The Impact of China Shock on Occupational Employment of High-skilled Workers: Evidence from US Local Labor Markets

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This paper analyzes the impact of US import competition from China on the occupational employment of college educated workers in the US local labor markets over recent decades. I find that the US import competition from China reallocated college-educated workers from manufacturing to non-manufacturing jobs in the US commuting zones. The college-educated workers reallocated both upward to high-skill, non-routine occupations as well as downward to low-skill, non-routine jobs. High human capital regions exposed to the China shock exhibit upward occupational reallocation of college-educated workers whereas downward reallocation is seen for low human capital regions.

KEYWORDS
Occupational Employment, *China Shock*, High-Skilled Workers, International Trade, Labor Markets

1 | INTRODUCTION

An extensive literature documents that the spectacular rise in Chinese imports over the past two and a half decades significantly reduced US manufacturing employment (Autor et al. (2013), Pierce and Schott (2016), Acemoglu et al. (2016)). At the same time, U.S. has also experienced large reorganization of production and employment towards non-manufacturing (Autor and Dorn (2013), Bernard et al. (2017), Fort et al. (2018)). Recent literature provides evidence that the China Shock reallocated employment from manufacturing to non-manufacturing in areas with high human capital (Bloom et al. (2019), Quintana (2021)). In other words, China Shock reallocated college-educated workers from manufacturing to non-manufacturing sector, offsetting some of job losses by service sector expansion. One of the most remarkable developments in the US labor market has been the rapid, simultaneous growth of employment in both the highest and lowest-skilled jobs (Autor and Dorn (2009), Acemoglu and Autor (2011), Autor and Dorn (2013)). There has been a change in the composition of jobs in the US during the last two and a half decades. The skill composition of the labor force affects the types of jobs that firms want to create (Acemoglu (1999), Acemoglu and Restrepo (2018, 2019, 2020)). An important, unstudied question raised is: what is the job composition of these reallocated high-skilled workers in the non-manufacturing sector? In particular, how the job opportunities change due to the import competition from China and affect worker re-allocation across occupations? As the exposure to Chinese imports increases, do the college-educated workers reallocate both upward (high-skill, non-routine occupations) and downward (low-skill, non-routine work)to adapt to changing occupational opportunities? Analyzing this process of worker reallocation across occupations offers insights into the shifting opportunity set faced by reallocated college-educated workers.

This article is based on the central insights from the two aforementioned literature. The first is the recent trade and labor literature that offer an appropriate setting of local labor markets to investigate the impacts of trade exposure. The second is the job polarization literature that provides evidence that employment growth can vary in interesting ways across occupations and how different forces such as trade exposure, technical change shape labor-market outcomes at the local labor market. In this paper, I investigate the impact of rising import exposure from China on the allocation of college-educated workers displaced from manufacturing across jobs in non-manufacturing sector in the US local labor markets. Specifically, I analyze the impact of import competition on the job composition of reallocated college-educated adults in the non-manufacturing sector. This paper provides new empirical evidence on how the China Shock contributes to the reallocation of college-educated workers in the local labor markets.

I use commuting zone as the geographic unit in the analysis which represents a cluster of counties with strong commuting ties between employers and employees (Tolbert and Sizer (1996)). Exploiting variation in exposure to Chinese imports across commuting zones, I investigate the effects of Chinese import growth on the reallocation of college educated workers from the manufacturing sector to both high-skill and low-skill non-routine occupations in the local non-manufacturing sector between 1991 and 2007, with a rich set of controls, a time period dummy for the two periods 1991-1999 and 1999-2007 and a set of census division dummies. To address simultaneity associated with US industry import demand shocks, I use changes in Chinese imports by eight other advanced nations as an instrument for growth in Chinese imports to the US, following Autor et al. (2013). I also control for the potential pre-trends that might be correlated with the outcome variable by including the pre-trend of outcome variable between 1980 and 1990 as the control variable. The main findings of this study can be summarized as follows. I find that exposure to Chinese import competition had a positive impact on the employment rate of the college-educated adults in the non-manufacturing sector for both low-skill and high-skill occupations. Chinese import exposure reallocated college in the non-manufacturing sector both upward to high-skill non-routine occupations and downward to low-skill, non-routine work. This resulting reorganization is due to the college graduates reallocating to the high-skill non-routine

abstract jobs such as managers, professionals, technicians, finance, public safety in the non-manufacturing sector in high human capital regions, and workers with some college education reallocating to the low-skill service occupations in the non-manufacturing sector in low human capital regions. Comparing two CZs over the period of 1999 through 2007, one at the 25th percentile and the other at the 75th percentile of China's import exposure growth, the more exposed CZ would be expected to experience a differential 0.10 and 0.21 percentage point larger increase in the annual employment rate for the college-educated adults employed in non-routine low-skill and high-skill occupations in the non-manufacturing sector respectively.

The rest of the paper is structured as follows: The next section reviews the related studies. Section 3 introduces data sources and explains in detail how the key dependent variables are constructed and presents the empirical strategy. Section 4 presents the results. Section 5 concludes.

2 | RELATED LITERATURE

An incredibly rich literature has investigated the effects of the China shock on a wide variety of outcomes, such as innovation (Autor et al. (2020b), Bloom et al. (2016)), political outcomes (Autor et al. (2020a), Colantone and Stanig (2018), Heins (2016)), provision of public goods (Feler and Senses (2017)), health (Colantone et al. (2015), Adda and Fawaz (2019)), crime and government transfers (Che et al. (2018)), price and consumer welfare (Amiti et al. (2020)) marriage market (Autor et al. (2019)), self-employment (Unel (2021)). My paper mostly relates to literature that have investigated effects of Chinese import competition on US economies, especially on US labor markets. Autor et al. (2013), Pierce and Schott (2016) and Acemoglu et al. (2016) analyze the impact of China's import penetration on the US manufacturing employment linking the sharp drop in US manufacturing employment to increases on Chinese imports. They also show a highly significant negative effect on overall employment (also Autor et al. (2015)). Recent literature focus on the reorganization of labor from manufacturing to non-manufacturing in areas with high human capital in US (Bloom et al. (2019), Quintana (2021)). Bloom et al. (2019), using confidential US Census firm-level data, find that Chinese import competition lowered employment in manufacturing, but had a significant positive effect on service sector jobs particularly in research, management and wholesale in high-human capital areas. They also find that the low-human capital areas saw large job losses and the adverse effect of Chinese import disappears after 2007. Quintana (2021) find that high human capital regions exposed to the China shock undergo a faster transition from manufacturing to skill-intensive service industries. The negative effects of the China shock concentrate in exposed regions with a low density of college-educated workers. This paper contributes to the existing literature by analyzing in detail the impact of imports from China at the commuting zone level on the employment rate of the college-educated adults in the non-manufacturing sector across different occupation groups. The analysis of this paper helps to understand the contribution of import exposure from China on the job composition of reinstated labor in the non-manufacturing sectors displaced from manufacturing. My results are in line with the existing literature with regards to high human capital regions where the reallocation of high-skilled labor from exposed manufacturing industries to the service sector is upward to high-skill jobs such as managerial, professional, technical, finance and public safety occupations. I additionally show that there is also a downward reallocation of the labor with some college education to low-skill service occupations in low human capital regions.

This paper also contributes to a large literature on job polarization. Autor and Dorn (2013) document local labor market job polarization via a reallocation of low-skill workers into the broad occupational category of low-skill services. Autor et al. (2015), extending their analysis in Autor et al. (2013), show that rising local exposure to Chinese import penetration generates occupational polarization, defined as stronger employment growth in non-routine and

abstract occupations relative to employment growth in routine occupations (and overall negative employment growth). Lake and Millimet (2016) documents a reallocation of workers among 1444 different jobs. By defining jobs at a very disaggregate level, they assess how trade exposure differentially affects local employment growth of 'good'versus 'bad'jobs. They differ from the aforementioned literature as they do not focus explicitly on the impacts of trade exposure on manufacturing or overall employment growth. However, to the best of my knowledge there are no studies investigating the contribution of Chinese import competition to the reallocation of college-educated adults in the non-manufacturing sector at the commuting zone level to both high and low-skill occupations. This paper contributes to the empirical findings by providing evidence that the college-educated adults displaced from the manufacturing sector are clearly better prepared to adapt to changing occupational opportunities, and thus are reallocating both upward to high-skill, non-routine occupations and downward to low-skill, non-routine service occupations.

My paper also contributes to the literature on the changing skill composition of the US labor force. Acemoglu (1999) provides evidence that there has been a change in the composition of jobs in the US during the last two decades. The skill composition of the labor force affects the types of jobs that firms want to create, and thereby, the unemployment rate. Acemoglu and Restrepo (2018, 2019, 2020) focus on how technological change such as automation, AI, robots displace workers from routine intensive jobs but at the same time create new tasks in many service industries. A potential mismatch between technology and tasks and the skills of the workforce contributes to inequality, and slow adjustment of labor demand. This article extends the literature by providing empirical evidence that the China shock also contributes to the displacement of labor from routine intensive manufacturing jobs to low-skill service occupations due to lack of required skills and hence jobs in the low human capital regions.

3 | DATA AND EMPIRICAL STRATEGY

3.1 | Data Sources and Measurement

My analysis draws on the Census Integrated Public Use Micro Samples (IPUMS) for the years 1980, 1990, and 2000, and the American Community Survey (ACS) for year 2007. I pool the Census ACS 2006 through 2008 files for the year 2007 to increase sample size and hence the measurement precision. The 1980, 1990 and 2000 Census samples include 5 percent of the U.S. population, while the pooled ACS sample include 3 percent of the population. The advantage of using IPUMS data is that it provides the household data with all the necessary information about demography (i.e., gender, age, race), education (e.g., years of schooling), work (e.g., employment status, worker class, industry worked, occupation, income, etc.), and so on. I do not use the data beyond 2007, which is prior to the onset of the recession, to avoid disturbances generated by the Great Recession.

I use commuting zones (CZs) as geographical units that can be consistently constructed over a long time period. The local labor markets are represented using the construct of commuting zones developed by Tolbert and Sizer (1996), who analysed county-level commuting data from the 1990 Census data to create 741 clusters of counties that are characterised by strong commuting ties within CZs, and weak commuting ties across CZs. Commuting represent clusters of counties that idenrifies labor market areas in which individuals live and work. I use the crosswalk file from Autor and Dorn (2013) that provides a probabilistic matching of Public Use Microdata Areas (PUMA) in US Census Public Use Files to CZs. The analysis includes the 722 CZs that cover the mainland US (both metropolitan and rural areas)[1]. Commuting zones are particularly apt for the analysis of local labour markets because they cover both urban and rural areas, are based primarily on economic geography. I further define a commuting zone as urban, and interchangeably as metropolitan area or high human capital region, that meet the Bureau of the Census' criterion of

[1]Alaska and Hawaii are excluded

a 100,000 population minimum in 1990.

I restrict the sample to individuals who were between age 16 and 64 and who are not residents of institutional group quarters such as prisons and psychiatric institutions. Using the IPUMS data, I construct the dependent variables of the analysis representing the share of college-educated working age population employed in different occupation groups in the non-manufacturing sector. College adults are those with at least some college education i.e. those with any complete years of post secondary schooling. Details of the construction of the occupational classification and a full list of the resulting 330 occupations are given in Dorn (2009). I classify the occupations into six major occupation groups from Autor and Dorn (2013). There are three broad categories of non-routine occupations. The first category of occupations is "service occupations" that is based on the occupational classification of the 2000 Census. Service occupations consists of jobs such as food preparation and service workers; building and grounds cleaning workers and gardeners; health service support workers (such as health and nursing aides, but excluding practical or registered nurses); protective service workers; housekeeping, cleaning, and laundry workers; personal appearance workers (such as hairdressers and beauticians); child care workers; recreation and hospitality workers (such as guides, baggage porters, or ushers); and other personal service workers. Protective service occupations such as police officers and fire fighters have much higher educational attainment and wage levels than all other service workers, and hence excluded from the primary definition of service occupations. The two other major occupation groups also characterized by relatively low routine task content are: White-collar managerial, professional, technical, finance, and public safety occupations that typically employ highly educated workers specializing in abstract job tasks; blue-collar transportation, construction, mechanical, mining, and farm occupations are rich in manual job tasks. The three remaining occupations categories which are specialized in routine job tasks are: clerical, administrative support, and retail sales occupations; precision production and craft occupations; and machine operator and assembler occupations. Non-routine occupations are classified as high-skill if they fall in the top half of the employment-weighted distribution

TABLE 1 Summary Statistics

	I. Levels			II. Annual Changes Δs	
	1990	2000	2007	1990-2000	2000- 2007
% of college educated working-age pop employed in non-manuf:					
Managers/professionals/technicians/	37.64	37.75	38.3	0.01	0.07
finance/ public safety	(4.36)	(4.38)	(4.52)	(0.16)	(0.18)
Clerical/retail sales	16.37	16.28	15.56	-0.01	-0.11
	(1.72)	(1.35)	(1.31)	(0.11)	(0.12)
Service occupations	5.86	6.73	8.13	0.09	0.2
	(1.11)	(1.19)	(1.2)	(0.06)	(0.08)
Production/craft	0.68	0.74	0.74	0.01	0
	(0.21)	(0.17)	(0.2)	(0.02)	(0.02)
Machine operators/assemblers	0.6	0.54	0.44	-0.01	-0.01
	(0.16)	(0.14)	(0.15)	(0.01)	(0.02)
Transportation/construction/	6.74	6.46	6.55	-0.03	0.01
mechanics/mining/farm	(1.97)	(1.86)	(1.85)	(0.07)	(0.09)

N = 722 CZs. Statistics in columns 1 and 4 are weighted by 1990 population, statistics in columns 2 and 5 are weighted by 2000 population, and statistics in column 3 are weighted by 2007 population respectively. SD in parentheses.

of mean wages in non-routine occupations in 1980, and are classified as low skill otherwise. Based on this classification, white-collar managerial, professional, technical, finance, and public safety occupations are high skill occupations and service occupations are low-skill occupations. I supplement the data with additional controls at the commuting zone from Autor et al. (2013).

Table 1 reports descriptive statistics on the share of college-educated working age population employed in the different occupation groups in the non-manufacturing sector over the sample years. It can be seen that share of the college-educated working age population employed in the high-skill abstract occupations such as managers, professionals, technicians, finance, public safety as well as low-skill service occupation is increasing in both the periods 1990-2000 and 2000-2007.

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

3.2 | Measuring Import Exposure from China

I use Acemoglu et al. (2016) measure of CZ manufacturing import exposure from China ΔIP_{it}^{CZ}, which is defined as a CZ's annual change in US imports from China over period t, where imports are apportioned to a CZ according to its share of initial industry employment. The variation in ΔIP_{it}^{CZ} across local labor markets stems entirely from variation in local industry employment structure at the start of period t. For example, a CZ initially with a large share of its employment in sectors that produce plastic footwear (a product imported extensively from China in 2007,) would have more exposure Chinese import competition. A CZ impor exposure from China measure ΔIP_{it}^{CZ} essentially is a weighted average of annual changes in US manufacturing imports from China over period t, weighted by share of initial industry employment in a CZ. Formally, it can be written as

$$\Delta IP_{it}^{CZ} = \sum_{s} \frac{L_{is,t_0}}{L_{i,t_0}} \Delta IP_{st}, \tag{1}$$

where L_{is,t_0} denotes the start-of-period employment in manufacturing sector s and commuting-zone i and L_{i,t_0} is the start of the period total employment for commuting-zone i. ΔIP_{st} is the annual change in import penetration for the manufacturing sector s and time period t measured as:

$$\Delta IP_{st} = \frac{\Delta M_{st}^{UC}}{Y_{st_0} + M_{st_0} - X_{st_0}}, \tag{2}$$

where ΔM_{st}^{UC} denotes the change in US imports from China in manufacturing sector s for the time period t = 1991-1999 or 1999-2007 and t_0= 1991. To normalize, ΔM_{st}^{UC} is divided by the initial industrial domestic absorption, which consists the industrial real shipment,Y_{st_0}, plus industry real net imports, $M_{st_0} - X_{st_0}$ both at initial year t_0 = 1991 and deflated by the Personal Consumption Expenditures (PCE) price index. The industry import penetration represents the change in US imports from China as a share of initial domestic absorption, showing how much of the domestic consumer demand is coming from imports.

A potential concern for identification is that imports are not only determined by supply side factors, but also through US demand shocks. For example, a positive domestic demand shock that increases imports and employment may result in an underestimated OLS coefficient on the import variable. To address this endogeneity issue, I follow Autor et al. (2013) and Acemoglu et al. (2016) instrumenting the CZ import exposure from China by annual change in import exposure from China in eight other high-income countries[2]:

$$\Delta IP_{it}^{OTH} = \sum_{s} \frac{L_{is,t_0}}{L_{i,t_0}} \Delta IP_{st}^{OTH}, \tag{3}$$

where IP_{st}^{OTH} is the industry level instrument for import exposure measured as:

$$\Delta IP_{st}^{OTH} = \frac{\Delta M_{st}^{OC}}{Y_{st_0} + M_{st_0} - X_{st_0}}, \tag{4}$$

where ΔM_{st}^{OC} measures the change in other countries' imports from China (OC) in sector s during the period t by these eight other nations which is normalized by the initial domestic sectoral absorption in 1988 (t_0 = 1988). Employment counts in 1988 are used mitigate the simultaneity bias. The validity of this instrument relies on the assumption that high-income countries are similarly exposed to import competition that is driven by the supply shock in China. China's export growth was largely the result of internal supply shocks (China's transition to a market-oriented economy) and falling global trade barriers (China's accession to the WTO). The identifying assumption is that industry import demand shocks are uncorrelated across high-income economies and that there are no strong increasing returns to scale in Chinese manufacturing which might imply that US demand shocks will increase efficiency in the affected Chinese industries and induce them to export more to other high-income countries)[3].

3.3 | Empirical Specification

I adopt the following empirical specification to identify the effect of manufacturing import exposure from China on the share of college-educated working age population employed in different occupation groups in the non-manufacturing sector across commuting zones:

$$\Delta L_{it} = \beta_t + \beta_1 \Delta IP_{it}^{CZ} + S_{it_0}^{'} \gamma + \delta_r + e_{it}, \tag{5}$$

where ΔL_{it} is the annual change in the share of college-educated working age population employed in different occupation groups in the non-manufacturing sector in commuting-zone i over time period t (t is either 1991-1999, or 1999-2007).[4] β_t controls for different time trends between the two time periods capturing period-specific macro shocks and δ_r is a set of census division dummies to control for regional specific trends. The vector S_{it_0} contains

[2] These countries are: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. The reason these eight countries are used is that their disaggregated HS trade data are available since 1991.

[3] Autor et al. (2013) adopt a gravity equation and use the inferred change in China's comparative advantage and market access vis-a-vis the United States. In that case, the common demand shocks in high-income countries are differenced out by importer and product fixed effects. Thus any correlated demand shocks if present are being eliminated with the help of fixed effects.

[4] For a variable V, $\Delta V_t = V_{1999} - V_{1991}$ for t= 1991-1999.

a rich set of controls for CZs' start-of-period[5] labor force and demographic composition that might independently affect labor market outcomes such as start-of-period local manufacturing employment share, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women, percentage of employment in routine occupations, and finally the average off-shorability index of occupations. When estimating this model, the annualized first differences is stacked for the two periods, 1991-1999 and 1999-2007. Standard errors are clustered at commuting zone level to account for spatial correlations across CZs. All regressions are weighted by 1991 commuting zone's share of national population.

3.4 | Bartik Instrument and Pre-trends of Dependent Variables

A growing literature (Borusyak et al. (2022), Goldsmith-Pinkham et al. (2020)) has raised concerns that Bartik-style instruments can be problematic when the outcome variable exhibits pre-trends which are correlated with the trade exposure. These concerns are related with the potential endogeneity of local industrial composition. Even if the factors driving the increase in imports (China's internal reforms and tariff reductions) of each industry are exogenous to US local conditions, 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 these 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 include the pre-trend of the dependent variables in the decade between 1980 and 1990. The inclusion of the pre-trend 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.

4 | RESULTS

Table 2 presents results for the impact of Chinese import penetration on the annual change in the share of college-educated working age population employed in different occupation groups for the period 1991-2007 (over two stacked sub-periods 1991-1999 and 1999-2007) using 2SLS regression as provided by Equation (5). The sample includes 722 commuting zones further dis-aggregated into 353 urban and 369 non-urban commuting zones. I define a commuting zone as urban, and interchangeably as metropolitan area or high human capital region, that meet the Bureau of the Census' criterion of a 100,000 population minimum in 1990. College adults are those with at least one year of college education. Panel A presents results for considering all the 722 commuting zones in the sample while Panel B and Panel C present results considering the 353 urban commuting zones and 369 non-urban commuting zones respectively.

All regressions are weighted by population share of the commuting-zone in 1991. All regressions have US census regions dummies, a time dummy for the second period and, a set of controls i.e. start-of-period percentage of employment in manufacturing, percentage of college-educated population, percentage of foreign born population, percentage of employment among women, percentage of employment in routine occupations, and the average off-shorability index of occupations. Robust standard errors in parentheses are clustered on commuting zones. "All" represents overall employment i.e. employment in all the occupation groups combined. Regressions results are reported with and without controlling for the pre-trend between 1980 and 1990 of the dependent variable.

[5] If t = 1991-1999 then t_0 is 1991 and if t = 1999-2007 then t_0 = 1999.

TABLE 2 US Imports from China and Non-Manufacturing Employment Changes in CZ by occupation groups for the college educated working age population, 1991–2007: 2SLS Estimates

	Dep Var: Annual change in employment shares out of college educated population						
		I. Occupations with low routine content			II. Occupations with high routine content		
	All	Service occs	Transport, construct, mechanics, mining, farm	Managers, prof, tech, finance,public safety	Administrative support, retail sales	Precision production craft workers	Machine operators, assemblers
Panel A: All 722 CZs							
Without controlling for pre-trends							
Δ Imports	0.370*	0.165**	−0.135*	0.327**	0.041	−0.058***	0.030*
	(0.223)	(0.070)	(0.079)	(0.157)	(0.100)	(0.022)	(0.018)
Controlling for pre-trends							
Δ Imports	0.376*	0.145**	−0.129	0.331**	0.049	−0.059***	0.025
	(0.222)	(0.071)	(0.080)	(0.152)	(0.102)	(0.022)	(0.018)
Panel B: 353 urban CZs							
Without controlling for pre-trends							
Δ Imports	0.541**	0.142*	−0.124	0.447**	0.103	−0.053**	0.025
	(0.263)	(0.085)	(0.089)	(0.189)	(0.122)	(0.026)	(0.021)
Controlling for pre-trends							
Δ Imports	0.544**	0.127	−0.117	0.444**	0.114	−0.056**	0.021
	(0.263)	(0.085)	(0.091)	(0.186)	(0.125)	(0.026)	(0.021)
Panel C: 369 non-urban CZs							
Without controlling for pre-trends							
Δ Imports	−0.064	0.280**	−0.227	0.102	−0.195	−0.062	0.037
	(0.232)	(0.122)	(0.158)	(0.213)	(0.151)	(0.043)	(0.035)
Controlling for pre-trends							
Δ Imports	−0.031	0.273**	−0.216	0.127	−0.210	−0.061	0.028
	(0.229)	(0.128)	(0.161)	(0.218)	(0.154)	(0.043)	(0.037)

Panel A: N = 1,444 (722 CZs x two time periods), Panel B: N = 706 (353 CZs x two time periods), Panel C: N = 738 (369 CZs x two time periods). All regressions are weighted by population share of the commuting-zone in 1991. All regressions have US census regions dummies, a time dummy for the second period and, a set of controls i.e. start-of-period local manufacturing employment share, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women, percentage of employment in routine occupations, and the average off-shorability index of occupations. Robust standard errors in parentheses, clustered on commuting-zone. *p<0.1; **p<0.05; ***p<0.01.

I find that import exposure from China significantly increases the employment rate among college-educated adults employed in non-routine abstract and manual task intensive occupations in the non-manufacturing sector. The first row of panel A show that a one percentage point increase in import exposure from China increases the employment rate of the college-educate adults for the high-skill occupations i.e. managerial, professional, technical, finance, and public safety & low-skill service occupations[6] by 0.33 and 0.17 percentage points respectively without controlling for the pre-trends. The next row of Panel A, when controlling for potential pre-trends, show that results remain similar to those reported in first row for the high-skill white-collar occupations, whereas the impact on low-skill service occupations is now lower. I will refer to the results with pre-trends included hereafter. Comparing two CZs over the period of 1999 through 2007, one at the 25th percentile and the other at the 75th percentile of China's import exposure growth, the more exposed CZ would be expected to experience a differential 0.10 and 0.21 percentage point larger increase in the annual employment rate for the college-educated adults employed in non-routine low-skill and high-skill occupations respectively.

Panel B and C of Table 2 show that the non-manufacturing job gains in the high-skill occupations is accounted for by the job gains in the urban commuting zones i.e. high human capital areas whereas low human capital areas (non-urban commuting zones) saw job gains in the low-skill service occupations. A one percentage point increase in import exposure increases the employment rate among college-educated non-manufacturing workers by 0.44 and 0.27 percentage points respectively for the non-routine high-skill and low-skill occupations respectively.

Table 3 shows that dis-aggregating college workers into those with some college and those with a four-year degree or higher, the increase in employment rate for the low-skill service occupations is completely accounted for by the college adults with some college education while for high-skill non-routine occupations by college graduates.

In sum, exposure to Chinese import competition had a positive impact on the employment rate of the college-educated adults in the non-manufacturing sector for both low-skill and high-skill occupations. Chinese import exposure reallocated college-educated adults in the non-manufacturing sector both upward to high-skill non-routine occupations and downward to low-skill, non-routine work. This resulting occupational reorganization is due to the college graduates reallocating to the high-skill non-routine abstract jobs in the non-manufacturing sector in high human capital regions and workers with some college education reallocating to the low-skill service occupations in the non-manufacturing sector in low human capital regions.

The intuition behind these findings can be as follows. The literature provides evidence that import competition from China reduces employment across all occupation groups in manufacturing, with a notable negative employment effect for higher skilled managerial, professional and technical jobs (Autor et al. (2015)). High human capital regions have more job opportunities for high-skill white-collar occupations such as managerial, professional, technical, finance and public safety occupations. Hence, high human capital regions exposed to the China shock is able to reallocate highly educated workers from manufacturing to non-manufacturing high-skill jobs. However, in low human capital regions, manufacturing sector was more adversely impacted by China Shock causing plant shrinkage and closure. Also, firms would not be willing to create high-skill job opportunities in low human capital regions with lower share of college graduates. The few college graduates in the low human capital regions would also reallocate to high-skill jobs in the non-manufacturing sector. Rising returns to skill would spur college graduates to increase labor supply and substitute home-based production of household services demand for in-person services increasing demand for service occupations. This increased demand for service occupations would also put an upward pressure on the wages such that the wages paid to manual tasks converge to a steady growth rate that equals or exceeds the growth rate of college wages (Autor et al. (2013)). Workers with some college education would therefore reallocate to low-skill

[6] Nonroutine occupations are classified as high-skill if they fall in the top half of the employment-weighted distribution of mean wages in nonroutine occupations in 1980, and are classified as lowskill otherwise.

TABLE 3 US Imports from China and Non-Manufacturing Employment Changes in CZ for College Graduates and Workers with Some College for high and low skill occupations, 1991–2007: 2SLS Estimates

	Dep Vars: Annual change in employment shares out of college educated population					
	I. Service Occupations			II. Managers/professionals/technicians/ finance/ public safety		
	All	Some College	College Graduates	All	Some College	College Graduates
Panel A: All 722 CZs						
Without controlling for pre-trends						
Δ Imports	0.165**	0.201***	−0.036	0.327**	0.005	0.322**
	(0.070)	(0.068)	(0.033)	(0.157)	(0.096)	(0.130)
Controlling for pre-trends						
Δ Imports	0.145**	0.182***	−0.041	0.331**	0.013	0.318**
	(0.071)	(0.068)	(0.033)	(0.152)	(0.094)	(0.128)
Panel B: 353 urban CZs						
Without controlling for pre-trends						
Δ Imports	0.142*	0.183**	−0.041	0.447**	0.038	0.409**
	(0.085)	(0.083)	(0.042)	(0.189)	(0.118)	(0.159)
Controlling for pre-trends						
Δ Imports	0.127	0.169**	−0.050	0.444**	0.039	0.406**
	(0.085)	(0.082)	(0.043)	(0.186)	(0.115)	(0.159)
Panel C: 369 non-urban CZs						
Without controlling for pre-trends						
Δ Imports	0.280**	0.303***	−0.023	0.102	−0.042	0.143
	(0.122)	(0.117)	(0.035)	(0.213)	(0.135)	(0.176)
Controlling for pre-trends						
Δ Imports	0.273**	0.287**	−0.017	0.127	−0.010	0.146
	(0.128)	(0.121)	(0.035)	(0.218)	(0.139)	(0.179)

Panel A: N = 1,444 (722 CZs x two time periods), Panel B: N = 706 (353 CZs x two time periods), Panel C: N = 738 (369 CZs x two time periods). All regressions are weighted by population share of the commuting-zone in 1991. All regressions have US census regions dummies, a time dummy for the second period and, a set of controls described in Table 2. Robust standard errors in parentheses, clustered on commuting zones. *p<0.1; **p<0.05; ***p<0.01.

service occupations comparing the benefit of reasonably high wages with the higher cost of re-allocation to better job opportunity region[7] or cost of college education. Also, the employment rate of reallocated college-educated workers

[7] Autor et al. (2013) provide evidence that labor is immobile in the context of import competition from China.

in service occupations increases significantly for the prime age group 30-54 (Appendix Table 2) who would prefer to do any job with a good source of income without having to re-allocate to a different location.

5 | CONCLUSION

Many empirical studies focus on the significant adverse effects of the import competition from China on social and economic outcomes in the United States. This paper contributes to the China shock literature by studying its effects at the commuting zone level on the occupational employment of the college-educated adults, who play an important role in job dynamism and wealth generation. This paper addressed questions such as how the job opportunities change due to the import competition from China and affect worker re-allocation across occupations and if the college-educated workers reallocate both upward and downward to adapt to changing occupational opportunities in response to the China shock.

In this paper, I investigate the impact of changes in local import competition from China on the employment growth of college-educated working age population in the non-manufacturing sector across different occupation groups in US local labor markets between 1990 and 2007.

I find that the US import competition from China reallocated college-educated workers from manufacturing to non-manufacturing jobs and the concurrent occupational reorganization in the US commuting zones. The college-educated workers reallocated both upward to high-skill, non-routine occupations as well as downward to low-skill, non-routine jobs. The college graduates in the high human capital regions exposed to the China shock reallocated upward to high-skill non-routine occupations such as managers, professionals, technicians, finance, public safety whereas the workers with some college education reallocated downward to low-skill service occupations.

These findings offer insights into the shifting opportunity set faced by the college-educated workers displaced from routine intensive manufacturing jobs, due to the China shock, and reinstated in the non-manufacturing sector. The results are consistent with existing literature that the skill abundant regions are not affected by the China shock as they will undergo a positive and skill-oriented sectoral transformation. However, the lack of job opportunities in the low human capital regions, severely affected by the manufacturing job losses, can change the skill composition of the labor force causing the relatively skilled labor reallocated to relatively lower skill occupations.

This paper can be extended along several directions. One can investigate further into the reallocation of college-educated adults to low-skill service occupations to find the possible reasons behind it. One can extend the current analysis by using the service occupations at a dis-aggregate level. One can extend the period of analysis to see if the impact of Chinese imports exists beyond 2007 or whether there is any trend reversal.

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6 | APPENDIX

APPENDIX TABLE 1 Quantiles of CZ Level Trade Variables

	Annual Changes	
	1991-1999	1999- 2007
Δ Import exposure from China to US (in %)		
90th Percentile	0.09	0.22
75th Percentile	0.06	0.16
50th Percentile	0.04	0.11
25th Percentile	0.03	0.08
10th Percentile	0.02	0.05

N = 722 CZs. All statistics are weighted by start-of-period population.

APPENDIX TABLE 2 US Imports from China and Non-Manufacturing Employment Changes in CZs by occupation and age groups for the college educated working age population, 1991–2007: 2SLS Estimates

	Dep Vars: Annual change in employment shares out of college educated population					
	I. Service Occupations			II. Managers/professionals/technicians/ finance/ public safety		
	Age 16-29	Age 30-54	Age 55-64	Age 16-29	Age 30-54	Age 55-64
Panel A: All 722 CZs						
Without controlling for pre-trends						
Δ Imports	0.100*	0.093*	−0.028	0.104	0.306*	−0.083
	(0.052)	(0.052)	(0.020)	(0.119)	(0.182)	(0.065)
Panel B: Controlling for pre-trends						
Δ Imports	0.087*	0.081	−0.028	0.109	0.292	−0.082
	(0.051)	(0.053)	(0.021)	(0.120)	(0.180)	(0.064)
Panel B: 353 urban CZs						
Without controlling for pre-trends						
Δ Imports	0.096	0.081	−0.035	0.169	0.328	−0.050
	(0.064)	(0.064)	(0.026)	(0.156)	(0.227)	(0.082)
Panel B: Controlling for pre-trends						
Δ Imports	0.080	0.073	−0.035	0.172	0.302	−0.048
	(0.063)	(0.065)	(0.026)	(0.158)	(0.227)	(0.079)
Panel C: 369 non-urban CZs						
Without controlling for pre-trends						
Δ Imports	0.101	0.164**	0.015	−0.118	0.360	−0.140*
	(0.086)	(0.080)	(0.026)	(0.096)	(0.223)	(0.082)
Panel B: Controlling for pre-trends						
Δ Imports	0.103	0.157*	0.012	−0.105	0.363	−0.131
	(0.087)	(0.080)	(0.026)	(0.094)	(0.226)	(0.084)

Panel A: N = 1,444 (722 CZs x two time periods), Panel B: N = 706 (353 CZs x two time periods), Panel C: N = 738 (369 CZs x two time periods). All regressions are weighted by population share of the commuting-zone in 1991. All regressions have US census regions dummies, a time dummy for the second period and, a set of controls described in Table 2. Robust standard errors in parentheses, clustered on commuting zones. *p<0.1; **p<0.05; ***p<0.01.

APPENDIX TABLE 3 US Imports from China and Non-Manufacturing Employment Changes in CZ by occupation groups for the college educated working age population, 1991–2007: 2SLS Estimates using Autor et al. (2013) Import exposure variable and instrument

	Dep Var: Annual change in employment shares out of college educated population						
		I. Occupations with low routine content			II. Occupations with high routine content		
	All	Service occs	Transport, construct, mechanics, mining, farm	Managers, prof, tech, finance,public safety	Administrative support, retail sales	Precision production craft workers	Machine operators, assemblers
Panel A : No pre-trends							
Δ Imports	0.173	0.096***	−0.073*	0.150*	0.003	−0.021**	0.018**
	(0.127)	(0.030)	(0.041)	(0.078)	(0.052)	(0.010)	(0.008)
Panel B: Controlling for pre-trends							
Δ Imports	0.180	0.089***	−0.069*	0.152**	0.007	−0.021**	0.015*
	(0.127)	(0.030)	(0.042)	(0.075)	(0.053)	(0.011)	(0.008)

N = 1,444 (722 CZs x two time periods). All regressions are weighted by population share of the commuting-zone in 1991. All regressions have US census regions dummies, a time dummy for the second period and, a set of controls described in Table 2. Robust standard errors in parentheses, clustered on commuting-zone. *p<0.1; **p<0.05; ***p<0.01.