply
shock.[29]

Table 6 shows the results of the regression of log employment and log real wages
change in industry-commuting zones on the 'labor market exposure' to the China
shock (eq. (6)). The units of observations are two ten year-equivalent changes for
each observation. Columns 1, 3, 5, and 7 show the results of the specification in
eq. (7), and columns 2, 4, 6, and 8 the results in eq. (8).

Table 6 shows in columns 1-4 that the competition on local labor markets is a
relevant channel in the propagation of the China shock from directly exposed indus-
tries to the rest of the economy. Columns 1 and 3 show that the elasticity between the
predicted lost employment in manufacturing and employment expansion in the non-
manufacturing sector is close to 0.7. Columns 2 and 4 show that the effects are signifi-
cantly different for groups of industries with diverse skill intensity. Service industries
with the lowest skill intensity do not benefit from a contraction of local manufac-

---

[29]Under the hypothesis from appendix B, the estimates should be positive, and increasing in the
level of skill intensity. In other words, comparing the same sector across locations, those industries lo-
cated in commuting zones more exposed to the China shock should grow faster, and this effect should
be stronger among industry employing a larger share of college-educated workers.

turing employment. Instead, high-skill industries expand their employment significantly. The most skill intensive industries benefit from the 'labor market exposure' to the China shock and absorb part of the labor leaving the exposed industries. The estimated elasticity is larger than 1, which indicates that skill-intensive service industries increase employment by more than the expected loss in manufacturing employment. This figure implies that the reallocation of labor to these skill-intensive services has a net positive multiplier. On top of that, as long as these industries employ a relatively larger share of college-educated workers, the shift in demand is skill-biased.

Columns 5-8 in Table 6 show the effects on wages of the 'labor market exposure' to the shock. First, among the low- and mid-skill intensive industries I find a negative effect on wages. This result should be expected from a standard demand and supply mechanism. The labor supply that these service industries are facing has increased due to the contraction of competing manufacturing industries and the new price for labor falls consequently. However, the most relevant result arises from the effect on wages paid by high-skill intensity industries. In this case, the increase in labor supply meets a positive shift in the labor demand of these industries. This is the consequence of the agglomeration effects: high-skill intensive service industries benefit from expanding through the employment lost by neighboring manufacturing firms.

Therefore, the labor reallocation mechanism can reconcile the findings in Section 4. The interaction of high exposure to import competition with the abundance of skill-intensive non-manufacturing industries creates a positive shift in the demand of labor of the later. Finally, this process is reinforced by a positive inflow of college-educated workers from other regions attracted by the higher wages in skill-intensive sectors.

A corollary from the findings in Table 6 is that, conditional on a similar level of exposure to the trade shock, the losses of manufacturing employment are larger in skill-intensive labor markets. Beyond the push factor (negative shock to manufacturing), there is a pull factor that reallocates labor from the manufacturing to non-manufacturing sector (agglomeration effects).

Table 7 provides additional evidence of the sectoral reallocation of labor following the China shock. The two panels in table 7 show commuting zone-level changes in the employment of directly exposed industries and STEM-intensive industries. The econometric specification for these regression are the eq. (1) as in section 4, in which I regress decade changes in the log number of workers in each sector in the level of exposure to import competition.

Table 6: - Effect of 'labor market-mediated' import penetration on employment

	Δ Log employment				Δ Log Avg. wage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All industries	0.956***		1.329***		-0.252**		-0.108**	
	(0.205)		(0.328)		(0.116)		(0.052)	
Low Skill industries		-0.022		0.780		-0.574***		-0.301*
		(0.470)		(0.786)		(0.074)		(0.160)
Mid Skill industries		1.254***		1.393***		-0.235**		-0.119***
		(0.155)		(0.255)		(0.095)		(0.036)
High Skill industries		1.284***		1.604***		0.086**		0.123**
		(0.393)		(0.517)		(0.041)		(0.057)
Industry-year FE	✓	✓	✓	✓	✓	✓	✓	✓
CZ-year FE			✓	✓			✓	✓
N	21760	21760	21760	21760	21760	21760	21760	21760
Sh. local emp	✓	✓	✓	✓	✓	✓	✓	✓
Lag Δ ln emp	✓	✓	✓	✓	✓	✓	✓	✓

Stacked quasi-decade differences in log employment and wages in industry-CZ observations. Sample of non-manufacturing industries without direct or upstream exposure to China shock. The main regressor is the measure of labor market-mediated exposure to the China shock. By row, I interact the exposure measure with a dummy for industries terciles of skill intensity. Robust standard error clustered by SIC industry and CZ. Industry-CZ observations with at least 10 employees in 1988, 1991, 1999, and 2007

$* \ p < .10, \ ** \ p < .05, \ *** \ p < .01$

Column 1 in the left panel in table 7 shows the main result in ADH. Commuting zones with a higher exposure to the China shock suffer a contraction of employment in industries competing with foreign manufacturers. Columns 2-4 show that this reduction in employment is stronger in areas in which the non-manufacturing industries are relatively more skill intensive. Conditional on having a similar manufacturing sector (and therefore a similar exposure to Chinese import competition), more workers leave the sector when the services industries in the region are skill intensive.

The right panel in table 7 complements the previous paragraph. The interaction of the China shock and the skill intensity of services industries has a positive effect in terms of employment of STEM-sectors. Combining both panels, among skill intensive regions, a higher exposure to import competition produces a reduction of employment in exposed manufacturing industries and the expansion of industries employing intensively college-educated workers. The employment contraction in manufacturing is stronger in these regions, as a consequence of the stronger demand of labor from service industries. On the other hand, among the least skilled regions, the effect of the China shock is still an employment contraction in exposed industries, but it is not compensated by the growth of employment in other sectors.

Table 7: - Effect of Import Penetration on Exposed and STEM Industries

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Log Employment in Exposed sectors				*Log Employment in STEM sectors*			
$\Delta\text{IP}_{c,t}$	-1.04***	4.90**	8.01*	9.16**	-0.1	-4.47***	-5.81***	-5.19***
	[0.09]	[1.97]	[4.25]	[4.33]	[0.19]	[1.47]	[2.22]	[1.80]
$\Delta\text{IP}_{c,t} \cdot \text{Skill}_{c,t-1}$		-19.54***	-34.93**	-38.26***		12.34***	20.60***	18.68***
		[6.52]	[14.09]	[14.11]		[4.35]	[5.97]	[4.40]
Interacted Controls:								
Mfg. Sector Controls		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Exports				✓				✓

NOTE - N=632 (321 Urban Commuting Zones × 2 time periods). Two stacked ten-year equivalent differences between 1990-2000 and 2000-2007. All the models include the full set of controls in levels described in the text. Columns 2-4 include sequentially the sets of interacted controls. Regressions include time trends interacted with Census regions fixed effects, $\text{Skill}_{c,t-1}$, and the sum of employment in directly exposed industries. Regressions include the pre-trend between 1980 and 1990 of the dependent variable. Robust standard errors clustered at the state level. Models are weighted by start of the period commuting zone share of national population. * $p < .1$, ** $p < .05$, *** $p < .01$

These findings reconcile the facts from Section 4. Increasing import competition forces local manufacturing to reduce employment. That labor can be employed in the rest of the economy that is not directly competing with Chines manufacturing exports. When the industries absorbing those workers are skill-intensive services, there is an additional gain in productivity due to agglomeration effects. Thus, when the China shock affects a commuting zone densely populated by this type of services, the decline in manufacturing turns into a skill-biased shift of labor demand, a rise of real wages, and an inflow of college-educated workers migrating to the skilled-and-exposed regions.

6. Conclusions

In this paper I document the contribution of import competition to the regional divergence among local labor markets in the US. I analyze the impact that the sharp rise of Chinese manufacturing imports had on the spatial skill polarization and the divergence of skill premium over the period between 1990 and 2007.

Although the average effect of the China shock on this variable was not significant, there were systematic differences depending on characteristics of the local labor markets. In particular, the skill intensity of local non-manufacturing sectors shaped the impact of rising import competition on regional divergence. Among commuting zones where the service sector employed a large fraction of college-educated workers, a higher exposure to the China shock meant a higher density of college-educated workers and an increase of the college-wage premia. On the other hand, when import competition affected local labor markets where the non-manufacturing sector had a low skill intensity, the density of college-educated workers and the skill premia dropped. I find that the heterogeneous effects of the China shock explains above than one third and one fourth of the variation of the spatial skill polarization and the divergence of skill premium, respectively.

I find that the interaction between the China shock and the level of skill intensity in the non-manufacturing sector increases simultaneously the supply and the wages of college-educated workers in non-manufacturing industries. When the non-manufacturing sector of a commuting zone is skill-intensive, the trade-induced manufacturing decline is followed by a growth of real wages of college-educated workers and positive migration flows of skilled workers to the region.

Finally, I document that the reallocation of labor from manufacturing to non-manufacturing industries explain the systematic differences in the effect of import competition. Non-manufacturing industries benefit from the contraction in the local manufacturing sector. These industries in regions with a high exposure to the China shock benefit from having access to a larger pool of labor. When the non-manufacturing is densely populated by skill intensive industries, the agglomeration externalities increase the productivity of the sector and the negative shock to the manufacturing industry turns a shift in the demand of college-educated labor. In commuting zones with skill intensive non-manufacturing industries, the same shock of import competition entails a larger reduction in manufacturing employment and a faster expansion of skilled services.

Figure 4: Ranking of college-educated workforce and change in import penetration
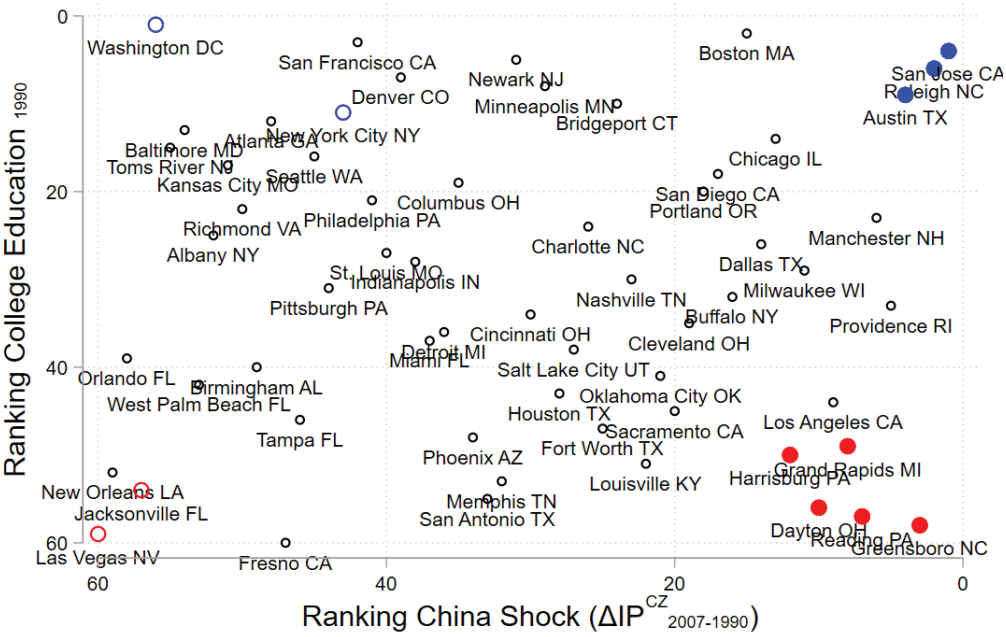
Table 8: - Correlation of covariates with non-manufacturing skill intensity

	$\left(\mathrm{Skill}^{\mathrm{CZ}}_{i,t_0}, \mathrm{X}^{\mathrm{CZ}}_{i,t_0}\right)$	$\left(\Delta \mathrm{IP}_{c,t} \cdot \mathrm{Skill}^{\mathrm{CZ}}_{i,t_0}, \Delta \mathrm{IP}_{c,t} \cdot \mathrm{X}^{\mathrm{CZ}}_{i,t_0}\right)$
Manufacturing sector characteristics		
Skill-intensity	0.70	-0.01
Share Management occupations	0.62	-0.06
Offshorability index	-0.63	-0.16
Share Routine occupations	-0.40	0.07
Average wage	0.43	-0.04
Demographic characteristics		
Log Population	0.52	-0.19
Share foreign born pop.	0.21	0.02
Female labor participation	0.49	0.18
Share young pop. (25-35 y.o.)	0.44	0.01
Export Potential (Feenstra et al. (2017))	-0.07	0.16

A. Data and Sample Appendix

This section describes the sample and data sources employed in the empirical analysis of the paper. There are two main empirical settings in the paper. In the first one, the level of analysis is the local labor market. In the second one, the units of analysis are pairs of industries and local labor markets.

The geographical units in both parts are commuting zones (CZ), as defined by Tolbert and Sizer (1996). I restrict my sample to the 321 urban commuting zones overlapping with Metropolitan Statistical Areas in contiguous continental US.[30] These commuting zones are clusters of US counties that replicate local labor markets.

The first econometric setting analyzes changes in outcomes of commuting zones. Following the previous literature (Autor et al. (2013), Acemoglu et al. (2016)), the sample consists of two stacked ten-year equivalent differences in the outcomes of interest for the periods 1990-2000 and 2000-2007.

The second setting examines changes in employment in pairs of industries and commuting zones. The sample consists as well in two stacked quasi-decade changes in log employment for the periods 1990-2000 and 2000-2007.

Local labor markets

The primary source for data at the commuting zone level are the Census Integrated Public Use Micro Samples (Census IPUMS) for the years 1970, 1980, 1990 and 2000, and American Community Survey (ACS) for 2006 through 2008, again Ruggles et al. (2016). I restrict the Census samples to individuals between age 25 and 60.

Using this source I construct the main dependent variables of the analysis. I compute changes in the workforce size by educational level and changes in real wages and college wage premium. I use additional data on the characteristics of commuting zones from Autor et al. (2013) as control variables. This variables includes characteristics of local labor markets as offshorability and routine intensity of occupations,

Real wages and Wage Premium

I compute average wages at the commuting zone level for workers with between 25 and 60 y.o. excluding self-employed workers, public employees, individuals with missing wages or weeks or who worked less than 26 weeks in the previous year. The

---

[30]Excluding Alaska, Hawaii, and Puerto Rico

main measure of wages are log weekly wages, computed as th log of total wage income over the number of worked weeks. Wages below the first percentile of the national distribution are set equal to the value of the first percentile.

To have a more meaningful estimation of changes in labor conditions across regions, I compute change in real wage changes rather than nominal ones. I deflate wages by commuting zone-specific price indexes. These deflators might be potentially correlated with changes in import penetration. 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. Similarly, higher housing prices may offset nominal gains in booming areas (Feler and Senses (2017),Hsieh and Moretti (2015),Xu et al. (2019)).

Given that there is no off-the-shelf index that covers the entire sample, I follow Moretti (2013) and I deflate changes in nominal wages as

$$\Delta LogRealWage_{i,t} = \Delta LogNominalWage_{i,t} - \frac{1}{3} \cdot \Delta MedianRentalPrice_{i,t} - \frac{2}{3} \cdot \Delta CPU_t \tag{9}$$

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 disparities in the cost of living between cities comes from differences in housing prices. Following Albouy (2016), I assume that housing expenditure accounts for roughly one third of disposable income.

On the other hand, the national CPU index captures the change in prices of tradable goods[31], accounting for two thirds of the consumption. However, this component vanishes in the econometric setting with the inclusion of time fixed effects.

Finally, the change in college wage premium is the difference between the log change of wages for workers with and without a college degree. My definition of real wage changes does not affect the change of college wage premium, as long as the local deflator assumes the same share of consumption of local goods for workers with any level of education.

---

[31]I am implicitly assuming that changes in tradable consumption goods are homogeneous across locations.

Migration Rates

Migration rates are defined as

$$\text{Migration rate}_{i,s,t+1} = \frac{F_{i,s,t+1}}{N_{i,s,t}} \tag{10}$$

Where $F_{i,t+1}$ are the in-migration or out-migration flows of population group s in commuting zone i between t and $t+1$. I compute migration flows for total population, college and non-college educated groups. I express migration rates as the ratio of migration flows over the initial size of the respective population group at the beginning of the period ($N_{i,s,t}$). Hence, the migration rate are the contribution of migration to the growth rate of the respective population subgroup.[32][33]

Industrial Composition

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.

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))

Exporting Potential

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.

---

[32]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.

[33]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

B. Model of Labor Reallocation

This section introduces a parsimonious model of labor reallocation across sectors and regions. The goals are twofold. First, provide a theoretical framework that rationalizes the findings on import competition and regional divergence from the Section 4. The negative shock to the local manufacturing sector increases simulatenously the supply and the salary of college-educated workers in those local labor markets with skill-intensive service industries. The theoretical model clarifies the role of local labor market competition on turning the negative shock to manufacturing into positive for local service industries. The skill intensity of local non-manufacturing industries determines the extent of the shift of college-educated workers.

Second, motivated by the theoretical model, I introduce a novel measure of exposure to manufacturing import competition of service industries. The variable of 'labor market' exposure to the China shock captures the changes that each pair of industry-location faces in the labor market conditions following the contraction of manufacturing industries in the same region.

The model solves a spatial equilibrium of endogenous workers' location and optimal industry size in a set of local labor markets. In the model, industries in different locations compete for workers in a set of occupations versus other industries in the same city and the same industry in the rest of the country. Workers choose their location endogenously. They get utility from their salary and from idiosyncratic preferences for locations. A negative shock to manufacturing industries alters the equilibrium of the model. Following manufacturing' contraction of labor demand, service industries expand its workforce. The reallocation of workers across sectors is subject to retraining costs. There are positive externalities from the agglomeration of an industry in a city. These externalities are stronger for industries employing a larger share of college-educated workers.

In regions where manufacturing industries exposed to the China shock employ a large share of local workforce, non-manufacturing industries expand absorbing part of the lost employment. These growing industries increase their productivity due to agglomeration externalities. Scale benefits are stronger for skill-intensive industries. This rationalizes the findings in the previous section of the heterogeneous effects of import competition according to local services' skill-intensity. In regions with a high density of skill-intensive service industries, the reallocation of labor following the China shock shifts up the demand for skilled workers.

Workers

Workers have occupation-specific skills and they are mobile across cities. They supply inelastically one unit of labor in occupation j in city c. Workers choose endogenously the utility-maximizing location. Individuals get utility from their salary and from their idiosyncratic taste for different locations. An individual s working on an occupation j in city c gets an utility equal to

$$U_{sjct} = \ln w_{jct} + z_{sc}$$

z_{sc} is the taste of individual s for city s. I assume that the distribution across individuals with occupation j of the idiosyncratic preferences (z_{sc}) for locations follow a Type I Extreme Value distribution, with parameter $\frac{1}{\eta_j}$. In other words, $\frac{1}{\eta_j}$ reflects how extreme are the preferences of individuals for different locations. Conversely, η_j is proportional to the responsiveness of workers with occupation j to changes in objective economic conditions.

Given the assumption on the distribution of z_{sc}, the elasticity of employment in occupation j with respect to changes in local economic conditions is

$$\widehat{L}_{jct+1} = \eta_j \underbrace{(\widehat{w}_{jct+1} - \widehat{w}_{jt+1})}_{\text{Change in relative wages}} \tag{11}$$

where $\widehat{w}_{jct+1}$ is the growth rate of wages for occupation j in city c between t and t+1, and $\widehat{w}_{jt+1}$ is the average change in the country of wages for occupation j during the same period.

Assumption 1: the propensity to migrate increases with education.

From Assumption 1, η_j is larger in those occupations in which the typical worker has a college education. As a consequence, industries employing a larger share of occupations that require a college degree will face a more elastic labor supply.

Firms

Each firm operates in a giving industry i and is located in city c. Firms take prices as given and each industry combines labor in each occupation to produce output.

$$Y_{ict} = A_{ict} \prod_{j \in J} (L_{jict})^{\alpha_{ji}} \tag{12}$$

$$\text{with} \quad \Sigma_{j \in J} \alpha_{ji} = 1$$

The importance of each occupation j within an industry i (α_{ji}) is the same across cities. However, the productivity of an industry-commuting zone pair (A_{ict}) increases with the number of workers in the sector. Industries benefit from (factor neutral) agglomeration externalities. Firms operating in an industry i and city c are more productive when the density of workers in the industry-commuting zone pair increases.

$$A_{ict} = \exp\left(G_i \ln L_{ict}\right) \tag{13}$$

Assumption 2: the strength of agglomeration externalities (G_i) increases with skill-intensity of the industry

Firms' Labor Demand

The optimization problem of firms consists in choosing the optimal level of employment in each occupation (L_{ict}). Firms pay competitive wages and take the labor supply as given. When hiring workers previously employed in a different industry, firms has to pay re-training costs. Firms have to devote a fraction of their current workforce to train workers switching their industry for their new positions. These re-training costs are convex in the growth rate of employment in each occupation.

Although every unit of labor within an occupation enters symmetrically in the production function, the contribution of workers to the profit function will be different if they are switching their industry (L_{jt}^s, - *switchers*) or they were already employed in the same industry. Among the workers already in the industry, firms can keep their workforce from the previous period (L_{jt-1}) or adjust their workforce with workers in the same industry migrating from a different city (L_{jt}^m, - *migrants*).

$$\max_{\left\{L_{jt}^m, L_{jt}^s\right\}_{j \in J}} A_t \prod_{j \in J} (L_{jt-1} + L_{jt}^m + L_{jt}^s)^{\alpha_j} - \Sigma_{j \in J} w_{jt}^m L_{jt}^m - \Sigma_{j \in J} w_{jt}^s L_{jt}^s - \Sigma_{j \in J} \mathbb{C}\left(\frac{L_{jt}^s}{L_{jt-1}}\right)$$

$$\tag{14}$$

The optimal labor demand will be different for workers switching from manufacturing to services than for workers in the same industry changing location, as long as the former entails an additional marginal cost for the firm.

$$
\begin{aligned}
\frac{\partial Y_t}{\partial L_{jt}} &= w_{jt}^m \\
\frac{\partial Y_t}{\partial L_{jt}} &= w_{jt}^s + \mathbb{C}'\left(\frac{L_{jt}^s}{L_{jt-1}}\right)
\end{aligned}
$$

Given that adjustment costs are a function of the growth rate of employment in each occupation, the level of employment at the beginning of the period becomes a state variable for the firm. With convex adjustment costs, industries increase the workforce in each occupation j in period t+1 proportionally to the number of workers in the occupation they employed in period t. This implies that, conditional on the contraction of local manufacturing employment, service industries will grow faster in regions where it has a comparative advantage.

I take these comparative advantages as exogenous and I solve the model in terms of changes from the existing equilibrium instead of levels. The solution of the model will deliver elasticities between industry-commuting zone employment and the China shock

$$
\max_{\widehat{L}_{jt+1}^s, \widehat{L}_{jt+1}^n} \quad Y_t \widehat{Y}_{t+1} - \mathbb{C}\left(\widehat{L}_{jt+1}^s\right) - w_{jt+1}^s L_{jt} \widehat{L}_{jt+1}^s - w_{jt+1}^m L_{jt} \widehat{L}_{jt+1}^m \tag{15}
$$

where $\widehat{L}_{jt+1}^s = \frac{L_{jt+1}^s}{L_{jt}}$ is the growth of employment from workers switching sectors, $\widehat{L}_{jt+1}^m = \frac{L_{jt+1}^m}{L_{jt}} - 1$ is the growth of employment from hiring workers in the same industry and different location, and $\mathbb{C}\left(\widehat{L}_{jt+1}^s\right) = C\left(\frac{\widehat{L}_{jt+1}^{s2}}{2}\right) w_{jt} L_{jt}$ are the re-training costs.

Convex re-training costs pins down the growth rate of hiring of switching workers in each occupation proportionally to the industry productivity growth ($\widehat{A}_{t+1}$) and the relative drop of the cost of labor ($\widehat{w}_{jt+1}^s = \frac{w_{jt+1}^s}{w_{jt}} - 1$)

Workers moving from the same industry in a different location do not entail any re-training costs, so the wage that an industry i in city c offers increases proportionally to the productivity change.

$$
\widehat{A}_{t+1} - \widehat{w}_{jt+1}^s = \widehat{L}_{jt+1}^s \tag{16}
$$

$$\widehat{A}_{t+1} = \widehat{w}^{\mathrm{m}}_{jt+1} \tag{17}$$

Equation (16) highlights the fact that different occupations are complementary through the existence of the agglomeration externalities.

Labor market clearing conditions

The amount of *switching* workers hired in service industries equates the quantity of workers leaving the manufacturing sector following the China shock

$$\Sigma_i L_{ijt} \widehat{L}^{\mathrm{s}}_{ijt+1} = L_{jct} \Delta \mathrm{IP}_{jct+1} \tag{18}$$

The right-hand side of eq. (18) shows the employment lost in an occupation j in city c. The term $\Delta \mathrm{IP}_{jct+1}$ is the level of exposure to import penetration of an occupation j in city c. This value is the weighted sum of the change in import penetration of each industry, weighted by the employment share that each manufacturing industry has on the occupation in the city.

The spatial equilibrium from eq. (11) pins down the supply of *migrant* workers in occupation j for firms in industry i and city c.

$$\widehat{L}^{\mathrm{m}}_{jict+1} = \eta_j \left(\widehat{w}^{\mathrm{m}}_{jct+1} - \widehat{w}_{jt+1} \right) \tag{19}$$

I assume that the supply of labor in an occupation does not change at the national level, so the total flows of workers must cancel out at the aggregate level.

$$\Sigma_c L_{ijct} \widehat{L}^{\mathrm{m}}_{ijct+1} = 0 \tag{20}$$

Labor market equilibrium

For each occupation j a firm in industry i and city c hires workers from the manufacturing sector increasing its workforce by $\widehat{L}^{\mathrm{s*}}_{jict+1}$

$$\widehat{L}^{\mathrm{s*}}_{jict+1} = \widehat{A}_{ict+1} + (1 - G_i) \Delta \mathrm{IP}_{jct+1} \tag{21}$$

Additionally, it adjusts its workforce with migrant workers $\widehat{L}^{\mathrm{m*}}_{jict+1}$

$$\widehat{L}^{\mathrm{m*}}_{jict+1} = \eta_j \left(\widehat{A}_{ict+1} - \widehat{w}_{ijt+1} \right) \tag{22}$$

Aggregating up the growth rate in each occupation and adding the two sources of employment growth, the total employment growth in industry i and city c is

$$\widehat{L}^*_{ict+1} = \left(1 + \Sigma_j \frac{L_{jict}}{L_{ict}} \eta_j\right) \widehat{A}_{ict+1} + (1 - G_i) \Sigma_j \frac{L_{jict}}{L_{ict}} \Delta \text{IP}_{jct+1} - \Sigma_j \frac{L_{jict}}{L_{ict}} \eta_j \widehat{w}_{ijt+1} \qquad (23)$$

The first term in eq. (23) corresponds to the increase in demand due to the increase of total productivity of the industry. The second term reflects the fact that service industries in cities exposed to greater import penetration benefit from having access to a larger supply of labor. The third term is the term that reflects the increase in competition at the national level and its common to an industry in any region.

Finally, substituting the expression of the agglomeration effects by actual changes in employment (eq. (13)), the growth rate of employment in industry i and city c between t and t+1 is

$$\widehat{L}^*_{ict+1} = \left[\frac{1 - G_i}{1 - G_i \left(1 + \Sigma_j \frac{L_{ijt}}{L_{it}} \eta_j\right)}\right] \Sigma_j \frac{L_{jict}}{L_{ict}} \Delta \text{IP}_{jct+1} + \Gamma_{it+1} \qquad (24)$$

Equation (24) delivers the elasticity between employment in non-exposed industries and the rise of import penetration in exposed industries. It contains three elements: the 'labor market exposure' to the China shock of non-manufacturing industries, the skill-dependent elasticity of employment with respect to the previous component, and an industry-time fixed effect.

B.1 Labor Market-mediated exposure to the China shock

The term $\Sigma_j \frac{L_{jict}}{L_{ict}} \Delta \text{IP}_{jct+1}$ illustrates the transmission of the China shock from the directly exposed manufacturing sector to non-exposed service industries. Non-manufacturing industries face a change in the supply of labor following the employment contraction in the manufacturing sector. This shock is not the same for an industry in different locations neither for all the industries within the same location.

$$\Delta \ln \text{Supply}_{ict+1} \equiv \Sigma_j \frac{L_{jict}}{L_{ict}} \Delta \text{IP}_{jct+1} = \underbrace{\Sigma_j \frac{L_{ijt}}{L_{it}}}_{B} \cdot \underbrace{\Sigma_{h \in \text{mfg}} \frac{L_{hjct}}{L_{jct}} \Delta \text{IP}_{ht+1}}_{A} \qquad (25)$$

Term A in eq. (6) shows the change of import penetration that an occupation j faces in city c. This is the weighted sum of the change in import penetration of each manufacturing industry h (this term is industry-specific, and does not change across locations), weighted by the importance that each industry has for a given occupation in the city. This term has geographical variation as long as some local labor markets are more specialized in exposed industries.

Term B in eq. (6) weights the exposure to the China shock of each occupation j in a city c by the weight that the occupation has in the employment of industry i.

B.2 Skill Intensity and Labor Reallocation

Conditional on a given level of 'labor market exposure' to the China shock, the growth rate of employment of non-manufacturing industries will vary depending on its skill-intensity. The term $\frac{1-G_i}{1-G_i\left(1+\Sigma_j \frac{L_{ijt}}{L_{it}}\eta_j\right)}$ illustrates the two mechanisms why skill-intensive service industries in a city will grow faster that their less skill-intensive counterparts.

First, skill-intensive industries benefit from stronger agglomeration externalities (G_i). The productivity of sectors employing a high share of college-educated workers benefit from a higher density of workers in the industry more than less skill-intensive industries. Thus, conditional on any number of workers moving from manufacturing to services, skill-intensive industries in highly exposed regions become more productive than their peers in other locations and will be able to poach workers from their competitor in the rest of the country.

Second, skill-intensive industries face a more elastic labor supply $\left(\Sigma_j \frac{L_{ijt}}{L_{it}}\eta_j\right)$. This is the consequence of the increasing propensity to migrate with respect to the level of education. Conditional on any increase of productivity (due to agglomeration forces), the shift of the demand of skill-intensive sectors will translate into a larger growth of employment as long as they employ a larger share of college-educated (and therefore more mobile) workers. On the other hand, industries employing mainly unskilled (and therefore relatively immobile) workers would have to restrict the hiring to workers already in their area.

The predictions of the model reconcile the findings of Section 4. The impact of import competition depresses wages and employment in exposed regions. The lost employment reallocates to local service industries with competitive advantages, these industries benefit from agglomeration externalities, and they become more productive than their industry counterparts in regions without exposure to import compe-

tition. Therefore, the overall effect is not homogeneous and depends on the characteristics of the non-manufacturing sector. Skill-intensive industries benefit from stronger agglomeration effects and a more elastic labor supply. In regions where the non-manufacturing sector is densely populated by skill-intensive industries, the consequence of the China shock is a positive shift in the labor demand of skilled services. Therefore, in skilled-and-exposed regions, the wages of college-educated workers rise because of the China shock at the same time that they receive positive migration flows. In regions with low skill-intensity service industries, the non-manufacturing sector does not compensate the the drop in wages and employment in manufacturing.

References

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics* (Vol. 4, pp. 1043-1171). Elsevier.

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., & Price, B. (2016). Import competition and the great US employment sag of the 2000s. *Journal of Labor Economics*, *34*(S1), S141-S198.

Adao, R., Arkolakis, C., & Esposito, F. (2019). *Spatial linkages, global shocks, and local labor markets: Theory and evidence* (No. w25544). National Bureau of Economic Research.

Adao, R., Kolesár, M., & Morales, E. (2019). Shift-share designs: Theory and inference. *The Quarterly Journal of Economics*, *134*(4), 1949-2010.

Adda, J., & Fawaz, Y. (2020). The health toll of import competition. *The Economic Journal*, *130*(630), 1501-1540.

Albouy, D. (2016). What are cities worth? Land rents, local productivity, and the total value of amenities. *Review of Economics and Statistics*, *98*(3), 477-487.

Autor, D., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, *103*(5), 1553-97.

Autor, D., Dorn, D., & Hanson, G. H. (2013). The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review*, *103*(6), 2121-68.

Autor, D., Dorn, D., Hanson, G., & Majlesi, K. (2020). Importing political polarization? The electoral consequences of rising trade exposure. *American Economic Review*, *110*(10), 3139-83.

Beaudry, P., Doms, M., & Lewis, E. (2006). *Endogenous skill bias in technology adoption: City-level evidence from the IT revolution* (No. w12521). National Bureau of Economic Research.

Bloom, N., Handley, K., Kurmann, A., & Luck, P. (2019, March). The impact of chinese trade on us employment: The good, the bad, and the apocryphal. In *American economic association annual meetings* (Vol. 2019).

Bloom, N., Draca, M., & Van Reenen, J. (2016). Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity. *The review of economic studies*, *83*(1), 87-117.

Borusyak, K., Hull, P., & Jaravel, X. (2018). *Quasi-experimental shift-share research designs* (No. w24997). National Bureau of Economic Research.

Burstein, A., Morales, E., & Vogel, J. (2019). Changes in between-group inequality: computers, occupations, and international trade. *American Economic Journal: Macroeconomics*, *11*(2), 348-400.

Caliendo, L., Dvorkin, M., & Parro, F. (2019). Trade and labor market dynamics: General equilibrium analysis of the china trade shock. *Econometrica*, *87*(3), 741-835.

Colantone, I., & Stanig, P. (2018). The trade origins of economic nationalism: Import competition and voting behavior in Western Europe. *American Journal of Political Science*, *62*(4), 936-953.

Colantone, I., Crino, R., & Ogliari, L. (2019). Globalization and mental distress. *Journal of International Economics*, *119*, 181-207.

Combes, P. P., & Gobillon, L. (2015). The empirics of agglomeration economies. In *Handbook of regional and urban economics* (Vol. 5, pp. 247-348). Elsevier.

Curuk, M., & Vannoorenberghe, G. (2017). Inter-sectoral labor reallocation in the short run: The role of occupational similarity. *Journal of International Economics*, *108*, 20-36.

Dorn, D., Hanson, G. H., Pisano, G., & Shu, P. (2020). Foreign competition and domestic innovation: Evidence from US patents. *American Economic Review: Insights*, *2*(3), 357-74.

Dorn, D., & Hanson, G. (2019). When work disappears: Manufacturing decline and the falling marriage market value of young men. *American Economic Review: Insights*, *1*(2), 161-78.

Eckert, F., Ganapati, S., & Walsh, C. (2019). Skilled tradable services: The transformation of US high-skill labor markets. *Available at SSRN 3439118*.

Elvery, J. A. (2010). City size and skill intensity. *Regional Science and Urban Economics*, *40*(6), 367-379.

Farr, M., & Shatkin, P. D. (2007). O* NET Dictionary of Occupational Titles. JIST Works, an imprint of JIST Publishing.

Feenstra, R. C., Ma, H., & Xu, Y. (2019). US exports and employment. *Journal of International Economics*, *120*, 46-58.

Feler, L., & Senses, M. Z. (2017). Trade shocks and the provision of local public goods. *American Economic Journal: Economic Policy*, *9*(4), 101-43.

Florida, R., Mellander, C., Stolarick, K., & Ross, A. (2012). Cities, skills and wages. *Journal of Economic Geography*, *12*(2), 355-377.

Giannone, E. (2017). Skill-biased technical change and regional convergence. In *2017 Meeting Papers* (No. 190). Society for Economic Dynamics.

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, *110*(8), 2586-2624.

Grossman, G. M., & Rossi-Hansberg, E. (2008). Trading tasks: A simple theory of offshoring. *American Economic Review*, *98*(5), 1978-97.

Hornbeck, R., & Moretti, E. (2018). *Who benefits from productivity growth? Direct and indirect effects of local TFP growth on wages, rents, and inequality* (No. w24661). National Bureau of Economic Research.

Hsieh, C. T., & Moretti, E. (2019). Housing constraints and spatial misallocation. *American Economic Journal: Macroeconomics*, *11*(2), 1-39.

Malamud, O., & Wozniak, A. (2012). The impact of college on migration evidence from the Vietnam generation. *Journal of Human resources*, *47*(4), 913-950.

Monras, J. (2018). Economic shocks and internal migration.

Moretti, E. (2012). *The new geography of jobs*. Houghton Mifflin Harcourt.

Moretti, E. (2013). Real wage inequality. *American Economic Journal: Applied Economics*, *5*(1), 65-103.

Notowidigdo, M. J. (2020). The incidence of local labor demand shocks. *Journal of Labor Economics*, *38*(3), 687-725.

Pierce, J. R., & Schott, P. K. (2016). The surprisingly swift decline of US manufacturing employment. *American Economic Review*, *106*(7), 1632-62.

Ruggles, S., Genadek, K., Goeken, R., Grover, J., & Sobek, M. (2017). Integrated public use microdata series: Version 6.0 [dataset]. *Minneapolis: University of Minnesota*, *10*, D010.

Tolbert, C. M., & Sizer, M. (1996). US commuting zones and labor market areas.

Valero, A., & Van Reenen, J. (2019). The economic impact of universities: Evidence from across the globe. *Economics of Education Review*, *68*, 53-67.

Wozniak, A. (2010). Are college graduates more responsive to distant labor market opportunities?. *Journal of Human Resources*, *45*(4), 944-970.

BANCO DE ESPAÑA PUBLICATIONS

WORKING PAPERS

2001 JAVIER ANDRÉS, PABLO BURRIEL and WENYI SHEN: Debt sustainability and fiscal space in a heterogeneous Monetary Union: normal times vs the zero lower bound.

2002 JUAN S. MORA-SANGUINETTI and RICARDO PÉREZ-VALLS: ¿Cómo afecta la complejidad de la regulación a la demografía empresarial? Evidencia para España.

2003 ALEJANDRO BUESA, FRANCISCO JAVIER POBLACIÓN GARCÍA and JAVIER TARANCÓN: Measuring the procyclicality of impairment accounting regimes: a comparison between IFRS 9 and US GAAP.

2004 HENRIQUE S. BASSO and JUAN F. JIMENO: From secular stagnation to robocalypse? Implications of demographic and technological changes.

2005 LEONARDO GAMBACORTA, SERGIO MAYORDOMO and JOSÉ MARÍA SERENA: Dollar borrowing, firm-characteristics, and FX-hedged funding opportunities.

2006 IRMA ALONSO ÁLVAREZ, VIRGINIA DI NINO and FABRIZIO VENDITTI: Strategic interactions and price dynamics in the global oil market.

2007 JORGE E. GALÁN: The benefits are at the tail: uncovering the impact of macroprudential policy on growth-at-risk.

2008 SVEN BLANK, MATHIAS HOFFMANN and MORITZ A. ROTH: Foreign direct investment and the equity home bias puzzle.

2009 AYMAN EL DAHRAWY SÁNCHEZ-ALBORNOZ and JACOPO TIMINI: Trade agreements and Latin American trade (creation and diversion) and welfare.

2010 ALFREDO GARCÍA-HIERNAUX, MARÍA T. GONZÁLEZ-PÉREZ and DAVID E. GUERRERO: Eurozone prices: a tale of convergence and divergence.

2011 ÁNGEL IVÁN MORENO BERNAL and CARLOS GONZÁLEZ PEDRAZ: Sentiment analysis of the Spanish Financial Stability Report. (There is a Spanish version of this edition with the same number).

2012 MARIAM CAMARERO, MARÍA DOLORES GADEA-RIVAS, ANA GÓMEZ-LOSCOS and CECILIO TAMARIT: External imbalances and recoveries.

2013 JESÚS FERNÁNDEZ-VILLAVERDE, SAMUEL HURTADO and GALO NUÑO: Financial frictions and the wealth distribution.

2014 RODRIGO BARBONE GONZALEZ, DMITRY KHAMETSHIN, JOSÉ-LUIS PEYDRÓ and ANDREA POLO: Hedger of last resort: evidence from Brazilian FX interventions, local credit, and global financial cycles.

2015 DANILO LEIVA-LEON, GABRIEL PEREZ-QUIROS and EYNO ROTS: Real-time weakness of the global economy: a first assessment of the coronavirus crisis.

2016 JAVIER ANDRÉS, ÓSCAR ARCE, JESÚS FERNÁNDEZ-VILLAVERDE and SAMUEL HURTADO: Deciphering the macroeconomic effects of internal devaluations in a monetary union.

2017 JACOPO TIMINI, NICOLA CORTINOVIS and FERNANDO LÓPEZ VICENTE: The heterogeneous effects of trade agreements with labor provisions.

2018 EDDIE GERBA and DANILO LEIVA-LEON: Macro-financial interactions in a changing world.

2019 JAIME MARTÍNEZ-MARTÍN and ELENA RUSTICELLI: Keeping track of global trade in real time.

2020 VICTORIA IVASHINA, LUC LAEVEN and ENRIQUE MORAL-BENITO: Loan types and the bank lending channel.

2021 SERGIO MAYORDOMO, NICOLA PAVANINI and EMANUELE TARANTINO: The impact of alternative forms of bank consolidation on credit supply and financial stability.

2022 ALEX ARMAND, PEDRO CARNEIRO, FEDERICO TAGLIATI and YIMING XIA: Can subsidized employment tackle long-term unemployment? Experimental evidence from North Macedonia.

2023 JACOPO TIMINI and FRANCESCA VIANI: A highway across the Atlantic? Trade and welfare effects of the EU-Mercosur agreement.

2024 CORINNA GHIRELLI, JAVIER J. PÉREZ and ALBERTO URTASUN: Economic policy uncertainty in Latin America: measurement using Spanish newspapers and economic spillovers.

2025 MAR DELGADO-TÉLLEZ, ESTHER GORDO, IVÁN KATARYNIUK and JAVIER J. PÉREZ: The decline in public investment: "social dominance" or too-rigid fiscal rules?

2026 ELVIRA PRADES-ILLANES and PATROCINIO TELLO-CASAS: Spanish regions in Global Value Chains: How important? How different?

2027 PABLO AGUILAR, CORINNA GHIRELLI, MATÍAS PACCE and ALBERTO URTASUN: Can news help measure economic sentiment? An application in COVID-19 times.

2028 EDUARDO GUTIÉRREZ, ENRIQUE MORAL-BENITO, DANIEL OTO-PERALÍAS and ROBERTO RAMOS: The spatial distribution of population in Spain: an anomaly in European perspective.