Good Jobs, Bad Jobs:
What's Trade Got To Do With It?

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October 14, 2017

Abstract

Exploiting data on US local labor markets between 1990 and 2010, we analyze the heterogeneous impact of rising import penetration on employment growth of 'good' and 'bad' jobs. Three salient findings emerge. First, job polarization – defined as an increase in good and bad jobs and a decrease in middle quality jobs – occurred over this time period in US local labor markets, but is not due to local trade exposure. Instead, local exposure to routine-biased technological change (RBTC) is found to be the primary catalyst. Second, rising local exposure to import penetration reduces employment growth across the entire job quality distribution. However, the advserve effects of import penetration are more pronounced for both good and bad jobs. Thus, trade exposure is found to have an anti-polarization effect. Finally, local employment growth across the job quality distribution is driven by local exposure, rather than occupation-specific exposure, to RBTC and import competition.

JEL: F13, J21, J31

Keywords: Trade Liberalization, China, Local Labor Markets, Job Polarization

*We are grateful to Douglass Campbell, Maggie Chen, Martin Davies, Mina Kim, Bill Powers, Erick Sager, Andrey Stoyanov and Beyza Ural for useful comments and discussion as well as many seminar and conference participants at the DC Junior Trade Study Group, Fall 2015 Midwest Trade Meetings, STATA Camp Econometrics 2015, George Washington University, University of Nevada Las Vegas, University of Richmond, USITC, and Washington and Lee University.

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1 Introduction

Recent years have witnessed a renewed interest in two issues concerning the US labor market. The first issue is the impact of trade on labor market outcomes, receiving significant attention due to the increased economic and political clout of China and the potential for trade deals of unprecedented size (e.g., the Trans-Pacific Partnership and the Transatlantic Trade and Investment Partnership). In turn, new research has emerged which, in stark contrast with the previous literature, documents substantial labor market impacts of China's rapid accession in international markets since 1990.

The second issue is the disappearance of middle class jobs. Together with the relative rise in employment of low-skill and high-skill jobs, this has been labelled the 'dumbbell' or 'hourglass' economy in the popular press and job polarization in academia (Goos and Manning (2007); Samuel (2013)). Acemoglu and Autor (2011, p.1046) state that US and European Union labor markets have undergone "systematic, non-monotonic shifts in the composition of employment across occupations" resulting in "rapid simultaneous growth of both high education, high wage occupations and low education, low wage occupations." In the language of Goos and Manning (2007), there has been simultaneous growth in "lousy" jobs and "lovely" jobs and a decline in "middling" jobs.

In this paper, we investigate the impact of rising trade exposure on the allocation of workers across jobs in the US. To this end, we merge central insights from the two aforementioned literatures. From the recent trade and labor literature, we borrow the insight that local labor markets offer an appropriate setting to investigate the impacts of trade exposure. From the job polarization literature, we borrow the insight that employment growth can vary in interesting ways across the distribution of job quality (where job quality is a function of wages and education).[1] Further, we borrow an important insight from Ebenstein et al. (2014, 2015) who find a worker's occupational exposure to globalization is far more important than their industry exposure. Indeed, an occupational view of jobs, rather than an industry view, fits well with the empirical definition of a job used in the literature on job polarization. Thus, we base our measure of local trade exposure on *occupational* trade exposure and the occupational composition of a local labor market. We then analyze the heterogeneous effects of *local* trade exposure on *local* employment growth between 1990 and 2010 across the job quality distribution. By defining jobs at a very disaggregate level, we assess how trade exposure differentially affects local employment growth of 'good' versus 'bad' versus 'middling' jobs.

Our analysis yields several salient insights. Our first main result relates to the debate about whether rising trade exposure or routine-biased technological change (RBTC) drives job polarization. Like our measure of local trade exposure, we base our measure of local RBTC on the extent of occupation-specific

[1] The notion of job quality is not intended to carry any normative connotations, but is rather a convenient way to describe a job's position in the distribution of wages and/or education.

RBTC and the occupational composition of a local labor market. To do so, we use the 1980 occupation-specific routine-task intensity measures from Autor and Dorn (2013), measured at the 3-digit Census occupation level, to capture the extent to which an occupation was exposed to RBTC between 1990 and 2010. In turn, we find that job polarization in local labor markets is intimately related with local RBTC. Specifically, our results indicate that job polarization *only* occurs in local labor markets sufficiently impacted by local RBTC. In contrast, we find *no evidence* that local trade exposure causes job polarization within local labor markets. This is consistent with the broad conclusion in the job polarization literature that trade and/or offshoring are not responsible for job polarization.[2,3] Our analysis broadens these prior findings to the level of local labor markets.

Our second main result concerns the impact of local trade exposure on employment growth across the distribution of job quality. While we do not find a link between local trade exposure and job polarization within local labor markets, we do find strong impacts of local trade exposure on local employment growth. Specifically we find that increases in local trade exposure *depress* employment growth across the *entire* distribution of job quality. In fact, these impacts are most pronounced for low quality and high quality jobs and fade, or even disappear, for middle quality jobs. Thus, local trade exposure engenders job *anti-polarization*. The broad depression of employment growth across the job quality spectrum is consistent with the finding in Autor et al. (2015) regarding the impact of rising local trade exposure on employment shares at the local labor market level.

Our final main result addresses whether our findings on job-specific employment growth within local labor markets are driven by *local* RBTC and *local* trade exposure or, instead, by (national) *occupation-specific* RBTC and (national) *occupation-specific* trade exposure. Using data on disaggregated jobs across local labor markets provides the opportunity to disentangle these separate effects because we can exploit both the *within* job variation across different locations and the *between* job variation in a given location; disentangling these separate effects cannot be done by studies examining aggregate labor market outcomes. Because local RBTC and local trade exposure are essentially uncorrelated with occupation-specific RBTC and occupation-specific trade exposure, we can indeed empirically identify separate effects of these local versus occupation-specific attributes. In so doing, we find that the occupation-specific effects are statistically insignificant and/or economically very small and leave the effects of local RBTC and local trade exposure unchanged. Thus, we find that *local* exposure rather than *occupation-specific* exposure to RBTC and import competition drives employment growth across the distribution of job quality in local labor markets. Thus, trade and technology shocks in our analysis spillover across occupations within a location

[2] Countries analyzed in this literature include the US (Autor et al. (2006); Autor and Dorn (2013)), the EU (Goos and Manning (2007); Goos et al. (2014)), Germany (Spitz-Oener (2006)), Denmark (Keller and Utar (2016)), and a set of eleven OECD countries (Michaels et al. (2014)).

[3] Keller and Utar (2016) (using Danish individual level data) and Cozzi and Impullitti (2016) (in the context of global technological convergence) represent exceptions to this broad conclusion.

rather than spilling over across locations for a given occupation.

Three main strands of the literature motivate our analysis. First, beginning with Autor et al. (2013), a growing literature has documented the adverse local labor market effects of the rapid rise in import penetration from China since the early 1990s. The key finding in Autor et al. (2013) is that this surge in Chinese import penetration (IP) accounts for roughly 25% of the decline in the US manufacturing sector over the 1990-2007 period. Subsequent studies have documented similar effects in Norway (Balsvik et al. (2015)), Germany (Dauth et al. (2014)), and Spain (Donoso et al. (2015)).[4] Our analysis documents a broader decline in US employment growth across the entire distribution of jobs.[5]

Second, beginning with Goos and Manning (2007), RBTC has been offered as a primary explanation for job polarization. Rather than the traditional concept of skill-biased technological change, the authors compellingly argue that the RBTC hypothesis of Autor et al. (2003) provides a valid explanation for job polarization in the UK. Specifically, technological change has reduced labor demand for routine tasks and jobs that use these tasks intensively have disappeared, leading workers to move to either low or high quality jobs. Among others, Autor et al. (2006) and Autor and Dorn (2013) have made a similar argument for job polarization in the US and Goos et al. (2014) for Western Europe more generally. Offshoring has been posited as a possible secondary explanation in the literature, yet the typical conclusion here is that of Goos et al. (2014, p. 14) who find that "RBTC is much more important than offshoring". In contrast, Keller and Utar (2016) find evidence of job polarization created by Chinese import competition when analyzing Danish worker-level data. Further, the authors argue that trade, rather than RBTC or offshoring, has the unique ability to explain job polarization in Denmark. Our local labor markets analysis suggests the opposite in the US, with RBTC rather than trade providing the unique explanation for US job polarization.

Third, the focus on workers' occupations in Ebenstein et al. (2014) provides a natural link between the existing trade and local labor markets literature and the job polarization literature. Ebenstein et al. (2014, 2015) find that the exposure to globalization of a worker's occupation, and not their industry, is the more salient determinant of their labor market outcomes. Intuitively, this follows from the fact that the occupational dimension of a job, and not the industry, will typically guide the job search processes of displaced workers. The focus on occupations link our analysis with prior studies of job polarization, as jobs are defined on the basis of either detailed occupations or the cross between detailed occupations and aggregated industries. To compute an occupation's trade exposure, Ebenstein et al. (2014, 2015) aggregate measures of industry-specific trade exposure using an occupation's distribution of employment across industries. Similarly, our measure of local trade exposure aggregates (national) *occupation*-specific

[4] Interestingly, Shen and Silva (2017) find no adverse employment impacts in the US when looking at value added exports from China.

[5] Rather than look at impact of trade liberalization via imports on local labor market outcomes, a growing literature has looked at the impact via tariff liberalization (see, e.g., Hasan et al. (2007). Topalova (2007), McCaig (2011) and McLaren and Hakobyan (2016)).

trade exposure using a location's distribution of employment across *occupations*. This contrasts with prior studies on the impact of local trade exposure, e.g. Autor et al. (2013) among others, that aggregate *industry*-specific trade exposure using a location's distribution of employment across *industries*.

The paper now proceeds as follows. Section 2 describes the empirical methodology and data. Section 3 presents the baseline results. Section 4 analyzes the relative impact of local shocks versus occupation shocks. Section 5 discusses numerous sensitivity analyses. Section 6 concludes.

2 Empirics

2.1 Empirical model

We assess the effects of local exposure to import competition on employment growth across the job quality distribution in US local labor markets between 1990 and 2010. To do so, we build upon insights from the literatures on job polarization and the local labor market effects of trade exposure. To motivate our baseline specification, we first describe common empirical specifications from these literatures.

A typical specification in the job polarization literature (e.g., Goos and Manning (2007)) is

$$\Delta n_j = \beta_0 + \beta_1 q_j + \beta_2 q_j^2 + \varepsilon_j \tag{1}$$

where Δn_j is a measure of the national employment growth for job j between some initial and terminal time periods, q_j is a measure of job quality for job j, and ε_j is a mean zero error term. Goos and Manning (2007) define jobs as either 3-digit occupations or the interaction of 3-digit occupations and 1-digit industries; Autor et al. (2006) define jobs as 3-digit occupations. Goos and Manning (2007) measure q_j using the median wage for job j in the initial time period, while Autor et al. (2006) measure q_j using the percentile position of job j in the national distribution of wages or education. In any case, interest has centered around the result that $\beta_1 < 0$ and $\beta_2 > 0$, producing a U-shaped relationship whereby employment growth for middle quality jobs is low relative to both low and high quality jobs.

While Section 2.2 discusses our data, we follow Goos and Manning (2007) and define jobs as the interaction of 3-digit occupations and 1-digit industries, yielding 2679 unique jobs. We follow the spirit of Autor et al. (2006) by defining a job's quality as, essentially, its percentile position in the joint distribution of median education and median wage. Thus, quality varies from zero to one. Finally, we define the employment growth of a job as the change in its employment-to-working age population ratio. Column (1) in Table 1 and Figure 1 verify the stylized fact of job polarization at the national level in our data.

In contrast to the job polarization literature, a typical empirical specification in the literature analyzing the local labor market effects of trade exposure (e.g., Autor et al. (2013)) is

$$\Delta n_c = \beta_0 + \theta_1 \Delta T_c + x_c \delta + \varepsilon_c \tag{2}$$

where Δn_c is a measure of manufacturing employment growth in US local labor market c between some initial and terminal time periods (often the change in the employment-to-working age population ratio), ΔT_c represents a measure of the change in trade exposure faced by location c (often based on changes in import penetration from China), x_c is a vector of location-specific controls (e.g., location-specific demographics), and ε_c is a mean zero error term. Here, θ_1 is the coefficient of interest and captures the impact of local trade exposure on local manufacturing employment growth.

Again, much of the data details are presented in Section 2.2. However, we follow Autor et al. (2013) by defining locations as commuting zones (CZs). Letting Δn_c be the change in manufacturing employment-to-working age population ratio between 1990 and 2010 and regressing Δn_c on our measure of local Chinese import competition (instrumented using Chinese exports to other high income countries) along with local demographic controls and state fixed effects, a one standard deviation change in local Chinese import competition yields a nearly one-half standard deviation change in Δn_c. Thus, our data conveys the well known and large impacts of local Chinese import competition on local labor markets over the 1990-2010 period.

We combine the two specifications in (1) and (2) into the following baseline specification to examine the impact of local trade exposure on *job polarization* in local labor markets:

$$\Delta n_{jc} = \beta_0 + \beta_1 q_j + \beta_2 q_j^2 + \theta_1 \Delta T_c + \theta_2 \Delta T_c q_j + \theta_3 \Delta T_c q_j^2 + \gamma_1 R_c + \gamma_2 R_c q_j + \gamma_3 R_c q_j^2 + x_{jc} \delta + \varepsilon_{jc} \tag{3}$$

where Δn_{jc} is employment growth (i.e., the change in the employment-to-working age population ratio, as in Autor and Dorn (2013)) of job j in US local labor market c between 1990 and 2010. Henceforth, we slightly abuse terminology by using the term 'employment growth' to describe Δn_{jc}. As an explanation for the job polarization illustrated in Figure 1, we include our measure of the change in local Chinese import competition between 1990 and 2010, ΔT_c, and its interactions with q_j and q_j^2. Given RBTC is the standard explanation in the literature for job polarization, we also include a control for local RBTC exposure, R_c, and its interactions with q_j and q_j^2. The presence of q_j and q_j^2 uninteracted with ΔT_c or R_c captures residual explanations for local job polarization. Additionally, x_{jc} is a vector of controls including location-specific economic and demographic attributes of locations as well as state, industry, and occupation fixed effects.[6] These allow general patterns of worker reallocation due to trends in location-specific socioeconomic factors as well as state-specific, industry-specific, or occupation-specific effects. Finally, ε_{jc} is a mean zero error

[6] For time-varying variables in x_{jc}, we control for initial levels and changes over the sample period.

term; standard errors are clustered at the local labor market level.[7,8]

While our local labor markets approach follows the recent literature exploring the effects of trade exposure, perfectly integrated national labor markets effectively imply a single observation for each country-labor market pair (Goldberg and Pavcnik (2016)). With perfect mobility across locations for a given job (i.e., viewing jobs as distinct labor markets), one could thus consider the national-level alternative to (3), given by:

$$\Delta n_j = \beta_0 + \beta_1 q_j + \beta_2 q_j^2 + \theta_1 \Delta T_j + \theta_2 \Delta T_j q_j + \theta_3 \Delta T_j q_j^2 + \gamma_1 R_j + \gamma_2 R_j q_j + \gamma_3 R_j q_j^2 + \varepsilon_j, \tag{4}$$

where $\Delta T_j \equiv \Delta T_k$ is the (national) change in Chinese IP for occupation k (defined below in (6)) and $R_j \equiv R_k$ is the (national) measure of RBTC for occupation k.[9] Table 1 presents the results from this estimation. First, Column (1) shows that, despite the clear pattern of job polarization illustrated in Figure 1, the parameters β_1 and β_2 are imprecisely estimated. Second, unlike our later analysis, Columns (2)-(7) in Table 1 show that the impacts of Chinese IP and, to a lesser extent, RBTC are also imprecisely estimated when relying only on between occupation variation at the national level.

The imprecise nature of the estimates illustrates the "degrees of freedom problem" that can often plague national level analyses (Autor et al. (2013)). Autor et al. (2013) describe how using local labor markets as the geographic unit of analysis can mitigate this problem. Local labor market approaches identify the effects of trade exposure if workers have limited geographic mobility and local labor markets differ in trade exposure due to variation in industrial composition.[10] Nevertheless, relying on geographic immobility is not inherently problematic. As pointed out by Goldberg and Pavcnik (2016, p. 11), the estimates will produce no systematic relationships if the identifying assumption of limited geographic mobility is violated.

Our specification in (3) differs from the existing trade and local labor markets literature by assessing the impact of local trade exposure on the distribution of local employment across *narrowly* defined job types and permits *heterogeneous* impacts with respect to the initial quality of a job, q_j. Moreover, our focus on local employment growth within narrowly defined jobs allows us to augment (3) with measures of (national) *occupation-specific* trade exposure and RBTC, and their interactions with q_j and q_j^2. In so doing, we are able to directly compare the relative importance of occupation-specific shocks (hence, invariant across locations within a job) to location-specific shocks (hence, invariant across jobs within a

[7] We weight our regressions by CZ population.

[8] Our empirical results are robust, at conventional levels of statistical significance, to clustering the standard errors at the state level. These results are available upon request.

[9] We utilize a slight abuse of notation to keep things simple. Jobs are indexed by j, which is the cross-product of 3-digit Census occupations (k) and 1-digit NAICS industries. Thus, each job j maps into an occupation k. National Chinese IP growth and RBTC are measured strictly at the occupation level.

[10] One notable exception to the recent use of local labor markets is the national-level US study of Pierce and Schott (2016). The authors overcome the degrees of freedom problem by using annual data for the 28 year period between 1990 and 2007 and using more than 200 6-digit NAICS industries.

location). Disentangling these two channels is something that typical local labor market analyses cannot perform. However, this provides critical insights into the operation of labor markets. If occupation-specific shocks are quantitatively more important then, by impacting a given job regardless of location, geographic spillovers are important but workers are relatively insulated from shocks to other jobs. If location-specific shocks are more salient, then spillovers occur across occupations within a local labor market but these shocks are, relatively speaking, locally contained.

Our primary interest lies in the θ coefficients in (3). Because changes in local trade exposure may be endogenous, our baseline approach takes numerous approaches to mitigate any such problems. First, to control for industry- or occupation-specific shocks that may impact labor and/or import demand, we include 1-digit industry fixed effects and 3-digit occupation fixed effects. Second, to control for region-specific shocks that may impact labor and/or import demand, we include state fixed effects. Third, to control for CZ-occupation-specific technology shocks, we include R_c which captures the extent to which a CZ was prone to RBTC over the 1990-2010 period based on the 'routineness' of 3-digit occupations and a CZ's occupational distribution in 1980. Finally, to control for any other shocks that could affect labor and/or import demand, we follow Autor et al. (2013) and instrument for Chinese IP using Chinese exports to high-income countries other than the US. The main idea is that the common component of Chinese exports across high income destinations is driven by productivity and other supply-side shocks in China, not correlated import demand shocks across high-income countries.

We address several additional concerns via robustness checks. First, we extend the baseline model by allowing for the effects of (national) occupation-specific Chinese IP growth and RBTC on local employment growth to vary by job quality. Despite our inclusion of occupation fixed effects, one may be concerned about the omission of salient occupation-specific factors when modeling local job-specific employment growth. Specifically, while the occupation fixed effects capture any direct effects of occupation-specific attributes, they will not control for any differential effects by job quality. Moreover, by including both occupation- and CZ-specific factors in an extended model, we are able to assess the relative importance of (national) occupation-specific and (local) CZ-specific factors.

Second, we augment (3) to include the lag of Δn_{jc} (specifically, employment growth between 1980 and 1990). Despite our broad set of fixed effects, they will not account for (i) job-specific shocks, (ii) industry- or occupation-specific shocks that differentially affect locations, or (iii) state-level shocks that differentially affect jobs or locations within a state. As such, our results could reflect a spurious relationship between employment growth and trade exposure in the presence of secular industry- or location-specific trends in employment growth. By augmenting the estimating equation with the lag of Δn_{jc}, we identify the model exploiting variation *conditional* on local job-specific employment growth in the prior decade.

Finally, we explore alternative definitions of job quality and local trade exposure and investigate potentially important sources of heterogeneity along several dimensions: (i) age and cohort, (ii) local Chinese IP based on intermediate imports versus non-intermediate imports, and (iii) sample period.

2.2 Data

Estimating (3) requires definitions of local labor markets (c), jobs (j), local job-specific employment growth (Δn_{jc}), job quality (q_j), changes in local trade exposure (ΔT_c), local RBTC (R_c), the vector of controls (x_{jc}), and an instrument for local trade exposure. The sample period spans 1990 to 2010 but, as part of the sensitivity analysis, we also utilize data from 1980. The non-trade data are obtained from the 1980 and 1990 Decennial Census (5% sample) in IPUMS, the 2010 American Community Survey (ACS 1% sample) in IPUMS, the NBER-CES Manufacturing Database, and Autor and Dorn (2013).[11] The trade data are obtained from COMTRADE and the USITC. Table A1 in the Appendix provides summary statistics.

Local labor markets (c) Studies of local labor markets must choose the geographic unit of analysis. The most disaggregated geographic unit consistently defined over time and covering the entire US in the IPUMS data is a ConsPUMA (Consistent Public Use Microdata Area). McLaren and Hakobyan (2016) use ConsPUMAs when analyzing the local labor market impacts of NAFTA. However, we follow Autor et al. (2013), and the vast majority of the literature, by using commuting zones (CZs) as our measure of local labor markets. Despite the need to concord IPUMS geographic units to CZs, we use CZs as they were explicitly designed to capture the boundaries of local labor markets in terms of commuting patterns. The data include 741 CZs.

Job types (j) Prior job polarization studies define jobs as either detailed occupations or the cross-product of detailed occupation and industry codes. Using detailed 3-digit occupations and aggregate 1-digit industries, Goos and Manning (2007) define $370 \times 10 = 3700$ jobs and observe roughly 1600 in their data. We use 381 detailed occupations (1990 IPUMS Census occupation codes) and 8 1-digit NAICS industry codes (we concord 1990 IPUMS Census industry codes to SIC and NAICS industries), yielding 3048 possible jobs of which 2679 are observed in 1990.[12,13] Thus, our sample has $741 \times 2679 = 1,985,139$ location-job observations.

Local job-specific employment growth (Δn_{jc}) The dependent variable captures changes in local job-specific employment shares between 1990 and 2010. To begin, we compute the share of the working age population (aged 25 to 64 and not currently enrolled in school, institutionalized, or listing their occupation

[11] See `https://usa.ipums.org/usa/` and `http://www.ddorn.net/data.htm`.
[12] See the Appendix for concordance issues.
[13] Note, we actually observe 2691 jobs in 1990. However, 12 jobs have missing data on job quality.

as military) employed in job j in location c in year t. Denoting this share by n_{jct}, we define $\Delta n_{jc} = n_{jc,2010} - n_{jc,1990}$.[14]

Job quality (q_j) To measure job quality and avoid confounding temporal labor reallocation across jobs with changes in the quality of jobs, we follow the existing job polarization literature. Specifically, we use a time invariant measure of job quality obtained from the initial period, 1990.[15] Our primary measure of job quality is the Nam-Powers-Boyd (NPB) index of socioeconomic standing computed at the *national* level (i.e., the quality of a given job is constant across locations). We explore alternative measures in the sensitivity analysis.

The NPB index is a function of the median wage and median education level of a job, both of which have been used as independent measures of job quality (see, e.g., Autor et al. (2006)). Our simultaneous usage of both is in line with Acemoglu and Autor (2011, p.1046), who describe job polarization as the "simultaneous rapid growth of both high education, high wage occupations and low education, low wage occupations." The NPB index, which varies from 0 to 1, is the approximate percentage of the labor force in jobs with a *lower* combination of median wage and median education (Nam and Boyd (2004)).[16]

On the surface, sorting our 2679 observed jobs by the distribution of education and wages offers little transparency regarding the types of jobs that sit in various parts of the distribution. To give further insight, Table A2 in the Appendix describes the so-called good jobs and bad jobs across broad occupation and industry groups by splitting the sample into the bottom 25%, middle 50%, and top 25% of jobs according to the NPB index. Specifically, we show the distribution of low, middle, and high quality jobs across 1-digit NAICS industries and six occupation groups as defined in Autor and Dorn (2013). Table A2 presents both the distribution of *jobs* and the distribution of *workers* across occupations or industries within each quality bin.

As expected, the data depict steady changes in the occupational and industrial composition as one moves up the NPB index. In terms of industries, low quality jobs are concentrated in (i) Wholesale/Retail Trade & Transportation/Warehousing, (ii) Educational/Health Care/Social Assistance Services, and (iii) Arts/Entertainment/Recreation, Accommodation/Food Services (45% of jobs and 65% of workers). This

[14] As is typical in the literature, our employment shares are employment-to-working age population ratios. This accounts for the possibility that trade exposure may contribute to nonemployment (unemployment or other forms of nonemployment such as retirement or disability). It also avoids econometric complications arising from the fact that job invariant, location-specific attributes (i.e., any x_{jc} that does not vary across j such as economic and demographic attributes of local labor markets) cannot affect all employment shares in the same direction if the shares are restricted to sum to one.

[15] Note, this means that only jobs observed in 1990 can be included in the analysis. The quality of any new jobs appearing in later years have missing quality. However, as stated above, 2679 jobs are observed in 1990. Only four jobs appear in 2010 that did not exist in 1990; 638 jobs observed in 1990 are disapper in 2010.

[16] Specifically, we begin by computing the national median wage and national median education level for each job in 1990. We then convert these into empirical cumulative density functions (CDFs) using employment shares as weights. Finally, q_j is computed as the average percentile of job j across the empirical CDF for the median wage and the empirical CDF for median education level.

is unsurprising as one would expect these industries to be intensive in low-skilled labor. In fact, this is precisely the case as the two occupation groups of (i) Low Skill Services and (ii) Clerical, Retail Sales account for 42% of low quality jobs and 77% of workers in low quality jobs.

Middle quality jobs are skewed towards traditional 'blue-collar' industries and occupations. Here, (i) Manufacturing and (ii) Mining/Oil/Gas, Utilities/Construction account for 28% of jobs and 37% of workers (up from 15% and 9%, respectively, for low quality jobs). In terms of occupation groups, it is now (i) Managers, Professional, Technology, Finance, Public Safety, (ii) Clerical/Retail, and (iii) Transport, Construction, Mechanical, Mining, Farm that account for the bulk (70% of jobs and 80% of workers).

Finally, high quality jobs are dispersed primarily among (i) Manufacturing, which continues to be well represented (14% of jobs and 16% of workers), as well as (ii) Professional/Business services and (iii) Educational/Health Care/Social Assistance services (29% of jobs and 59% of workers). Unsurprisingly, high quality jobs across manufacturing and these service industries are dominated by the single occupation of Managers, Professional, Technology, Finance and Public Safety which accounts for 87% of jobs and 92% of workers (up from 21% and 20%, respectively, for middle quality jobs). Ultimately, the distribution of jobs according to the NPB index fits well with the notion of low quality jobs being dominated by low skill occupations/industries, middle quality jobs by blue-collar occupations/industries, and high quality jobs by professional occupations dispersed across several industries.

Local measure of Chinese import penetration growth (ΔT_c) Our measures of local trade exposure follow the approach popularized in Topalova (2007) and used recently elsewhere (e.g., Autor et al. (2013); Kovak (2013); McLaren and Hakobyan (2016)). However, while much of the prior trade literature dealing with local labor markets focuses primarily on industries, given that imports and trade policy are defined at the industry level, our analysis focuses on occupations as discussed earlier. Thus, our starting point follows Ebenstein et al. (2014), who define occupational exposure to trade shocks as a function of an occupation's employment composition across industries and the associated industry-specific trade shocks. We then define local trade exposure to trade shocks as a function of a CZ's employment composition across occupations and the associated occupation-specific trade exposure.

To proceed, we first calculate the change in (national) Chinese IP at the industry level, following Acemoglu et al. (2015), as

$$\Delta T_s \equiv \frac{\Delta M_s}{Y_{s,1991} + M_{s,1991} - X_{s,1991}}, \tag{5}$$

where s indexes the 84 traded Census industries and the change in Chinese imports, $\Delta M_s \equiv M_{s,2010} - M_{s,1991}$, is normalized by domestic absorption in 1991 as proxied by domestic shipments, $Y_{s,1991}$, plus net imports, $M_{s,1991} - X_{s,1991}$.[17,18] Table A3 in the Appendix lists the top 20 sectors in terms of growth in Chinese IP. As has been documented elsewhere, the rise in Chinese IP has been substantial. Across all 84 traded Census industries, the mean is an 11% point increase and 12 industries experienced at least a 25% point increase.

Next, we compute the change in (national) occupation-specific exposure to Chinese IP as

$$\Delta T_k \equiv \sum\nolimits_s \omega_{sk} \Delta T_s, \tag{6}$$

where $\omega_{sk} \equiv L_{sk,1990}/L_{k,1990}$ is the (time-invariant) 1990 employment share of Census occupation k in Census industry s computed using the 1990 Census data described above.[19,20] ΔT_k is the trade exposure variable in our national-level regressions in Table 1.

According to (6), *occupations* are deemed as highly exposed to Chinese import competition if their employment is concentrated in *industries* highly exposed to Chinese import competition. Table A4 in the Appendix lists the 20 3-digit Census occupations most exposed to growth in Chinese IP. Table A5 provides similar information for the six broad occupation groups defined in Autor and Dorn (2013). Table A5 also shows the distribution of occupations across 1-digit industries. All occupations except low skill services have a non-trivial share of their employment in manufacturing and/or agriculture. The two occupations of (i) Production, craft and (ii) Machine operators, assemblers have 64% and 76% of their employment in the manufacturing industry. In turn, they faced Chinese IP growth of 7% and 8.7% respectively. Additionally, Transport, construction, mechanical, mining, farm has 23% of their employment in manufacturing and agriculture and faced Chinese IP growth of 2.3%. The two occupations of (i) Managers, etc. and (ii) Clerical, retail sales have 11% of their employment in manufacturing and faced Chinese IP growth of 1.7% and 1.4%, respectively. Given the differences across occupations in their exposure to Chinese IP growth, one might hypothesize that occupation-specific exposure to Chinese IP growth, as opposed to CZ-specific exposure, drives job-specific employment growth within CZs. Later, we explore this issue.

Finally, we compute the change in local exposure to Chinese IP as

$$\Delta T_c \equiv \sum\nolimits_k \omega_{kc} \Delta T_k, \tag{7}$$

[17] We obtain the necessary trade data from COMTRADE and the domestic shipments data from the NBER-CES Manufacturing Industry Database (Becker et al. (2013)).

[18] Shipments data are only available for manufacturing industries and not all tradable industries. However, we do not set $\Delta IP_s = 0$ for non-manufacturing tradable industries. For these industries, we set ΔIP_s equal to the average ΔIP_s across all manufacturing industries.

[19] Using time-invariant employment shares mitigates endogeneity concerns due to employment composition responding to changes in Chinese IP over the sample period.

[20] We aggregate over all Census industries in (6), not just traded sectors, consistent with much of the literature (Topalova (2007); Topalova (2010); McLaren and Hakobyan (2016)).

where $\omega_{kc} \equiv L_{kc,1990}/L_{c,1990}$ is the (time-invariant) 1990 employment share of location c employment in Census occupation k computed using the 1990 Census data described above. Figure 2 illustrates the stark increase in local Chinese IP. Table A6 in the Appendix list the 20 CZs facing the largest increase in Chinese IP. Twelve of the top 20 CZs are located in Tennessee, Kentucky, and Virginia. Here, local Chinese IP growth ranges between 4% and 5% which is much higher than the overall mean of 2.6%. However, Figure 3 illustrates that the top quartile of most exposed CZs cover a much broader swath of the US, stretching from the South into the Rust Belt and then westward through the Midwest. Conversely, the bottom quartile of most exposed CZs are concentrated in the Southwest and Southeast.

Local measure of routine biased technological change (R_c) A common concern in the trade and labor literature is adequately controlling for technological change which theoretically can have similar impacts as rising trade exposure. Given our 3-digit occupation fixed effects, we control for occupation-specific technological change. This could, for instance, take the form of skill-biased technological change, whereby low skill occupations suffer from technological change and high skill occupations benefit. It could also take the form of RBTC, whereby technological change hurts occupations that rely heavily on routine tasks, as technology can automate these tasks relatively easily, and leaves the remaining occupations largely unaffected or even better off through positive complementarities created by automation. Our 1-digit NAICS industry fixed effects also control for broad industry-specific technological change.

That said, as argued in Autor and Dorn (2013), technological change may differentially affect locations depending on occupational composition. According to Goos et al. (2014, p.2511), "... the literature seems to be settling on using the RTI [routine task intensity] measure as the best way to capture the impact of recent technological progress". Indeed, Autor and Dorn (2013) show that locations endowed with a large share of routine task intensive jobs in 1980 experienced larger RBTC in the form of sharper growth in the adoption of information and communications technology over the following 25 years. Thus, our measure of location-specific RBTC (R_c) takes the Autor and Dorn (2013) measure of occupation-specific Routine Task Intensity (R_k) in 1980 and aggregates to the local level using 1980 local employment weights:

$$\widetilde{R}_c \equiv \sum\nolimits_s \omega_{kc,1980} R_k \tag{8}$$

where $\omega_{kc} \equiv L_{kc,1980}/L_{c,1980}$ is the (time-invariant) 1980 employment share of location c employment in Census occupation k computed using the 1980 Census data described above. For ease of interpreting the coefficient estimates, the measure of R_c used in our analysis normalizes $\widetilde{R}_c$ in (8) to have a minimum value of zero by subtracting the minimum value of $\tilde{R}_c$ across locations:

$$R_c \equiv \widetilde{R}_c - \min_c \widetilde{R}_c.$$

Covariates (x_{jc}) We control for numerous other attributes of locations and jobs including time-varying and location-specific variables related to the distribution of age, education, marital status, race, household size, language abilities, number of children less than age 18 within households, number of children under age five within households, nationality and home ownership. The only time invariant, location-specific variables are state fixed effects. Finally, the only time- and location-invariant attributes are the 3-digit Census occupation fixed effects (381 occupations) and the 1-digit NAICS industry fixed effects (8 industries).

Instrument We use instrumental variables (IV) estimation to address the potential endogeneity of local Chinese IP. Construction of the instrument follows Acemoglu et al. (2015), computed in four steps. First, we replace the numerator in (5) with the change in industry-level Chinese exports to eight non-US high income countries.[21] Second, we use industry-level US domestic absorption from 1989 rather than 1991 in the denominator of (5).[22] Third, we use occupation-industry shares from 1980 rather than 1990 when aggregating to the occupation level in (6). Fourth, we use local employment weights from 1980 rather than 1990 when aggregating to the local level in (7). As discussed in Acemoglu et al. (2015), the instrument is relevant if Chinese exports are correlated across high income countries and is valid if this correlation is driven by Chinese productivity and other supply-side shocks (rather than correlated import demand shocks among high income countries). Note, interactions between the instrument and q_j and q_j^2 are used to instrument for the interaction terms involving local Chinese IP.

3 Baseline results

Table 2 presents the baseline results. Column (1) regresses Δn_{jc} on q_j and q_j^2 only. Columns (2)-(5) display the Ordinary Least Squares (OLS) estimates, while Columns (6)-(9) display the IV estimates, after incorporating additional controls. Relative to Column (1), Columns (2) and (6) add local Chinese IP, ΔT_c, and its interactions with q_j and q_j^2. Columns (3) and (7) add location-specific covariates. Columns (4) and (8) add local RBTC, R_c, and its interactions with q_j and q_j^2. Finally, Columns (5) and (9) add state, 3-digit Census occupation fixed effects, and 1-digit NAICS industry fixed effects.

Column (1) confirms job polarization at the local labor market level in the US.[23] Moreover, Figure 4,

[21] The countries include Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

[22] COMTRADE data for US imports is unavailable before 1991. So, we use USITC import data for 1989.

[23] Autor and Dorn (2013) find a similar result via a reallocation of low skill workers into the broad occupational category of low skill services. In contrast, the results in Column (1) indicate a reallocation of workers among 2679 different jobs.

based on these estimates, is qualitatively similar to Figure 1, based on the national estimates in Table 1. Specifically, we find positive employment growth in good and bad jobs on average across CZs, but negative employment growth in middle quality jobs. In terms of the magnitude of the employment effects, it is important to realize that, with 2691 jobs, the mean employment share across all location-jobs is 0.032%.[24] As such, the magnitude of polarization is economically meaningful with predicted employment growth reaching about 16% (28%) of the average employment share when $q = 0$ ($q = 1$).

In terms of the remaining models, we focus our discussion around the IV results in Columns (6)-(9) as the OLS and IV estimates are qualitatively similar. Nonetheless, before turning to the parameter estimates, we note that the IV specification tests perform very well. In particular, we easily reject the null of underidentification at the $p < 0.01$ level and the first-stage F-statistics on the excluded instruments range from roughly 150 to more than 300. Finally, despite the similarity in the OLS and IV point estimates, we do reject the null of exogeneity in Columns (7)-(9) at the $p < 0.01$ level.

Turning to the parameter estimates, Column (6) adds local Chinese IP and the associated interactions with q_j and q_j^2 to the model. The point estimates for θ_1, θ_2, and θ_3 are individually and jointly statistically significant at the $p < 0.01$ level. This not only provides further evidence of significant effects of trade with China on US local labor markets, but also provides strong evidence that the impacts are heterogeneous across the distribution of job quality. Further, the sign pattern of the point estimates ($\widehat{\theta}_1 < 0$, $\widehat{\theta}_2 > 0$, $\widehat{\theta}_3 < 0$) as well as the fact that $\widehat{\theta}_1 + \widehat{\theta}_2 + \widehat{\theta}_3 < 0$ suggests an *anti-polarization* impact of local Chinese IP.

Formally, the marginal effect of local Chinese IP is

$$\frac{\partial \, \mathrm{E}[\Delta n_{jc}|\cdot]}{\partial \Delta T_c} = \theta_1 + \theta_2 q_j + \theta_3 q_j^2, \tag{9}$$

where q_j varies from zero to one and $\mathrm{E}[\Delta n_{jc}|\cdot]$ is the conditional expectation of local employment growth of job j given the covariates in the model. Based on the estimates in Column (6), we find that the marginal effect of local Chinese IP is negative for low and high quality jobs, yet positive for middle quality jobs.[25] Moreover, controlling for the local Chinese IP variables increases the point estimates of β_1 and β_2 in absolute value. These two observations imply job polarization in local labor markets would have been *more* pronounced had local Chinese IP stayed constant at 1990 levels. We illustrate this graphically below.

Column (7) adds controls for CZ-specific socioeconomic and demographic controls. The point estimates are essentially unchanged. However, Column (8) shows that controlling for local RBTC is consequential. While the point estimates for the impact of local Chinese IP remain individually and jointly statistically significant at the $p < 0.01$ level and continue to indicate an anti-polarization effect, the point estimates for the impact of local RBTC are also statistically significant at the $p < 0.01$ level. Formally, the marginal

[24] Note, 0.032% is less than 1/2691 due to nonemployment; see footnote 14.

[25] Specifically, the marginal effect is positive for values of q_j between 0.46 and 0.86.

effect of local RBTC is

$$\frac{\partial \, \mathrm{E}[\Delta n_{jc}|\cdot]}{\partial R_c} = \gamma_1 + \gamma_2 q_j + \gamma_3 q_j^2, \tag{10}$$

with the pattern of estimates ($\widehat{\gamma}_1 > 0$, $\widehat{\gamma}_2 < 0$, $\widehat{\gamma}_3 > 0$) and the fact that $\widehat{\gamma}_1 + \widehat{\gamma}_2 + \widehat{\gamma}_3 > 0$ indicating a *polarization* effect. That is, local RBTC increases employment growth of low quality and high quality jobs, but leads to lower employment growth of middle quality jobs.[26] Indeed, the impact of local RBTC is so pervasive that the point estimates on q_j and q_j^2 change signs and lose some statistical significance. In other words, as we illustrate visually below, our results imply that employment growth exhibits polarization *only* in locations sufficiently impacted by RBTC. Thus, consistent with the prior literature on job polarization, we find *local* RBTC to be the key determinant of job polarization in *local* labor markets.

Finally, Column (9) adds state, occupation, and industry fixed effects, thereby removing any unobservables along these dimensions that could influence local employment growth over the sample period. Two findings are noteworthy. First, the magnitude of the coefficient estimates on q_j and q_j^2 rise in absolute value and are once again statistically significant at the $p < 0.01$ level. However, as in Column (8), the signs of the coefficients indicates anti-polarization in the absence of RBTC. Second, the coefficient estimates on the local Chinese IP and local RBTC variables are virtually unchanged from Column (8). Thus, our preferred specification, Column (9), confirms the previous findings: local RBTC is the key explanation for job polarization within local labor markets and local Chinese IP has an anti-polarization effect. In fact, not only does local Chinese IP have an anti-polarization effect based on the results in Columns (8) and (9), but the marginal effect is negative across all values of q_j. That is, local Chinese IP reduces employment growth of all jobs, especially low and high quality jobs.

Figure 5 illustrates the polarization impact of local RBTC and the anti-polarization impact of Chinese IP. Based on the point estimates in Column (9), Panel A of Figure 5 shows the polarization impact of local RBTC by plotting $\mathrm{E}[\Delta n_{jc}|\cdot]$ while fixing all covariates, including local Chinese IP, at their sample means except for local RBTC. Local RBTC is varied from zero (i.e., the minimum value of local RBTC), to its 10^{th} percentile value (0.221), to its 90^{th} percentile value (0.657). When local RBTC is held at its minimum value, and local Chinese IP is set at the sample mean, we do not see job polarization at the local level. As local RBTC grows we eventually see job polarization, with positive employment growth at the lower and upper tails and negative employment growth in the middle. This visually illustrates the polarization effect of local RBTC.

Conversely, Panel B of Figure 5 illustrates the anti-polarization impact of local Chinese IP. Based on the point estimates in Column (9), the figure plots $\mathrm{E}[\Delta n_{jc}|\cdot]$ fixing all covariates, including local RBTC, at their sample means except for the change in local Chinese IP. The change in local Chinese IP is varied

[26] Specifically, the marginal effect is negative for values of q_j between 0.40 and 0.85.

from zero (i.e., local Chinese IP is held constant at 1990 levels), to its 10^{th} percentile value (0.018), to its 90^{th} percentile value (0.030). When local Chinese IP is held constant at 1990 levels, and local RBTC is set at the sample mean, we see job polarization at the local level. As local Chinese IP growth is increased, we see employment growth declining across the entire job quality distribution, with more extreme declines at the lower and upper tails. This visually illustrates the anti-polarization effect of local Chinese IP. In fact, as the figure illustrates, if local Chinese IP growth is high enough (and local RBTC continues to be held fixed at the sample mean), we would no longer see job polarization on average across CZs. Instead, we would see negative employment growth of all jobs except those of the highest quality.

4 Local shocks versus occupation shocks

Our baseline analysis investigated whether and how local shocks, either local RBTC or local Chinese IP shocks, have impacted job polarization in local labor markets. In so doing, our preferred baseline specification includes occupation fixed effects which implicitly control for (national) occupation-specific Chinese IP growth and RBTC. However, these occupation fixed effects do not allow for heterogeneous impacts of (national) occupation-specific Chinese IP growth and RBTC by job quality. In other words, our baseline analysis does not allow for the possibility that occupation-specific shocks may impact job *polarization* in local labor markets. Given occupations differ in their distribution of employment across industries, as illustrated in Table A5, one may be concerned that these occupation-specific shocks may have important impacts on job polarization in local labor markets.

Indeed, one benefit of our approach, i.e. focusing on local job-specific employment growth rather than the typical approach of looking at local overall (or just manufacturing) employment growth, is that we can distinguish between the impact of (national) occupation-specific and (local) CZ-specific factors. That is, our approach allows us to compare a given job in different locations and to compare different jobs in a given location. Formally, we now investigate the following expanded model

$$\begin{aligned} \Delta n_{jc} \;=\; & \beta_0 + \beta_1 q_j + \beta_2 q_j^2 + \theta_1 \Delta T_c + \theta_2 \Delta T_c q_j + \theta_3 \Delta T_c q_j^2 + \gamma_1 R_c + \gamma_2 R_c q_j + \gamma_3 R_c q_j^2 \\ & + \delta_2 \Delta T_j q_j + \delta_3 \Delta T_j q_j^2 + \phi_2 R_j q_j + \phi_3 R_j q_j^2 + x_{jc}\delta + \varepsilon_{jc}, \end{aligned} \tag{11}$$

where $\Delta T_j \equiv \Delta T_k$ is the (national) change in Chinese IP for occupation k (defined in (6)) and $R_j \equiv R_k$ is the (national) measure of RBTC for occupation k.[27,28] Table 3 displays the results; Column (2) contains the new results and, for comparison, Column (1) presents our baseline results from Column (9) of Table 2.

[27] As before (see footnote 9), we utilize a slight abuse of notation to keep things simple. Jobs are indexed by j, which is the cross-product of 3-digit Census occupations (k) and 1-digit NAICS industries. Thus, each job j maps into an occupation k. National Chinese IP growth and RBTC are measured strictly at the occupation level.

[28] Note, occupation fixed effects absorb the uninteracted terms, ΔT_k and R_k.

Three points stand out. First, adding the (national) occupation-specific variables interacted with q_j and q_j^2 leaves the local variables and their interactions with q_j and q_j^2 unchanged. Thus, the (national) occupation-specific variables and their local counterparts are essentially uncorrelated. This allows us to empirically distinguish their impacts on local job-specific employment growth across the distribution of job quality.

Second, the effects of (national) occupation-specific RBTC are insignificant, both statistically and economically. Thus, our results suggest that *local* exposure to RBTC rather than occupation-specific exposure to RBTC drives job polarization within local labor markets.

Third, while the effects of (national) occupation-specific Chinese IP growth are statistically significant, their economic significance is quite small in magnitude. This can be seen by comparing Figures 5 and 6. Figure 6 evaluates simultaneous changes in both local *and* (national) occupation-specific Chinese IP growth based on the estimates in Column (2). Panel B of Figure 5 is from the baseline specification and thus varies only local Chinese IP growth. The similarity of the two figures reveal that allowing for heterogenous effects of (national) occupation-specific Chinese IP growth has little impact on local job-specific employment growth across the distribution of job quality. Stated differently, our results indicate that the impacts of Chinese IP growth on job anti-polarization in CZs stems from *local* exposure rather than (national) *occupation-specific* exposure.

5 Sensitivity analyses

We perform numerous sensitivity analyses to assess the robustness of the baseline results.

Alternative specifications Table 4 presents results from a number of alternative specifications of our baseline model. For comparison, Column (1) replicates our preferred estimates from Column (9) in Table 2. In Column (2) the lag of Δn_{jc}, defined as local job-specific employment growth from 1980 to 1990, is added to our baseline specification. This addition addresses a common concern within trade and local labor market analyses; namely, that economically declining locations may tend to specialize in import-competing goods. If this is the case, then these locations will experience the greatest changes in local trade exposure. In turn, this may generate a spurious relationship between local trade exposure and local labor market employment growth due to omitted location-specific secular trends. By controlling for trends in previous local employment growth, this concern should dissipate. The results reveal essentially no change in the estimates.[29] Thus, our baseline results hold even when *conditioning* on the CZ-job specific employment growth between 1980 and 1990.

[29] Despite using state, occupation and industry fixed effects, the absence of CZ fixed effects means that the usual Nickell (1981) bias present in standard dynamic panel data models with a lagged dependent variable does not arise.

The remaining specifications are identical to our preferred baseline model, but explore alternative measures of job quality. In Column (3) we allow the quality of a given job to vary across regions; in contrast, recall, our baseline measure of job quality is constant across the US. Specifically, we now compute job quality, denoted by q_{jr}, separately for each of the nine US Census regions, indexed by r.[30] In so doing, we allow for potentially important regional variation in real wages due to price differences or in educational attainment and nominal wages.[31]

In Column (4) we revert back to a national measure of job quality, but instead use a time invariant measure based on the 2010 median wages and education levels observed in each job. This addresses the potential concern that the quality ranking of jobs may substantially change over the sample period and render our time-invariant notion of job quality based on data in 1990 misleading. Note, this change reduces the sample size as some jobs observed in 1990 no longer exist in 2010 and therefore have missing job quality (see footnote 15).

Finally, Columns (5)-(7) are identical to Columns (1), (3), and (4) except that the underlying quality measure (from either 1990 or 2010 and at either the regional or national level) is based solely on the median wage of a job, not the NPB index of median wages and median education levels.

Turning to the results in Columns (3)-(7), we find that the qualitative results from our baseline specification are unchanged. For ease of interpretation, Figure 7 plots the results. While there is variation across the panels in the figure, the basic conclusion that local Chinese IP has an anti-polarization impact is quite robust. In all cases, we find that local Chinese IP growth reduces employment growth of low and high quality jobs and, at best, has no impact of middle quality jobs.

Heterogeneous effects Table 5 displays the results from various extensions to our baseline model that explore possible heterogeneities in the determinants of local employment growth. Again, Column (1) repeats our preferred estimates from Column (9) of Table 2 for comparison.

In Columns (2) and (3) we assess the possibility of heterogeneous effects of local Chinese IP growth depending on the nature of the goods being imported. Specifically, we construct two measures of local Chinese IP growth, one based solely on imports of intermediate inputs and one based solely on imports of non-intermediate inputs. Formally, we create two alternative measures of ΔT_c that differ from our baseline measure through slightly varying (5). The first alternative measure of (5) only uses data for intermediate inputs. The second alternative measure of (5) only uses data for non-intermediate inputs. In terms of the results, we find the magnitude of the point estimates to be modestly larger in Column (3), where local

[30] We do not attempt to measure job quality at a more disaggregate level than Census regions since many jobs are not observed. Even when computing regional measures of job quality, often a region does not contain a particular job. In these cases, we use the national measure of its quality for the region.

[31] See Ural Marchand (2012) and Fajgelbaum and Khandelwal (2016) for recent empirical work emphasizing the importance of trade liberalization on prices.

Chinese IP growth is measured using non-intermediate inputs. However, this is misleading since actual local Chinese IP growth is larger for intermediate input imports than non-intermediate input imports. Figure 8 reveals that the impacts of local Chinese IP growth are virtually indistinguishable.

In Column (4) we assess the possibility of heterogeneous effects in the pre-Great Recession period. Here, the changes in all variables are computed over the period 1990 to 2000. The results confirm our baseline findings despite the change in magnitudes of the estimates. As shown in Figure 9, local Chinese IP growth continues to have an anti-polarization effect. Thus, our baseline results are not driven by the Great Recession.

In Columns (5)-(7) we explore whether the effects of local Chinese IP growth differentially affect local employment growth across three different cohorts of workers: (i) 'young' individuals aged 25-44, (ii) 'old' individuals aged 45-64, and (iii) the 'cohort' of individuals aged 25-44 in 1990 and 45-64 in 2010. Formally, the dependent variable in all models, including our baseline specifications, can be written as $\Delta n_{jc} = n_{jc,2010} - n_{jc,1990}$, where $n_{jc,t}$ is the employment share in a CZ-job in year t. In the baseline model, employment shares in year t are computed using individuals aged 25-64. In Column (5), employment shares in year t are instead computed using only individuals aged 25-44. In Column (6), only individuals aged 45-64 are used. In Column (7), $n_{jc,1990}$ is computed using individuals aged 25-44, while $n_{jc,2010}$ is computed using individuals aged 45-64. Thus, Columns (5) and (6) allow us to assess whether the labor market impacts of local Chinese IP growth differentially impact younger and older workers. Column (7) allows us to asses the within cohort impacts of local Chinese IP growth.

While the general pattern of coefficient estimates is similar across the columns, interesting differences arise when examining Figure 10. Panel A shows the anti-polarization effect for young workers as seen in our baseline specification. Panel B continues to show a strong, negative impact of local Chinese IP growth on employment growth in low quality jobs for older workers. However, the impact on employment growth among older workers in high quality jobs appears muted. Finally, when examining within cohort changes, we find no impact of local Chinese IP growth on employment growth in middle to high quality jobs; the negative impact on low quality jobs remains. The implication is that local Chinese IP growth reduces the availability of high quality jobs to the next cohort of workers. However, there is little impact on the overall availability of middle and high quality jobs for those already possessing such jobs.

6 Conclusion

In this paper, we investigate the possible heterogeneous effects of changes in local trade exposure on the employment growth of good versus bad jobs across US local labor markets between 1990 and 2010. We obtain several salient and robust findings.

First, we verify the existence of job polarization at the level of local US labor markets over this time period. Moreover, this polarization is due primarily to local routine-biased technological change, not local trade exposure. Second, not only does local trade exposure not cause job polarization, it actually has an anti-polarization effect. In the absence of significant growth in Chinese import penetration over the sample period, the degree of job polarization in the US labor market would have been much more pronounced. Finally, we confirm the importance of examining employment growth at the level of the local labor market as *local* exposure to trade and routine-biased technological change play a much larger role than *national* but *occupation-specific* exposure.

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Appendix

Here, we describe the various concordance issues that arise in the data.

Occupations and occupation groups The RTI variable from Autor and Dorn (2013) uses their self-compiled occupation variable *occ*1990*dd*. Further, the six occupation groups defined by Autor and Dorn (2013) collapse *occ*1990*dd*. However, we use the IPUMS Census variable *occ*1990. Thus, we concord from *occ*1990*dd* to *occ*1990. A further complication is that *occ*1990*dd* is based on the Census occupation variable *occ*1990 which differs from the IPUMS Census variable *occ*1990. Nevertheless, we carry out the concordance using David Dorn's concordance between the Census *occ*1990 variable and *occ*1990*dd* (`http://www.ddorn.net/data.htm`) and the IPUMS concordance between its own Census *occ*1990 variable and the Census *occ*1990 variable (`https://usa.ipums.org/usa/volii/occ_ind.shtml`).

Industries Industry level trade and shipments data is available at the 4-digit SIC level (from WITS COMTRADE and the NBER-CES Manufacturing database, respectively). However, we use the IPUMS Census industry variable *ind*1990. Thus, we concord from SIC to *ind*1990. To do so, we used a Census concordance that, in the past, was available at `http://www.cdc.gov/niosh/soic/pdfs/PT19Y99AppB.pdf`. While this url link is no longer active, interested readers can download this file, together with STATA and Excel versions, from the corresponding author's website: `http://people.smu.edu/jlake/data_code/SIC_IPUMS_industry_concordance.zip`.

Locations While we use CZs as the definition of local labor markets, this variable is not in IPUMS Census data. Thus, we concord from the most disaggregated geographic unit in the IPUMS Census data to CZs.

In Census microdata, the most disaggregated level of geography needs to have at least 100,000 people (`http://www.ddorn.net/data/Dorn_Thesis_Appendix.pdf`, p.136). This gives rise to the notions of "county groups" (in the form of the CNTYGP97 and CNTYGP98 Census variables for 1970 and 1980) or "PUMAs" (in the form of the PUMA, PUMA1990 and PUMA2000 Census variables for 1990 onwards) whose definition changes over time to achieve the minimum population threshold for a geographical Census unit. CZs aggregate these most disaggregated geographical Census units in a way that carefully attempts to respect "local labor markets".

Note that the PUMAYYYY variables and the PUMA variable convey somewhat different information. In 2010, the PUMA2000 variable is still the most disaggregated geographical unit (`https://usa.ipums.org/usa/volii/2000pumas.shtml`) with the caveat that 3 PUMAs in LA were merged into one PUMA because of Hurricane Katrina affecting the Census population threshold described above. In the Census data, the PUMAYYYY variable is only non-missing in the year YYYY. But, the PUMA variable is non-missing for 1990, 2000 and 2010 and records the associated year-specific PUMAYYYY. However, the form of the numeric values differ across the PUMA and PUMAYYYY variables. Specifically, the PUMAYYYY variable contains state *and* PUMA information whereas PUMA numbers are not unique across states (i.e. a location according to the PUMA variable is really a (PUMA, STATEFIP) pair). Specifically,

$$PUMAYYYY = STATEFIP \times 10,000 + PUMA.$$

Before aggregating these disaggregated geographical units in the Census, CZs split these geographical units. The splitting process is explained in detail by David Dorn (`http://www.ddorn.net/data/Dorn_Thesis_Appendix.pdf`, pp.136-138). Moreover, David Dorn provides concordances that map from the various disaggregated geographic units in the Census to time-invariant 1990 CZs (`http://www.ddorn.net/data.htm`). Indeed, when using an n:n merge for the concordance from either (i) PUMA1990 to CZ1990 or (ii) PUMA2000 to CZ1990, there are not any PUMAs left unmatched nor are there any CZs left unmatched. The only subtlety arises because of the Hurricane Katrina issue above where PUMAs 221801, 221802 and 229105 are not in the Census microdata while PUMA 227777 (the newly aggregated PUMA) is not in Dorn's concordance. But, since the three old PUMAs all mapped to the same CZ then this is easily fixed manually. Having concorded PUMAs to CZs, one needs to adjust the person weights *perwt* that are in the Census microdata using the allocation factors *afactor* in David Dorn's concordance. Specifically, the new person weights are

$$perwt\_cz = perwt \times afactor.$$

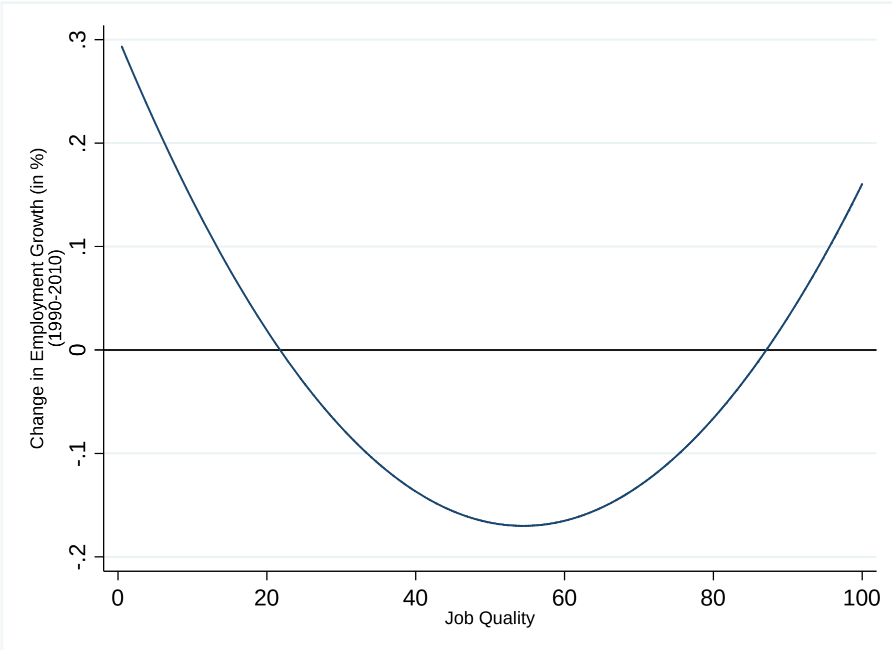


Figure 1. Changes in National Employment Shares as a Function of Initial Job Quality, 1990-2010.
Notes: Figure is obtained using the OLS results from Column (1) in Table 1. Job quality is measured as the NPB index (multiplied by 100). See text for further details.

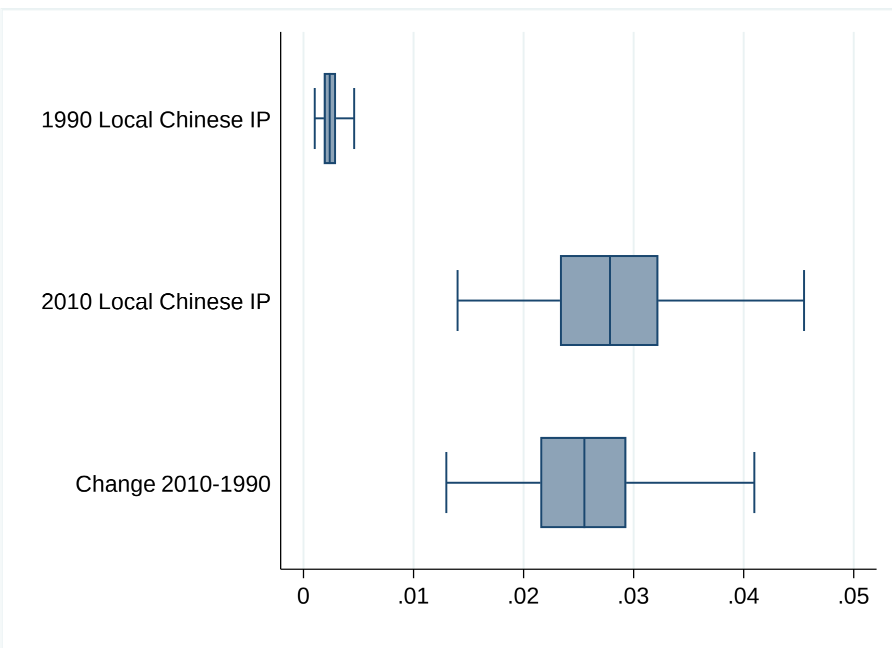


Figure 2. Increasing Local Chinese Import Penetration, 1990-2010.
Notes: Boxes represent the interquartile range, with the middle line corresponding to the median. The end lines correspond to the lower and upper adjacent values. See main text for definition of variables.

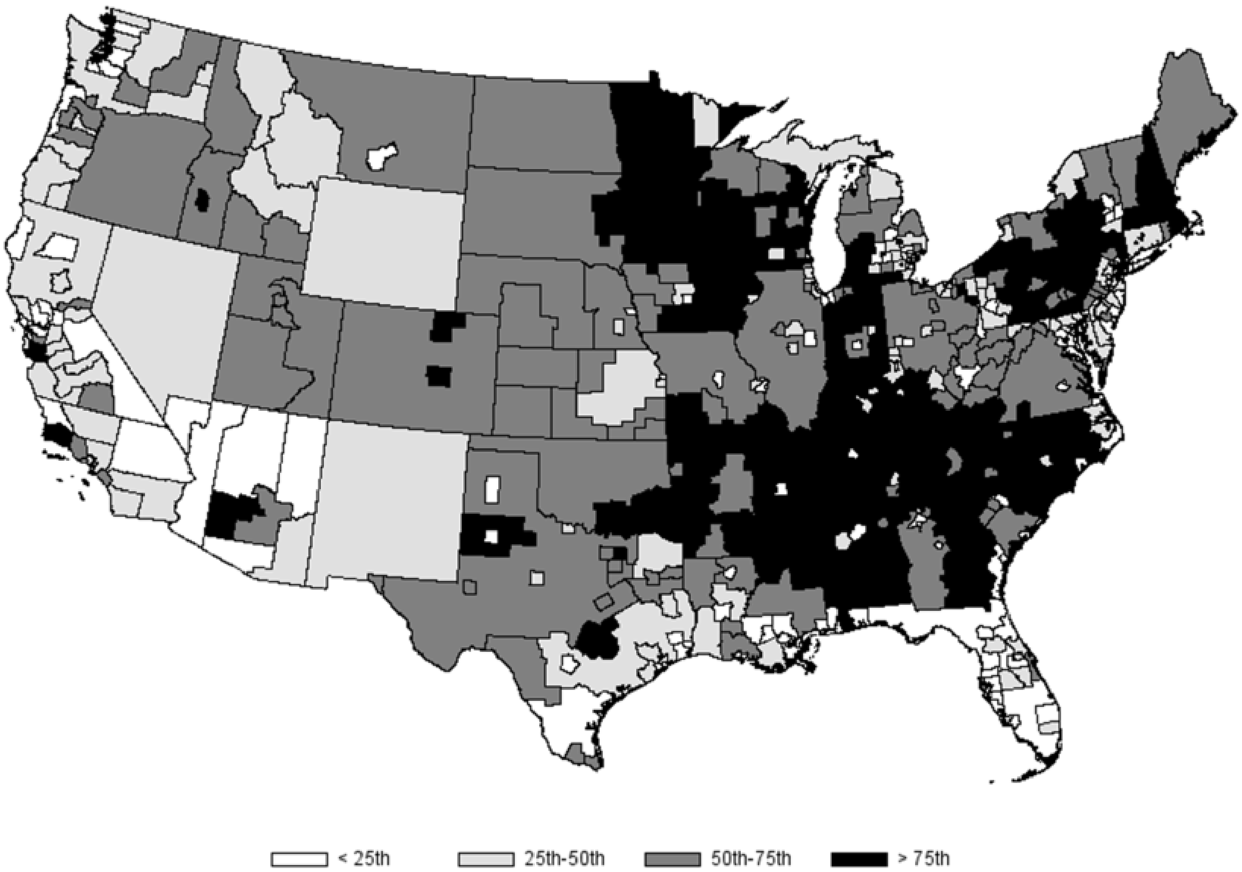


Figure 3. Graphical Illustration of Rising Local Chinese Import Penetration, 1990-2010.
Notes: The four color shades, from lightest to darkest respectively, correspond to below the 25th percentile, between the 25th and 50th percentiles, between the 50th and 75th percentiles and above the 75th percentile.

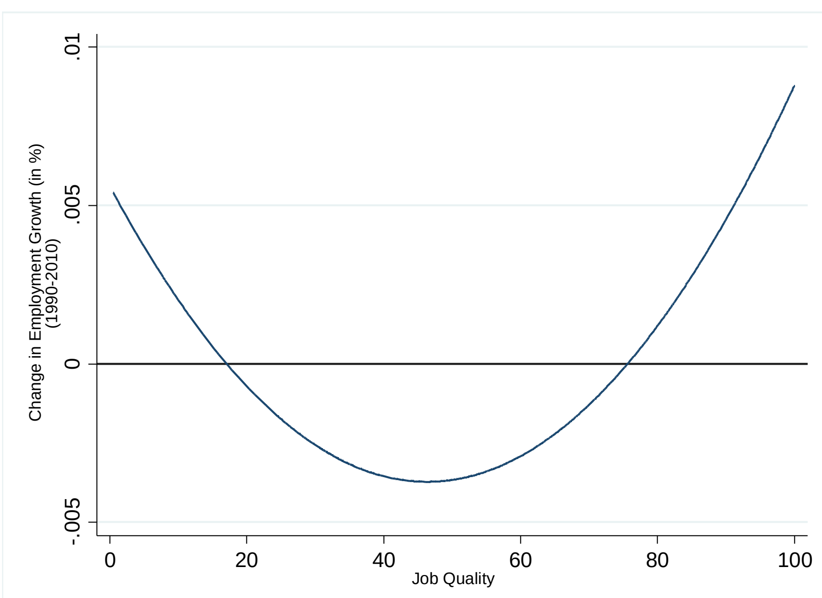
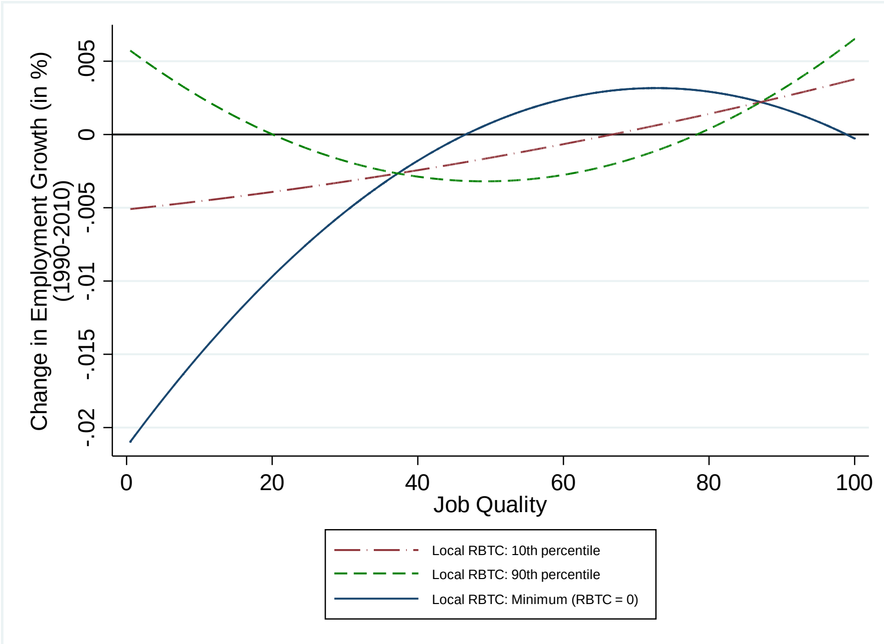
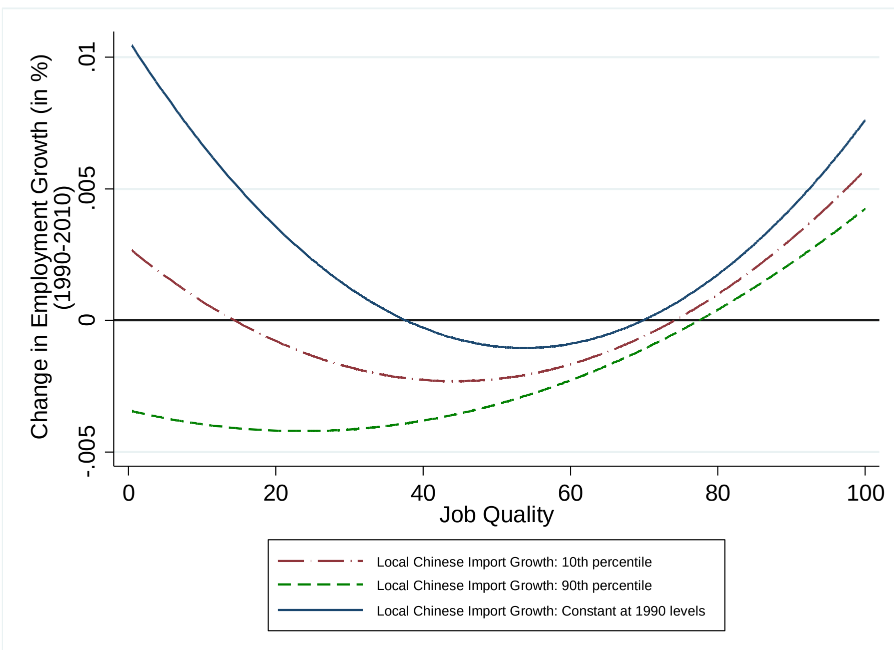


Figure 4. Changes in Local Employment Shares as a Function of Initial Job Quality, 1990-2010.
Notes: Figure is obtained using the OLS results from Column (1) in Table 2. Job quality is measured as the NPB index (multiplied by 100). See text for further details.



(A) Impact of Local RBTC



(B) Impact of Local Chinese Import Penetration

Figure 5. Impacts of Local Chinese Import Penetration & Local RBTC on Changes in Local Employment Shares, 1990-2010.
Notes: Figures obtained using the results from Column (9) in Table 2. Job quality is measured as the NPB index (multiplied by 100). See text for further details.

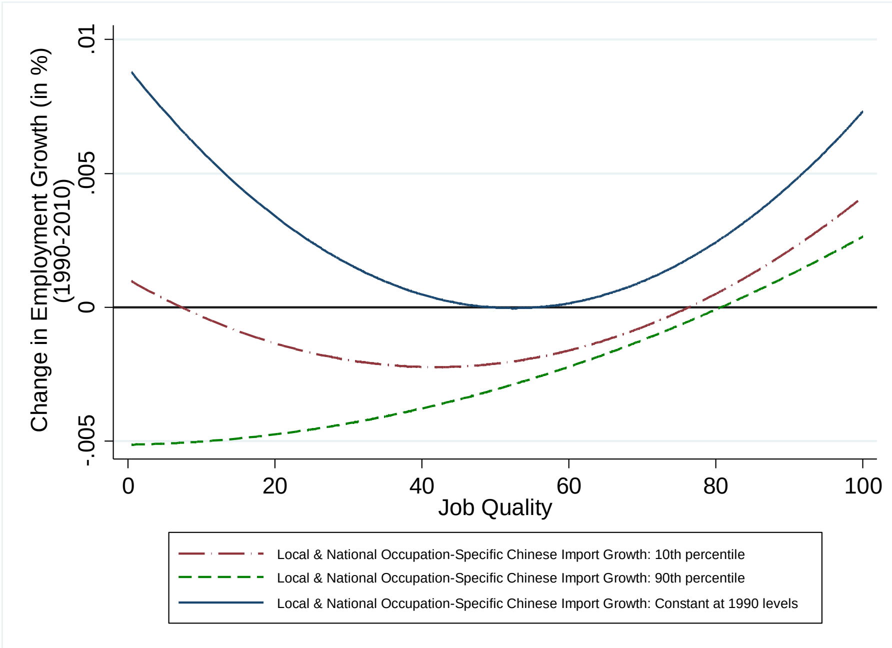
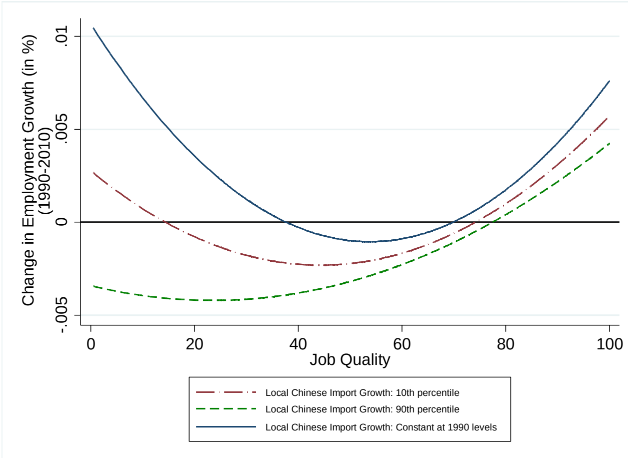
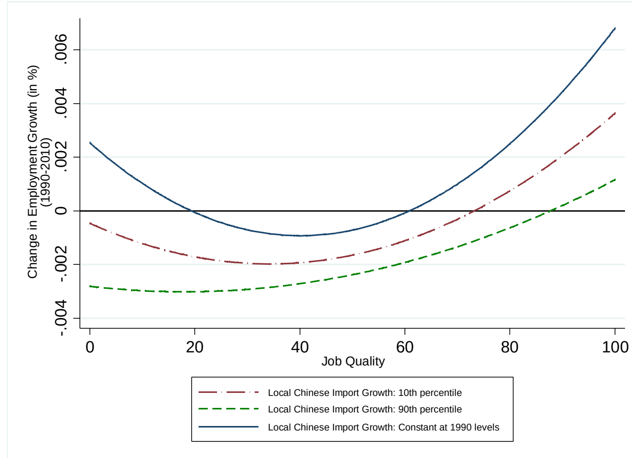


Figure 6. Impacts of Local and National Occupation-Specific Chinese Import Penetration on Changes in Local Employment Shares, 1990-2010.

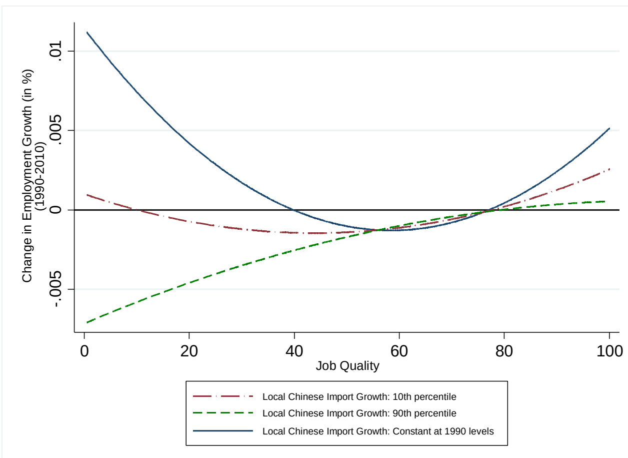
Notes: Figure is obtained using the results from Column (2) in Table 3. Job quality is measured as the NPB index (multiplied by 100). See text for further details.



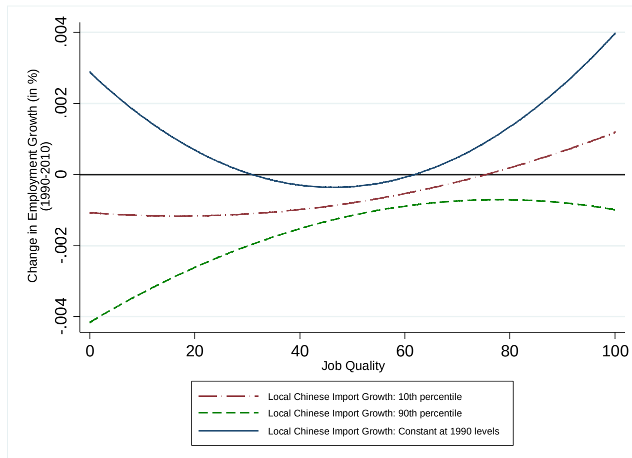
(A) NPB Index (National, 1990)



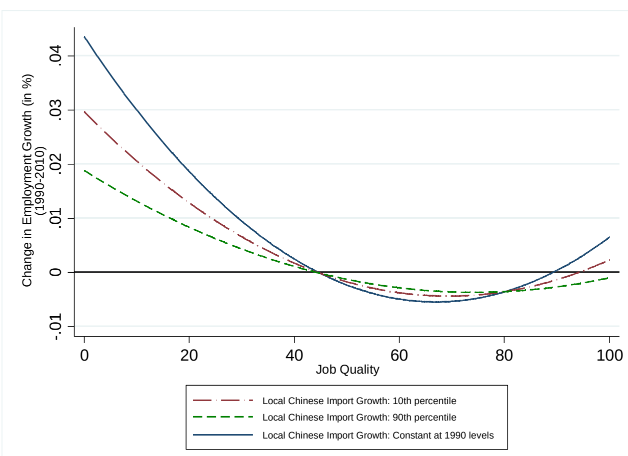
(D) Median Wage (National, 1990)



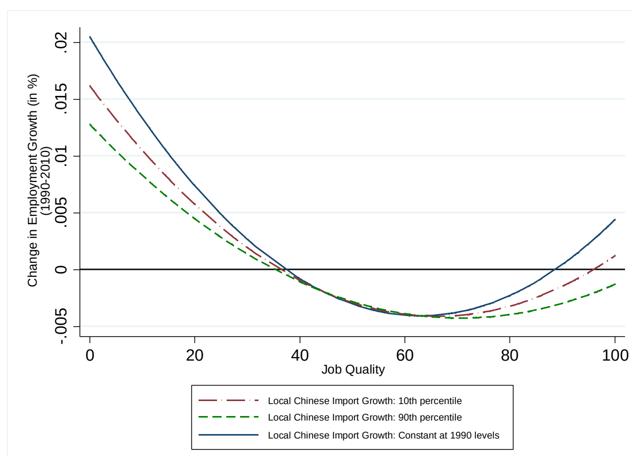
(B) NPB Index (Regional, 1990)



(E) Median Wage (Regional, 1990)



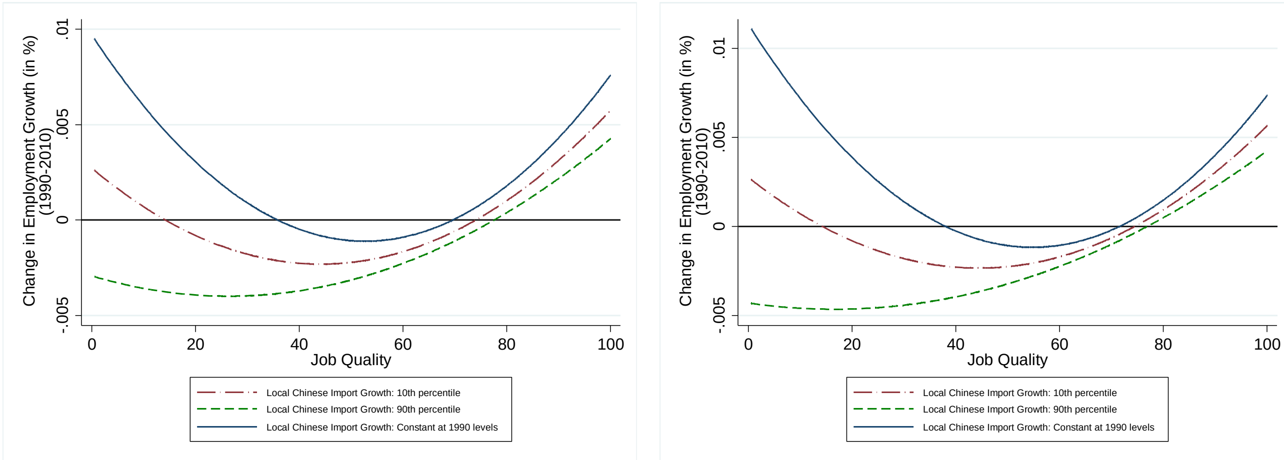
(C) NPB Index (National, 2010)



(F) Median Wage (National, 2010)

Figure 7. Impacts of Local Chinese Import Penetration on Changes in Local Employment Shares, 1990-2010: Alternative Measures of Job Quality.

Notes: Panel (A) is obtained using the results from Column (1) in Table 4; this is identical to Figure 5 but repeated for ease of comparison. Panels (B)-(F) are obtained using the results from Columns (3)-(7) in Table 4. Job quality is measured as the NPB index (multiplied by 100). See text for further details.



(A) Intermediate Inputs **(B) Non-Intermediate Inputs**

Figure 8. Impacts of Local Chinese Import Penetration on Changes in Local Employment Shares, 1990-2010: Heterogeneous Effects by Import Type.

Notes: Panel (A) is obtained using the results from Column (2) in Table 5. Panel (B) is obtained using the results from Column (3) in Table 5. Job quality is measured as the NPB index (multiplied by 100). See text for further details.

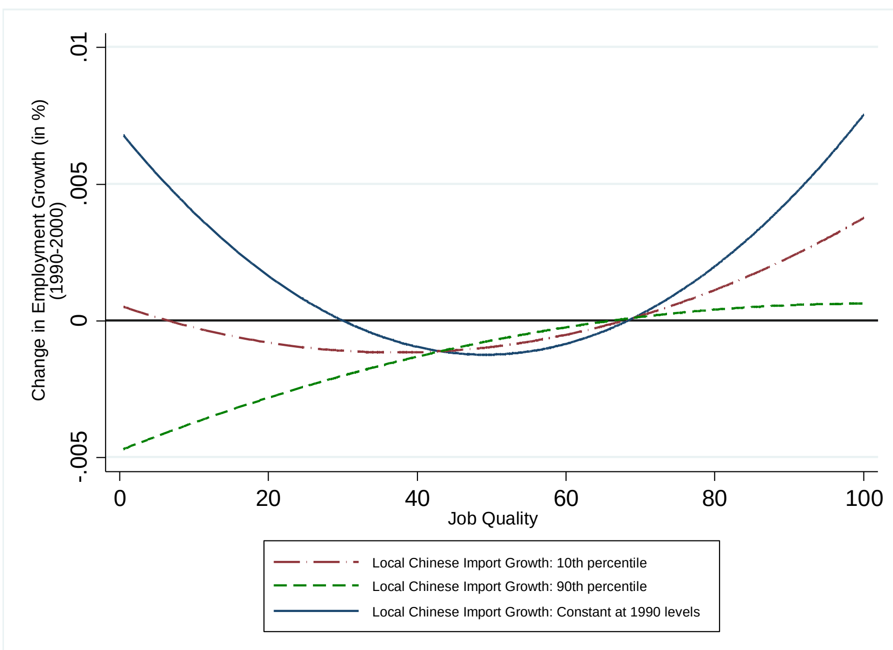
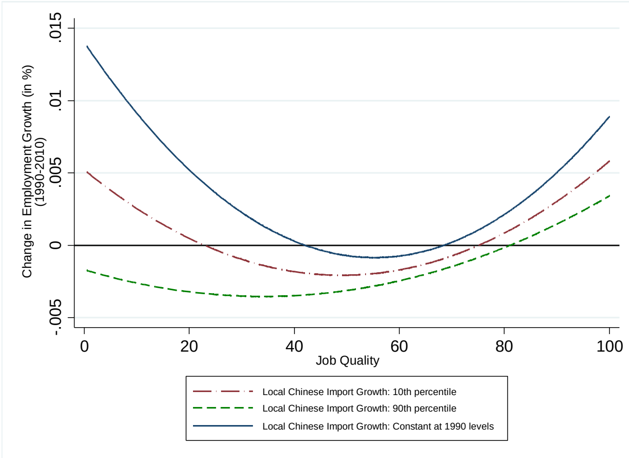
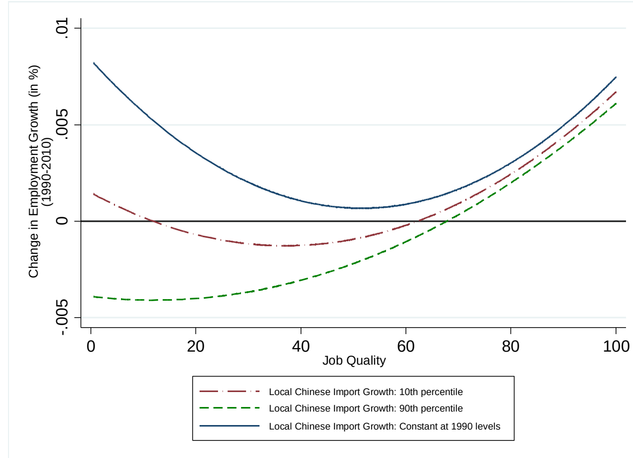


Figure 9. Impacts of Local Chinese Import Penetration on Changes in Local Employment Shares, 1990-2000.

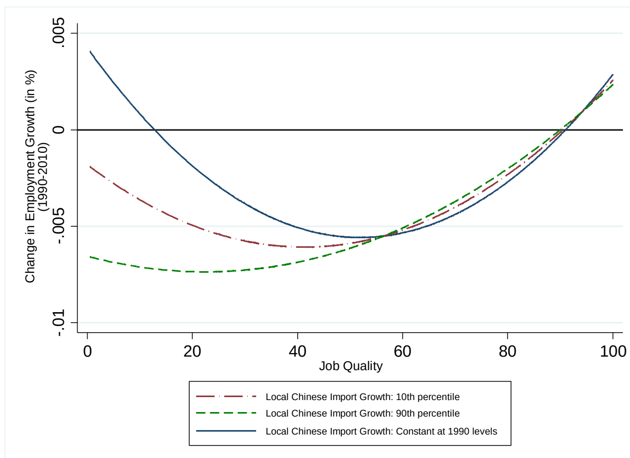
Notes: Figure is obtained using the results from Column (4) in Table 5. Job quality is measured as the NPB index (multiplied by 100). See text for further details.



(A) Workers Aged 25-44



(B) Workers Aged 45-64



(C) Within Cohort

Figure 10. Impacts of Local Chinese Import Penetration on Changes in Local Employment Shares, 1990-2010: Heterogeneous Effects by Worker Age.
Notes: Panel (A)-(C) are obtained using the results from Columns (5)-(7) in Table 5. Job quality is measured as the NPB index (multiplied by 100). See text for further details.

Table 1. Determinants of Changes in National Job Shares.

	OLS				IV		
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Job Quality	-1.734	-1.598	-0.800	1.414 #	-1.828	-0.965	1.291
	(1.217)	(1.497)	(1.489)	(0.790)	(1.699)	(1.646)	(0.812)
(Job Quality)^2	1.593	1.443	0.809	-1.127 #	1.624	0.937	-1.038 #
	(1.050)	(1.307)	(1.342)	(0.601)	(1.483)	(1.480)	(0.629)
Δ Occupation-Specific Chinese Import Penetration		-0.202	-0.342	0.208	-3.039	-3.214	-2.575
		(3.100)	(3.010)	(2.471)	(4.869)	(4.791)	(3.619)
Δ Occ.-Specific Chinese Import Pen. X Job Quality		-6.962	-6.404	-8.469	4.474	5.179	2.965
		(14.788)	(14.504)	(10.546)	(23.868)	(23.600)	(16.970)
Δ Occ.-Specific Chinese Import Pen. X (Job Quality)^2		6.453	6.118	9.372	-2.236	-2.667	0.760
		(12.884)	(12.734)	(8.948)	(20.502)	(20.330)	(14.301)
Δ Occupation-Specific RTBC			0.067	0.203 #		0.072	0.210 #
			(0.060)	(0.121)		(0.064)	(0.125)
Δ Occupation-Specific RTBC X Job Quality			-0.251	-0.766 #		-0.272	-0.793 #
			(0.177)	(0.403)		(0.194)	(0.422)
Δ Occupation-Specific RTBC X (Job Quality)^2			0.200	0.625 ^		0.217	0.648 ^
			(0.132)	(0.308)		(0.145)	(0.323)
Industry FEs	N	N	N	Y	N	N	Y
N	2679	2679	2679	2679	2679	2679	2679
Joint Significance: China variables		p = 0.01	p = 0.01	p = 0.03	p = 0.00	p = 0.00	p = 0.00
Underid p-value					p = 0.09	p = 0.09	p = 0.00
Rk F-statistic					p = 50.43	p = 50.25	p = 114.55
Endogeneity p-value					p = 0.10	p = 0.10	p = 0.09

Notes: Dependent variable is the change in employment to working age population ratio in a particular job from 1990-2010, where the shares in 1990 and 2010 are based on non-institutionalized individuals aged 25-64, who are not self-employed, in school, or in the military. RTBC = Routine Task Biased Change. Instrument for Δ Local Chinese Import Penetration (and its interactions with job quality) is Δ Local Chinese Import Penetration to Other Highly Developed Countries (and its interactions with job quality). For definitions of variables and list of other covariates not reported, see main text and Table A1 in the Supplemental Appendix. Regressions are weighted by employment in 1990. Standard errors clustered by occupation in parentheses. # $p < 0.10$, ^ $p < 0.05$, and * $p < 0.01$.

Table 2. Determinants of Changes in Local Job Shares.

	OLS					IV			
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Job Quality	-0.040 *	-0.088 *	-0.088 *	0.036 *	0.058 *	-0.091 *	-0.091 *	0.021 ^	0.042 *
	(0.002)	(0.007)	(0.007)	(0.009)	(0.009)	(0.008)	(0.008)	(0.010)	(0.010)
(Job Quality)^2	0.043 *	0.077 *	0.077 *	-0.025 *	-0.045 *	0.082 *	0.082 *	-0.008	-0.029 *
	(0.002)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)
Δ Local Chinese Import Penetration		-0.662 *	-0.701 *	-0.324 *	-0.320 *	-0.668 *	-0.729 *	-0.428 *	-0.422 *
		(0.076)	(0.076)	(0.065)	(0.064)	(0.078)	(0.079)	(0.070)	(0.070)
Δ Local Chinese Import Pen. X Job Quality		2.083 *	2.083 *	0.624 *	0.624 *	2.246 *	2.246 *	1.102 *	1.102 *
		(0.274)	(0.274)	(0.226)	(0.226)	(0.322)	(0.322)	(0.260)	(0.260)
Δ Local Chinese Import Pen. X (Job Quality)^2		-1.465 *	-1.465 *	-0.272	-0.272	-1.701 *	-1.701 *	-0.781 *	-0.781 *
		(0.238)	(0.238)	(0.197)	(0.197)	(0.300)	(0.300)	(0.242)	(0.242)
Δ Local RTBC				0.031 *	0.030 *			0.030 *	0.029 *
				(0.002)	(0.002)			(0.002)	(0.002)
Δ Local RTBC X Job Quality				-0.118 *	-0.118 *			-0.112 *	-0.112 *
				(0.008)	(0.008)			(0.009)	(0.009)
Δ Local RTBC X (Job Quality)^2				0.097 *	0.097 *			0.090 *	0.090 *
				(0.007)	(0.007)			(0.008)	(0.008)
Baseline Covariates	N	N	Y	Y	Y	N	Y	Y	Y
Change in Covariates	N	N	Y	Y	Y	N	Y	Y	Y
Industry FEs	N	N	N	N	Y	N	N	N	Y
Occupation FEs	N	N	N	N	Y	N	N	N	Y
State FEs	N	N	N	N	Y	N	N	N	Y
N	1985139	1985139	1985139	1985139	1985139	1985139	1985139	1985139	1985139
Joint Significance: China variables		p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00
Underid p-value						p = 0.00	p = 0.00	p = 0.00	p = 0.00
Rk F-statistic						326.968	218.483	210.765	166.892
Endogeneity p-value						p = 0.14	p = 0.00	p = 0.00	p = 0.00

Notes: Dependent variable is the change in employment to working age population ratio in a particular job and Commuting Zone from 1990-2010, where the shares in 1990 and 2010 are based on non-institutionalized individuals aged 25-64, who are not self-employed, in school, or in the military. RTBC = Routine Task Biased Change. Instrument for Δ Local Chinese Import Penetration (and its interactions with job quality) is Δ Local Chinese Import Penetration to Other Highly Developed Countries (and its interactions with job quality). For definitions of variables and list of other covariates not reported, see main text and Table A1 in the Supplemental Appendix. Regressions are weighted by Commuting Zone population in 1990. Standard errors clustered by Commuting Zone in parentheses. # $p < 0.10$, ^ $p < 0.05$, and * $p < 0.01$.

Table 3. Determinants of Changes in Local Job Shares: Expanded Model.

Variable	(1)	(2)
Job Quality	0.042 *	0.055 *
	(0.010)	(0.011)
(Job Quality)^2	-0.029 *	-0.032 *
	(0.009)	(0.010)
Δ Chinese Import Penetration (Local)	-0.422 *	-0.422 *
	(0.070)	(0.070)
Δ Chinese Import Pen. (Local) X Job Quality	1.102 *	1.102 *
	(0.260)	(0.260)
Δ Chinese Import Pen. (Local) X (Job Quality)^2	-0.781 *	-0.781 *
	(0.242)	(0.242)
Δ Chinese Import Pen. (Occ) X Job Quality		-0.129 *
		(0.027)
Δ Chinese Import Pen. (Occ) X (Job Quality)^2		0.050 #
		(0.026)
Δ RTBC (Local)	0.029 *	0.029 *
	(0.002)	(0.002)
Δ RTBC (Local) X Job Quality	-0.112 *	-0.112 *
	(0.009)	(0.009)
Δ RTBC (Local) X (Job Quality)^2	0.090 *	0.090 *
	(0.008)	(0.008)
Δ RTBC (Occ) X Job Quality		-0.001
		(0.001)
Δ RTBC (Occ) X (Job Quality)^2		-0.001
		(0.001)
N	1985139	1985139
Joint Significance: China variables	p = 0.00	p = 0.00
Underid p-value	p = 0.00	p = 0.00
Rk F-statistic	166.892	
Endogeneity p-value	p = 0.00	p = 0.00

Notes: Dependent variable is the change in employment to working age population ratio in a particular job and Commuting Zone from 1990-2010, where the shares in 1990 and 2010 are based on non-institutionalized individuals aged 25-64, who are not self-employed, in school, or in the military. 'Local' effects refer to variables measured at the local (Commuting Zone) level aggregated across all occupations. 'Occ' effects refer to occupation-specific variables measured at the national level. All specifications include baseline covariates, change in covariates, industry fixed effects, occupation fixed effects, and state fixed effects. Due to inclusion of occupation fixed effects, the 'Occ' effects of RTBC and Chinese Import Penetration (uninteracted with job quality) are not identified. RTBC = Routine Task Biased Change. For definitions of variables and list of other covariates not reported, see main text and Table A1 in the Appendix. Regressions are weighted by Commuting Zone population in 1990. Standard errors clustered by Commuting Zone in parentheses. # $p < 0.10$, ^ $p < 0.05$, and * $p < 0.01$.

Table 4. Determinants of Changes in Local Job Shares: Alternative Specifications.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Job Quality	0.042 *	0.047 *	0.018 #	-0.042 *	0.060 *	0.043 *	-0.015 #
	(0.010)	(0.009)	(0.009)	(0.014)	(0.009)	(0.008)	(0.008)
(Job Quality)^2	-0.029 *	-0.029 *	-0.014 #	0.021 #	-0.045 *	-0.035 *	0.007
	(0.009)	(0.008)	(0.008)	(0.012)	(0.009)	(0.007)	(0.009)
Δ Local Chinese Import Penetration	-0.422 *	-0.432 *	-0.556 *	-0.739 *	-0.160 *	-0.211 *	-0.231 *
	(0.070)	(0.066)	(0.062)	(0.099)	(0.046)	(0.040)	(0.052)
Δ Local Chinese Import Pen. X Job Quality	1.102 *	1.063 *	1.724 *	2.570 *	0.450 ^	0.684 *	0.889 *
	(0.260)	(0.256)	(0.230)	(0.400)	(0.194)	(0.176)	(0.234)
Δ Local Chinese Import Pen. X (Job Quality)^2	-0.781 *	-0.806 *	-1.305 *	-2.055 *	-0.459 ^	-0.622 *	-0.828 *
	(0.242)	(0.246)	(0.220)	(0.381)	(0.200)	(0.184)	(0.263)
Δ Local RTBC	0.029 *	0.029 *	0.020 *	0.033 *	0.021 *	0.014 *	0.016 *
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Δ Local RTBC X Job Quality	-0.112 *	-0.103 *	-0.080 *	-0.137 *	-0.100 *	-0.075 *	-0.082 *
	(0.009)	(0.007)	(0.009)	(0.010)	(0.009)	(0.007)	(0.006)
Δ Local RTBC X (Job Quality)^2	0.090 *	0.077 *	0.067 *	0.116 *	0.086 *	0.066 *	0.072 *
	(0.008)	(0.007)	(0.008)	(0.010)	(0.009)	(0.007)	(0.007)
Specification Change (relative to baseline specification in (1))		Add lagged dependent variable	Quality Measure: Regional NPB	Quality Measure: 2010 NPB	Quality Measure: Median Wage	Quality Measure: Regional Median Wage	Quality Measure: 2010 Median Wage
N	1985139	1985139	1985139	1512381	1985139	1985139	1512381
Joint Signific.: China variables	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00
Underid p-value	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00
Rk F-statistic	166.892	166.891	166.522	166.884	166.892	166.459	166.884
Endogeneity p-value	p = 0.00	p = 0.00	p = 0.00	p = 0.02	p = 0.00	p = 0.01	p = 0.02

Notes: Dependent variable is the change in employment to working age population ratio in a particular job and Commuting Zone from 1990-2010, where the shares in 1990 and 2010 are based on non-institutionalized individuals aged 25-64, who are not self-employed, in school, or in the military. All specifications include baseline covariates, change in covariates, industry fixed effects, and state fixed effects. RTBC = Routine Task Biased Change. For definitions of variables and list of other covariates not reported, see main text and Table A1 in the Appendix. Regressions are weighted by Commuting Zone population in 1990. Standard errors clustered by Commuting Zone in parentheses. # p < 0.10, ^ p < 0.05, and * p < 0.01.

Table 5. Determinants of Changes in Local Job Shares: Heterogeneous Effects.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Job Quality	0.042 *	0.048 *	0.037 *	0.025 *	0.029 ^	0.066 *	0.022 ^
	(0.010)	(0.010)	(0.010)	(0.009)	(0.014)	(0.011)	(0.011)
(Job Quality)^2	-0.029 *	-0.032 *	-0.025 *	-0.013	-0.022 #	-0.052 *	0.010
	(0.009)	(0.008)	(0.009)	(0.009)	(0.012)	(0.009)	(0.011)
Δ Local Chinese Import Penetration	-0.422 *	-0.315 *	-0.458 *	-1.113 *	-0.471 *	-0.367 *	-0.324 *
	(0.070)	(0.054)	(0.064)	(0.175)	(0.096)	(0.075)	(0.068)
Δ Local Chinese Import Pen. X Job Quality	1.102 *	0.823 *	1.214 *	4.200 *	1.288 *	0.798 *	0.918 *
	(0.260)	(0.204)	(0.236)	(0.688)	(0.373)	(0.233)	(0.238)
Δ Local Chinese Import Pen. X (Job Quality)^2	-0.781 *	-0.591 *	-0.848 *	-3.745 *	-0.981 *	-0.472 ^	-0.610 *
	(0.242)	(0.190)	(0.219)	(0.649)	(0.355)	(0.194)	(0.222)
Δ Local RTBC	0.029 *	0.031 *	0.028 *	0.019 *	0.027 *	0.030 *	0.032 *
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Δ Local RTBC X Job Quality	-0.112 *	-0.116 *	-0.108 *	-0.076 *	-0.109 *	-0.126 *	-0.079 *
	(0.009)	(0.008)	(0.009)	(0.007)	(0.011)	(0.009)	(0.010)
Δ Local RTBC X (Job Quality)^2	0.090 *	0.093 *	0.088 *	0.062 *	0.092 *	0.106 *	0.035 *
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.009)	(0.012)
Specification Change (relative to baseline specification in (1))		Intermediate Imports Only	Non-Intermediate Imports Only	1990-2000 Only	Workers Aged 25-44	Workers Aged 45-64	Within-Cohort
N	1985139	1985139	1985139	1985139	1985139	1985139	1985139
Joint Significance: China variables	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00
Underid p-value	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00
Rk F-statistic	166.892	218.401	184.069	54.769	166.892	166.892	166.892
Endogeneity p-value	p = 0.00	p = 0.01	p = 0.00	p = 0.00	p = 0.00	p = 0.00	p = 0.00

Notes: Dependent variable is the change in employment to working age population ratio in a particular job and Commuting Zone from 1990-2010, where the shares in 1990 and 2010 (except column 4 where the end period is 2000) are based on non-institutionalized individuals aged 25-64 (columns 1-4), who are not self-employed, in school, or in the military. Column 5 (Column 6) uses the change in employment shares for individuals aged 25-44 (45-64). Column 7 uses the change in employment shares for individuals aged 25-44 in 1990 and 45-64 in 2010. Columns 1, 4-7 compute import penetration using total imports. Column 2 (Column 3) computes import penetration using only intermediate (non-intermediate) imports. All specifications include baseline covariates, change in covariates, industry fixed effects, occupation fixed effects, and state fixed effects. RTBC = Routine Task Biased Change. For definitions of variables and list of other covariates not reported, see main text and Table A1 in the Appendix. Regressions are weighted by Commuting Zone population in 1990. Standard errors clustered by Commuting Zone in parentheses. # $p < 0.10$, ^ $p < 0.05$, and * $p < 0.01$.

Table A1. Summary Statistics

Variable	Mean	SD	Min	Max
Job Variables				
Δ Local Job Shares (x100)	-0.001	0.115	-7.284	3.854
Nam-Powers-Boyd Measure of Job Quality	0.568	0.236	0.005	1.000
Trade Variables				
Δ Local Chinese Import Penetration (x100)	0.026	0.006	0.013	0.051
Δ Local Foreign Chinese Import Penetration (x100)	0.027	0.007	0.013	0.053
Local Controls				
Local RBTC	0.518	0.201	0.000	1.002
Age (mean)	42.074	0.807	39.028	44.647
Born in US (%)	0.978	0.027	0.748	0.998
Homeownership (%)	0.752	0.048	0.546	0.875
Education				
High School or Equivalent (%)	0.357	0.056	0.190	0.531
Some College, No Degree (%)	0.198	0.041	0.101	0.324
Associate's Degree (%)	0.069	0.022	0.021	0.139
Bachelor's Degree (%)	0.115	0.035	0.035	0.238
Master's Degree (%)	0.037	0.012	0.016	0.105
Professional Degree (%)	0.012	0.004	0.003	0.040
Doctoral Degree (%)	0.005	0.004	0.001	0.037
Marital Status				
Separated/Divorced (%)	0.126	0.023	0.073	0.210
Widowed (%)	0.028	0.007	0.010	0.053
Never Married (%)	0.106	0.032	0.047	0.244
Race				
Black, Non-Hispanic (%)	0.065	0.103	0.000	0.541
Hispanic (%)	0.043	0.100	0.000	0.903
American Indian, Alaskan (%)	0.024	0.063	0.000	0.535
Asian, Pacific Islander (%)	0.007	0.039	0.000	0.628
Other, Non-Hispanic (%)	0.000	0.001	0.000	0.011
English				
Speaks English Well (%)	0.016	0.026	0.001	0.260
Speaks English Not Well or Not at All (%)	0.008	0.014	0.001	0.155
Speak Another Language and English (%)	0.073	0.100	0.009	0.853
Household Size				
2 (%)	0.284	0.030	0.146	0.371
3 (%)	0.210	0.024	0.147	0.282
4 (%)	0.212	0.016	0.152	0.253
5 (%)	0.103	0.016	0.062	0.178
6 (%)	0.036	0.013	0.012	0.111
7 (%)	0.014	0.009	0.003	0.072
8+ (%)	0.008	0.009	0.000	0.072
Own Children				
1 (%)	0.208	0.024	0.137	0.279
2 (%)	0.215	0.015	0.149	0.252
3 (%)	0.096	0.018	0.052	0.166
4 (%)	0.029	0.013	0.008	0.105
5+ (%)	0.013	0.012	0.003	0.125
Own Children Under Age 5				
1 (%)	0.113	0.010	0.086	0.150
2 (%)	0.033	0.008	0.014	0.067
3+ (%)	0.044	0.024	0.012	0.237

Notes: Unit of observation is a Commuting Zone-job cell. There are 741 Commuting Zones and 2679 jobs; 1,985,139 total observations. All variables are from 1990 unless denoting the change from 1990 to 2010. 1990 data are from the Census 5% sample. 2010 data are from the 1% American Community Survey.

Table A2. Job Quality by Industry and Occupation

	Job Shares			Employment Shares		
	Low Quality	**Middle Quality**	**High Quality**	**Low Quality**	**Middle Quality**	**High Quality**
Occupation Group:						
Managers, Professional, Technology, Finance, Public Safety	4.04%	21.63%	87.44%	0.56%	20.29%	92.15%
Clerical, Retail Sales	17.94%	16.70%	1.94%	30.48%	31.66%	5.80%
Low Skill Services	24.36%	6.94%	2.09%	46.26%	2.38%	0.43%
Production, Craft	9.57%	10.22%	2.54%	1.54%	6.02%	0.50%
Machine Operators, Assemblers	22.87%	13.05%	1.35%	9.16%	11.89%	0.01%
Transport, Construction, Mechanical, Mining, Farm	21.23%	31.47%	4.63%	12.00%	27.75%	1.10%
1-Digit NAICS Industry:						
Agriculture, Forestry, Fishing and Hunting	16.59%	9.84%	7.62%	4.32%	0.54%	0.20%
Mining/Oil/Gas, Utilities, Construction	6.13%	13.57%	15.40%	0.45%	12.82%	5.58%
Manufacturing	8.52%	14.32%	14.35%	9.03%	23.88%	16.30%
Wholesale/Retail Trade, Transportation & Warehousing	15.10%	12.98%	11.21%	23.27%	24.99%	7.14%
Professional & Business Services	11.96%	14.17%	13.15%	11.91%	18.01%	23.14%
Educational/Health Care/Social Assistance Services	13.60%	10.89%	15.84%	24.18%	8.35%	35.58%
Arts/Entertainment/Recreation, Accommodation/Food Services	16.14%	11.56%	7.47%	17.58%	2.85%	0.22%
Other Services, Public Administration	11.96%	12.68%	14.95%	9.26%	8.58%	11.84%

Notes: Low quality, middle quality, and high quality jobs correspond to the bottom 25%, the middle 50% and the top 25%, respectively, of jobs according to the 1990 Nam-Powers-Boyd Index. See main text for further details.

Table A3. Census Industries Facing Largest Changes in Chinese Import Penetration

Rank	Census Industry	Change
1	Toys, amusement, and sporting goods	0.7815
2	Computers and related equipment	0.7411
3	Leather products, except footwear	0.7160
4	Radio, TV, and communication equipment	0.6116
5	Footwear, except rubber and plastic	0.5580
6	Furniture and fixtures	0.5485
7	Household appliances	0.3034
8	Other rubber products, and plastics footwear and belting	0.2815
9	Pottery and related products	0.2777
10	Miscellaneous fabricated textile products	0.2676
11	Apparel and accessories, except knit	0.2623
12	Farm machinery and equipment	0.2552
13	Cutlery, handtools, and general hardware	0.1851
14	Miscellaneous manufacturing industries	0.1454
15	Office and accounting machines	0.1383
16	Tires and inner tubes	0.1345
17	Electrical machinery, equipment, and supplies, n.e.c.	0.1316
18	Machinery, except electrical, n.e.c.	0.1303
19	Miscellaneous fabricated metal products	0.1268
20	Glass and glass products	0.1123
	Mean across all 84 traded Census industries	0.1101

Notes: See main text for definition of Chinese import penetration.

Table A4. Occupations Facing Largest Changes in Chinese Import Penetration

Rank	Occupation	Change
1	Shoemaking machine operators	0.5417
2	Cabinetmakers and bench carpenters	0.2467
3	Textile sewing machine operators	0.2239
4	Furniture and wood finishers	0.2179
5	Shoe repairers	0.2023
6	Washing, cleaning, and pickling machine operators	0.1580
7	Solderers	0.1563
8	Wood lathe, routing, and planing machine operators	0.1561
9	Upholsterers	0.1547
10	Nail and tacking machine operators (woodworking)	0.1464
11	Other woodworking machine operators	0.1457
12	Other precision woodworkers	0.1319
13	Sawing machine operators and sawyers	0.1280
14	Assemblers of electrical equipment	0.1188
15	Electrical engineer	0.1175
16	Patternmakers and model makers	0.1171
17	Paper folding machine operators	0.1124
18	Shaping and joining machine operator (woodworking)	0.1123
19	Tailors	0.1108
20	Crushing and grinding machine operators	0.1106
	Mean across all 381 occupations	0.0293

Notes: See main text for definition of Chinese import penetration.

Table A5. Occupational Groups Facing Largest Changes in Chinese Import Penetration and Distribution Across Industries

	Change	1-Digit NAICS industry								
Occupation Group	**in IP**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**Total**
Managers, Professional, Technology, Finance, Public Safety	0.0173	0.35%	4.07%	11.46%	13.30%	23.37%	32.00%	3.13%	12.34%	100%
Clerical, Retail Sales	0.0136	0.41%	3.72%	10.83%	34.06%	25.66%	13.37%	2.75%	9.19%	100%
Low Skill Services	0.0029	0.47%	1.17%	3.76%	6.27%	12.00%	34.04%	28.93%	13.38%	100%
Production, Craft	0.0701	0.32%	9.17%	63.78%	13.67%	6.28%	2.83%	0.80%	3.15%	100%
Machine Operators, Assemblers	0.0873	0.49%	3.21%	76.33%	6.25%	8.89%	1.19%	0.30%	3.36%	100%
Transport, Construction, Mechanical, Mining, Farm	0.0232	5.52%	29.83%	17.92%	29.06%	7.06%	3.22%	1.08%	6.31%	100%

Industry Definitions:

1: Agriculture, Forestry, Fishing and Hunting
2: Mining/Oil/Gas, Utilities, Construction
3: Manufacturing
4: Wholesale/Retail Trade, Transportation & Warehousing
5: Professional & Business services
6: Educational/Health Care/Social Assistance Services
7: Arts/Entertainment/Recreation, Accommodation/Food Services
8: Other Services, Public Administration

Table A6. Commuting Zones (CZs) Facing Largest Changes in Local Chinese Import Penetration

Rank	PUMA	State	Change
1	25102	Missouri	0.0508
2	6301	Tennessee	0.0489
3	5201	Mississippi	0.0484
4	4601	Kentucky	0.0477
5	5402	Kentucky	0.0468
6	5000	Mississippi	0.0466
7	4602	Kentucky	0.0463
8	402	Virginia	0.0456
9	1002	North Carolina	0.0453
10	5100	Mississippi	0.0449
11	1100	North Carolina	0.0443
12	1301	South Carolina	0.0440
13	13103	Kentucky	0.0422
14	6402	Tennessee	0.0419
15	12902	Kentucky	0.0418
16	12702	Kentucky	0.0418
17	6302	Tennessee	0.0417
18	602	Virginia	0.0416
19	9500	Alabama	0.0416
20	2200	Virginia	0.0412
		Mean across all 741 CZs	0.0259

Notes: See main text for definition of Chinese import penetration.