Untangling Trade and Technology:
Evidence from Local Labor Markets[*]

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Abstract

We analyze the differential effects of trade and technology on employment patterns in U.S. local labor markets between 1990 and 2007. Labor markets whose initial industry composition expose them to rising import competition from China have experienced significant employment reductions particularly in the manufacturing sector. These employment losses are not limited to production jobs but also affect clerical and managerial occupations. Labor markets that are susceptible to computerization due to specialization in routine task-intensive activities have neither experienced an overall decline in employment, nor a differential change in manufacturing employment. However, the occupational structure of employment of these labor markets has polarized within each sector, as employment shifted from routine clerical and production occupations to more highly skilled managerial or professional occupations, as well as to lower skilled manual and service occupations. While the effect of trade competition is growing over time due to accelerating import growth, the effect of technology seems to have shifted from automation of production activities in the manufacturing sector towards computerization of information-processing tasks in the service sector.

1 Introduction

Many economists view trade and technology as two of the paramount forces shaping labor markets in the U.S. and other advanced countries. For example, a poll administered to forty economists at top U.S. academic institutions by the Chicago Booth School's Initiative on Global Markets in 2012 found that eighty-one percent either agreed or strongly agreed with the view that technological change is a leading cause of rising U.S. income inequality over the last three decades.[1] In the same year, an informal poll run by the *New York Times* found that academic economists view globalization as one of the leading causes for rising inequality and declining middle incomes in the U.S.[2] Despite the seemingly high degree of professional accord that trade and technology are both loosely responsible for the growth of inequality, there is little evidence distinguishing the precise role of each.

Absent countervailing evidence, it is natural to suspect that trade and technology play similar roles in shaping labor market developments in rich countries. The U.S. and many European countries have experienced growing income inequality and an increasing employment polarization (i.e., concentration of employment in the best and least paid occupations) over the past several decades.[3] The two most prominent potential causes for these "effects" are rapid technological change (e.g., the computer revolution) and growing international trade (e.g., the rise of China), and backward induction invites the inference that these forces are potentially jointly responsible for changing labor market dynamics. A second strand of reasoning that links trade and technology is an appeal to inevitability: whatever low skill work cannot presently be automated in rich countries, it appears, may soon be performed in the developing world. If so, trade and technology provide a unified explanation for many labor market developments—particularly the declining relative demand for less skilled labor. Finally, commencing with the influential work of Alan Blinder (2009), economists have posited that many of the job tasks that are potentially suitable for automation are also suitable for "offshoring."[4] This hypothesis again suggests that trade and technology may be viewed as a unified

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[1]The statement that participants were asked to evaluate was, "One of the leading reasons for rising U.S. income inequality over the past three decades is that technological change has affected workers with some skill sets differently than others." Detailed results are available at `http://www.igmchicago.org/igm-economic-experts-panel/poll-results?SurveyID=SV_0IAlhdDH2FoRDrm`.

[2]`http://economix.blogs.nytimes.com/2012/08/21/globalization-and-the-income-slowdown/`. In particular, Leonhardt writes, "In my exchanges with economists so far, globalization is certainly among the most commonly cited factors for the income slowdown. American workers today face vastly more competition from foreign workers—especially foreign workers who earn much less money than the typical American—compared with past decades."

[3]See, e.g., Autor, Katz and Kearney (2006, 2008), Dustmann, Ludsteck and Schoenberg (2009), and Goos, Manning and Salomons (2011).

[4]The reasoning here is that tasks that follow explicit codifiable procedures (what Autor, Levy and Murnane, 2003, call "routine" tasks) are both well suited to automation because they can be computerized and well suited to offshoring because they can be performed at a distance without substantial loss of quality. In reality, there are many tasks that are offshorable but not routine in the sense above (for example, interpreting medical x-rays) and there are many tasks that are codifiable but not clearly offshorable (e.g., adding vast arrays of numbers for actuarial analysis).

force impacting labor markets.

The objective of this paper is to explore the extent to which this unified viewpoint is supported by the data, specifically, whether the impacts of trade and technology on labor market outcomes are indeed largely comparable or, alternatively, are substantially distinct. Focusing on changes in employment, non-employment, and occupational composition within 722 consistently defined, fully inclusive Commuting Zones (CZs) that approximate local labor markets, we explore five descriptive questions on the causal effects of advancing automation and rising low-wage country imports on labor market outcomes. First, are the CZs that are most exposed to rising trade penetration also those most impacted by computerization, or are these sets disjoint? Second, do trade and technology have comparable effects on gross labor market aggregates such employment-to-population, unemployment and non-participation? Third, do trade and technology primarily affect the same demographic groups—males versus females, college versus non-college workers, and older versus young workers groups—or are different demographic groups more or less affected by each? Fourth, are the same broad sets of occupations or workplace tasks—abstract, routine, manual—displaced or augmented by both technology and trade? Finally, while the effects of international trade on domestic labor market will clearly be most concentrated in the manufacturing sector, is this also true for computerization, or are the sectoral effects of technology-induced labor demand shifts felt more broadly?

A critical input into our analysis is a set of credible measures of exposure to local labor markets' exposure to technological change and competition from international trade. On the technology front, we follow Autor and Dorn (forthcoming) who use Census data on industry and occupation mix by CZ and data from the Dictionary of Occupational Titles on job tasks by occupation (U.S. Department of Labor, 1977) to measure the degree to which CZs were historically specialized in routine, codifiable job activities that were intrinsically well-suited to computerization. As documented by Autor-Dorn, these markets differentially adopted workplace computing and simultaneously reduced employment in routine task-intensive occupations as the price of computing power fell precipitously over the last three decades.

On the trade front, we follow Autor, Dorn and Hanson (2012, ADH hereafter) in identifying trade shocks using cross-industry and cross-CZ variation in import competition stemming from China's rapidly rising productivity and falling internal barriers to trade. These forces have catapulted China's U.S. import penetration—that is, the ratio of Chinese imports to U.S. goods expenditure—from less than 0.2 percentage points in 1987 points to 4.8 percentage points in 2007. To isolate the components of this rise that are driven by shifts in China's competitive position rather than changes in U.S. demand, we exploit information on the contemporaneous composition and growth of Chinese exports

by industry to eight other developed countries. This identification strategy posits that growth in Chinese imports within a given industry (e.g., luggage, footwear) that occurs simultaneously in the U.S. and other high income countries is primarily driven by rising Chinese productivity and falling trade costs. We then project these industry-level import shocks to the level of local labor markets by interacting it with variation in CZ's industry mix in 1980, prior to the rise of China. Since manufacturers within an industry tend to be geographically clustered, China's rising penetration of specific industries results in sharp disparities in import exposure growth across local labor markets. As a case in point, the CZ containing Providence, Rhode Island, saw estimated increases in Chinese import exposure (that is, competing Chinese manufactures that would potentially be produced in Providence if not imported) of $2,500$ per worker between 1991 and 2000, and an additional $5,140$ per worker between 2000 and 2007. In contrast, the CZ containing New Orleans, Louisiana, saw comparatively small increase of \$210 and \$540 per worker during these same intervals.

Our paper builds on two broad and active literatures, the first exploring the impact of trade and technical change on skill demands, the second studying how these forces shape labor market outcomes at the sub-national (i.e., local labor market) level.[5] This paper contributes to this literature along two dimensions. A first is that our empirical approach exploits robust measures of exposure to trade and technology and considers their distinct impacts. This is in contrast to existing literature that almost universally focuses on either trade or technology as candidate explanatory variables but rarely places the two on equivalent empirical footing.[6] A second contribution of the paper is to examine a rich set of adjustment margins that help to illuminate how the effects of trade and technology may compare and contrast. These adjustment margins include changes in employment, unemployment and non-participation, and shifts in employment across broad occupational categories that differ in their intensity of abstract, routine and manual task input. In addition, we consider these outcomes separately by demographic groups comprised by gender, education and age, and by sector (manufacturing, non-manufacturing). In conjunction, we believe these analyses provide valuable evidence on whether trade and technology should be viewed as a monolithic force shaping rich country (or, more specifically, U.S.) labor markets, or if not, how their differences can be characterized and interpreted.

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[5]See the literature cited in Autor and Dorn (forthcoming) and Autor, Dorn and Hanson (2012).

[6]A number of papers consider the roles of both computerization and potential offshoring simultaneously (e.g., Autor and Dorn, forthcoming; Goos, Manning and Salomons, 2012; Firpo, Fortin and Lemieux, 2012; Oldenski, 2012; Michaels, Natraj and Van Reenen, forthcoming. We are not aware of any comparable effort to simultaneously consider the effects of computerization and competition from international trade in goods on labor market outcomes.

2 Measurement

2.1 Local labor markets

Our analysis requires a time-consistent definition of regional economies in the U.S. Our concept for local labor markets is Commuting Zones (CZs) developed by Tolbert and Sizer (1996), who used county-level commuting data from the 1990 Census data to create 741 clusters of counties that are characterized by strong commuting ties within CZs, and weak commuting ties across CZs. Our analysis includes the 722 CZs that cover the entire mainland United States (both metropolitan and rural areas). Commuting zones are particularly suitable for our analysis of local labor markets because they cover the entire U.S., are based primarily on economic geography rather than incidental factors such as minimum population, and can be consistently constructed using Census Public Use Micro Areas (PUMAs) for the full period of our analysis.[7]

2.2 Exposure to computerization

Following an extensive literature, we conceive of recent automation as taking the form of an ongoing decline in the cost of computerizing routine tasks, such as bookkeeping, clerical work, and repetitive production and monitoring activities, thereby potentially displacing the workers performing these tasks.

To measure the degree to which CZs were historically specialized in routine, codifiable job activities that were intrinsically well-suited to computerization, we proceed in two steps. Using data from the Dictionary of Occupational Titles (1977), we create a summary measure of the routine task-intensity RTI of each occupation, calculated as:

$$RTI_k = \ln\left(T^R_{k,1980}\right) - \ln\left(T^M_{k,1980}\right) - \ln\left(T^A_{k,1980}\right), \tag{1}$$

where T^R_k, T^M_k and T^M_k are, respectively, the routine, manual and abstract task inputs in each occupation k in 1980.[8] This measure is rising in the importance of routine tasks in each occupation and declining in the importance of manual and abstract tasks.

To measure cross-market variation in employment in routine-intensive occupations, we apply

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[7]Our analysis draws on Public Use Microdata from Ruggles et al. (2004). If a PUMA overlaps with several counties, our procedure is to match PUMAs to counties assuming that all residents of a PUMA have equal probability of living in a given county. The aggregation of counties to CZs then allows computing probabilities that a resident of a given PUMA falls into a specific CZ. Further details on our construction of CZs are given in Dorn (2009). Autor and Dorn (2009 and forthcoming) and Autor, Dorn and Hanson (2012) also use Commuting Zones as a local labor market construct.

[8]Tasks are measured on a zero to ten scale. For the five percent of microdata observations with the lowest manual task score, we use the manual score of the 5th percentile. A corresponding adjustment is made for abstract scores.

a simple binary approach to distinguish 'routine' and 'non-routine' occupations. We classify as routine occupations those that fall in the top-third of the employment-weighted distribution of the RTI measure in 1980. Using this classification, we then assign to each commuting zone j a routine employment share measure (RSH_{jt}) equal to the fraction of CZ employment at the start of a decade that falls in routine task-intensive occupations:

$$RSH_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \cdot 1\left[RTI_k > RTI^{P66}\right] \right) \left(\sum_{k=1}^{K} L_{jkt} \right)^{-1}. \tag{2}$$

Here, L_{jkt} is the employment in occupation k in commuting zone j at time t, and $1\left[\cdot\right]$ is the indicator function, which takes the value of one if the occupation is routine-intensive by our definition. By construction, the mean of this measure is 0.33 in 1980, and the population weighted 80/20 percentile range is 7 percentage points ($RSH^{P20} = 0.294$ and $RSH^{P80} = 0.365$).

To pin down the variation in RSH_{jt} that stems from stable differences in production structure across CZ's, we exploit historical cross-CZ differences in industry specialization as instruments for the observed level in each decade. This approach potentially isolates the long-run, quasi-fixed component of the routine occupation share that is determined prior to the onset of the era of rapid computerization.

Our instrumental variables approach is as follows: let $E_{ij,1950}$ equal the employment share of industry $i \in 1, ..., I$ in commuting zone j in 1950, and let $R_{i,-j,1950}$ equal the routine occupation share among workers in industry i in 1950 in all U.S. states *except* the state that includes commuting zone j.[9] The product of these two measures provides a predicted value for the routine employment share in each commuting zone, which depends only on the local industry mix in 1950 and the occupational structure of industries *nationally* in 1950:

$$\widetilde{RSH}_j = \sum_{i=1}^{I} E_{i,j,1950} \times R_{i,-j,1950}. \tag{3}$$

This measure is a logical instrumental variable for RSH: because it is determined three decades prior to 1980, we expect it to be correlated with the long-run component of the routine occupation share but uncorrelated with contemporaneous innovations to this share.[10]

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[9]Following Autor and Duggan (2003), we exclude own state employment from the construction of our instrument for local labor market conditions to remove any mechanical correlation between the instrument and the endogenous variable. Throughout the analysis, we implicitly consider commuting zones to be part of the state that contains the largest share of their population.

[10]Appendix Table 3 of Autor and Dorn (forthcoming) presents first-stage estimates for this instrumental variables model. The predictive relationship between $\widetilde{RSH}$ and RSH is sizable and highly significant, with t-ratios of six or above in each decade. The first stage coefficient is close to unity in 1950, and takes smaller values in successive periods, obtaining a coefficient of 0.27 in 2000. The decrease in magnitude is to be expected since initial conditions become less determinative over time.

2.3 Exposure to international trade

The rapid growth in U.S. imports from low-income countries since the early 1990s is driven by China's transition to a market-oriented economy, which has involved rural-to-urban migration of over 150 million workers (Chen, Jin, and Yue, 2010), Chinese industries gaining access to long banned foreign technologies, capital goods, and intermediate inputs (Hsieh and Klenow, 2009), and multinational enterprises being permitted to operate in the country (Naughton, 2007).[11] Compounding the positive effects of internal reforms on China's trade is the country's accession to the WTO, which gives it most-favored nation status among the 153 WTO members (Branstetter and Lardy, 2006). In light of the internal and global external factors driving China's exports, we instrument for the growth in U.S. imports from China using Chinese import growth in other high-income markets.[12] This approach requires that import demand shocks in high-income countries are not the primary cause of China's export surge.

Because trade shocks play out in general equilibrium, one needs empirically to map many industry-specific shocks into a small number of aggregate outcomes. For national labor markets at annual frequencies, one is left with few observations and many confounding factors. By taking regional economies as the unit of analysis, we circumvent the degrees-of-freedom problem endemic to estimating the labor-market consequences of trade.

Following the empirical specification derived by ADH, our main measure of local-labor-market exposure to import competition is the change in Chinese import exposure per worker in a region, where imports are apportioned to the region according to its share of national industry employment:

$$\Delta IPW_{uit} = \sum_j \frac{L_{ijt}}{L_{ujt}} \frac{\Delta M_{ucjt}}{L_{it}}. \tag{4}$$

In this expression, L_{it} is the start of period employment (year t) in region i and ΔM_{ucjt} is the observed change in U.S. imports from China in industry j between the start and end of the period.

Equation (4) makes clear that the difference in ΔIPW_{uit} across local labor markets stems entirely from variation in local industry employment structure at the start of period t. This variation arises from two sources: differential concentration of employment in manufacturing versus non-

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[11]While China dominates low-income country exports to the U.S., trade with middle-income nations, such as Mexico, may also matter for U.S. labor-market outcomes. The North American Free Trade Agreement (1994) and the Central American Free Trade Agreement (2005) each lowered U.S. barriers to imports. However, whereas China's export growth appears driven by internal conditions and global changes in trade policy toward the country, export growth in Mexico and Central America appears more related to import demand associated with U.S. outsourcing to the region. Consequently, it is more difficult to find exogenous variation in U.S. imports from Mexico and Central America. In recent work, McLaren and Hakobyan (2010) do not detect substantial effects of NAFTA on local U.S. labor markets, though they do find effects on wage growth nationally in exposed industries.

[12]Our identification strategy is related to that used by Bloom, Draca, and Van Reenen (2009), who consider the relationship between imports from China and innovation in Europe.

manufacturing activities and specialization in import-intensive industries within local manufacturing. Differences in manufacturing employment shares are not the primary source of variation, however; in a bivariate regression, the start-of-period manufacturing employment share explains less than 25% of the variation in ΔIPW_{uit}. In our main specifications, we control for the start-of-period manufacturing share within CZs so as to focus on variation in exposure to Chinese imports stemming from differences in industry mix within local manufacturing sectors.

A concern for our subsequent estimation is that realized U.S. imports from China in (4) may be correlated with industry import demand shocks, in which case the OLS estimate of how increased imports from China affect U.S. manufacturing employment may understate the true impact, as both U.S. employment and imports may be positively correlated with unobserved shocks to U.S. product demand. To identify the causal effect of rising Chinese import exposure on U.S. manufacturing employment and other local labor-market outcomes, we employ an instrumental-variables strategy that accounts for the potential endogeneity of U.S. trade exposure. We exploit the fact that during our sample period, much of the growth in Chinese imports stems from the rising competitiveness of Chinese manufacturers (a supply shock from the U.S. producer perspective) and China's lowering of trade barriers, dismantling of central planning, and accession to the WTO.

To identify the supply-driven component of Chinese imports, we instrument for growth in Chinese imports to the U.S. using the contemporaneous composition and growth of Chinese imports in eight other developed countries.[13] Specifically, we instrument the measured import exposure variable ΔIPW_{uit} with a *non*-U.S. exposure variable ΔIPW_{oit} that is constructed using data on contemporaneous industry-level growth of Chinese exports to other high-income markets:

$$\Delta IPW_{oit} = \sum_j \frac{L_{ijt-1}}{L_{ujt-1}} \cdot \frac{\Delta M_{ocjt}}{L_{it-1}}. \tag{5}$$

This expression for *non*-U.S. exposure to Chinese imports differs from the expression in equation (4) in two respects. First, in place of realized U.S. imports by industry (ΔM_{ucjt}), it uses realized imports from China to other high-income markets (ΔM_{ocjt}). Second, in place of start-of-period employment levels by industry and region, this expression uses employment levels from the *prior* decade. We use 10-year-lagged employment levels because, to the degree that contemporaneous employment by region is affected by anticipated China trade, the use of lagged employment to apportion predicted Chinese imports to regions will mitigate this simultaneity bias.[14]

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[13]The eight other high-income countries are those that have comparable trade data covering the full sample period: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

[14]Autor, Dorn and Hanson (2012) provide an extensive discussion of possible threats to the validity of this approach, as well as a large set of robustness tests and complementary identification exercises.

3 Results

We now present evidence on the causal effects of advancing automation and rising low-wage country imports on local labor market outcomes, focusing on the five questions posed in the introduction.

3.1 The geography of trade and technology exposure

Are the CZs that are most exposed to rising trade penetration also those most impacted by computerization? To explore this question, Figures 1a to 1c illustrate the geography of trade and technology exposure at the Commuting Zone level. Each panel of the figure presents a map of the 48 contiguous U.S. states with all 722 CZ boundaries outlined in gray. In Figure 1a, the interior of each CZ is shaded to indicate its quartile rank within the distribution of CZs in the fraction of worker that were employed in routine task-intensive occupations in 1990.[15] Darker colors correspond to higher quartiles of RSH, with the lightest color denoting CZs in the lowest quartile and the darkest color denoting CZs in the fourth quartile.

Evident from this figure is that the CZs with the highest employment shares in routine task-intensive occupations constitute a mixture of manufacturing-intensive locations (e.g., manufacturing locations around the Great Lakes and in the Southeast) and human-capital intensive population centers such as New York, Boston, San Francisco, and Dallas. This pattern reflects the dual sources of routine task-intensive occupations: blue-collar production occupations associated with capital intensive manufacturing; and white-collar office, clerical and administrative support occupations associated with banking, insurance, finance and other information-intensive sectors.

Figure 1a

Routine Share by Commuting Zone, 1990-2007

☐ Lowest Quartile (least routine)
☐ 2nd Quartile
☐ 3rd Quartile
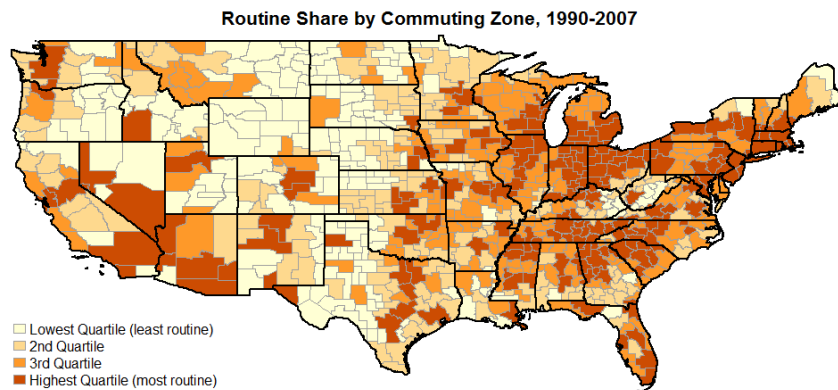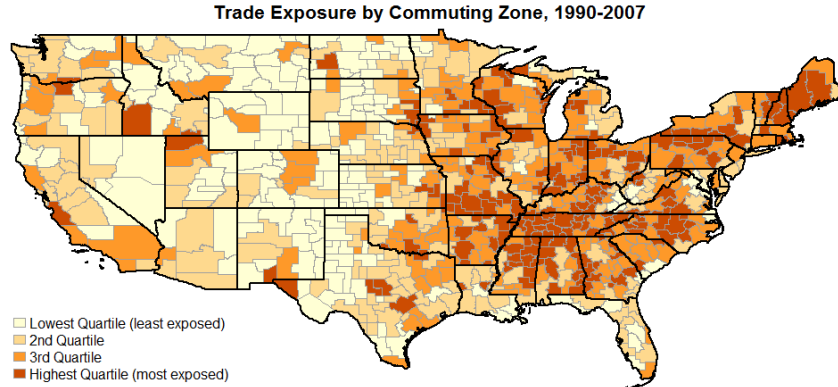■ Highest Quartile (most routine)

Figure 1b presents analogous information for exposure to import competition from China. In this panel, the lightest shading indicates CZs in the lowest quartile of trade exposure increase be-

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[15]Rankings are unweighted, and hence each quartile contains roughly one-fourth of the 722 total CZs.

tween 1990 and 2007 (measured as the change in real dollars of imports per worker) and the darkest color indicates CZs that are in the highest quartile of trade exposure increase. As expected, many manufacturing-intensive regions appear among the most trade-exposed CZs, including the substantial parts of the Northeast and South Central U.S., where labor-intensive goods manufacturing, such as furniture, rubber products, toys, apparel, footwear and leather goods, is concentrated.

Figure 1b

Trade Exposure by Commuting Zone, 1990-2007

☐ Lowest Quartile (least exposed)
☐ 2nd Quartile
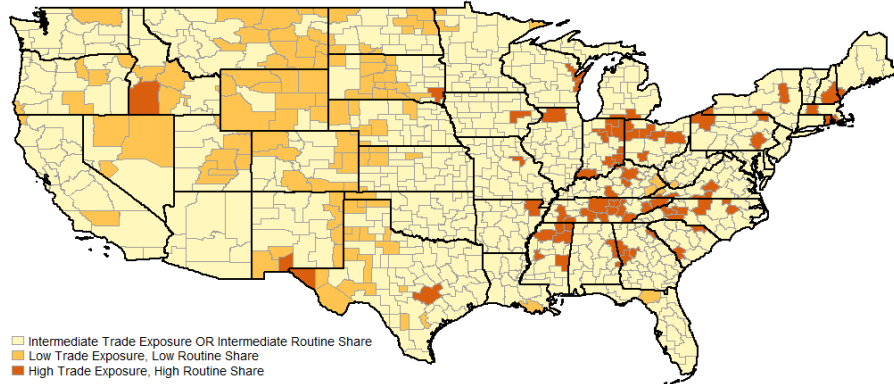■ 3rd Quartile
■ Highest Quartile (most exposed)

A comparison of the first two panels of Figure 1 indicates both clear overlaps and pronounced differences among the sets of CZs with high trade exposure and those with high technology exposure. Most notable, however, is that the geography of trade exposure is highly concentrated. A substantial fraction of the top quartile of trade-exposed CZs are located in a small number of states, including Tennessee, Missouri, Indiana, Alabama, North Carolina, Pennsylvania, New York, Rhode Island, New Hampshire and Maine. By contrast, routine task-intensive CZs are more dispersed throughout the U.S.

Figure 1c facilitates a direct comparison of exposure to technology and trade by dividing CZs into three groups: those in the highest quartile of both trade and technology exposure; those in the lowest quartile of both trade and technology exposure; and the remainder. If trade and technology exposure were perfectly positively correlated across locations, one-fourth of CZs would be found in each of the first two groups. If instead they were uncorrelated, roughly six percent (one-sixteenth) of CZs would be in the high-high and low-low groups, with remaining seven-ninths in the remaining category. In reality, nine percent of CZs are in the top quartile of both trade and technology exposure and 14 percent are in the bottom quartile of both trade and technology exposure. A simple population-weighted correlation between the trade and technology exposure variables finds that there is almost no relationship between the two: the correlation is -0.02 for the 1990 to 2000 period and 0.01 for the 2000 to 2007 period.[16]

[16]The unweighted correlations are 0.21 and 0.31 in 1990 and 2000 respectively. The difference between the weighted

Thus, a summary answer to our first empirical question regarding the geography of trade and technology exposure is that the sets of heavily trade-exposed CZs and of heavily technology-exposed CZs are largely disjoint. This feature of the data facilitates the identification of separate effects of trade and technology on local labor markets.

Figure 1c. The Joint Geographic Distribution of Trade and Technology Exposure

Intermediate Trade Exposure OR Intermediate Routine Share
Low Trade Exposure, Low Routine Share
High Trade Exposure, High Routine Share

3.2 Comparing the impacts of trade and technology on employment, unemployment and non-participation

We now turn to the main estimates comparing and contrasting the impacts of trade and technology on local labor markets. We focus initially on employment, unemployment and labor force participation using an estimating equation of the form:

$$\Delta Y_{ikt} = \gamma_t + \beta_1 \Delta IPW_{it} + \beta_2 RSH_{it} + X'_{it}\beta_2 + \delta_k + e_{ikt}. \tag{6}$$

Here, the dependent variable ΔY_{ikt} is the decadal change in the employment to population ratio, unemployment to population ratio, or non-participation rate among working age adults ages 16 to 64 in commuting zone i in U.S. Census division k during decade t.[17] The main variables of interest are the contemporaneous change in import exposure per worker ΔIPW_{it} and the start of decade routine employment share RSH_{it}, both measured at the CZ level. Also included are a full set of time period effects γ_t, a vector of eight Census division indicators δ_k that allow for differential employment trends across regions, and a vector of control variables X_{it} measuring start-of-period demographics and labor market structure in each CZ.[18] Most estimates stack two sets of first differences, 1990–2000

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and unweighted correlations almost surely reflects the fact that rural areas are typically neither manufacturing-intensive nor concentrated in intensive-information or production-intensive occupations, both of which have high routine task content. Absenting weighting, these rural areas increase the correlation substantially.

[17]For the period 2000 through 2007, we rescale the dependent variable to represent a decadal change by multiplying it by the factor 10/7.

[18]Controls include the share of employment in manufacturing, the share of population that is college-educated, the share of population that is foreign born, and the employment rate among females.

and 2000–2007, though we later explore estimates separately by decade. All regressions are weighted by CZ shares of national population, and standard errors are clustered by state to allow for over-time and within-state error correlations. Following our strategy outlined above, equation (6) is estimated using two stage least squares, with the import exposure variable instrumented by contemporaneous changes in Chinese imports to other non-U.S. high income countries and the routine share measure instrumented by CZs' historical industry structures.

Table 1. Effect of Exposure to Chinese Import Competition and Routine-Biased Technological Change on Employment Status among Working Age Population, 1990-2007: 2SLS Estimates.
Dep Var: 10-Year Equiv. Changes in Share of Working Age Population in Indicated Employment Status (in %pts)

	(1)		(2)	(3)	
A. Outcome: Share Employed					
(Δ Imports from China to US)/Worker	-0.70 (0.16)	**		-0.83 (0.22)	**
Share of Emp in Routine Occs			-0.05 (0.22)	-0.21 (0.25)	
B. Outcome: Share Unemployed					
(Δ Imports from China to US)/Worker	0.21 (0.06)	**		0.19 (0.05)	**
Share of Emp in Routine Occs			-0.01 (0.06)	-0.01 (0.07)	
C. Outcome: Share Not in Labor Force					
(Δ Imports from China to US)/Worker	0.49 (0.15)	**		0.65 (0.19)	**
Share of Emp in Routine Occs			0.06 (0.17)	0.21 (0.19)	

Notes: N=1444 (722 commuting zones x 2 time periods). All regressions control for the start of period levels of share of employment in manufacturing, share of population that is college educated, share of population that is foreign born, employment rate among females, and Census division dummies. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

The first panel of Table 1 presents estimates of the impact of trade and technology and exposure on the employment to population ratio. We start with the impact of trade exposure in column 1. The highly significant coefficient of −0.70 on the import exposure variable in the first row indicates that a $1,000 rise in a CZ's import exposure per worker (in real 2007 dollars) over a ten year period reduces the CZ's employment to population rate by seven-tenths of a percentage point. This economically large impact is well within the range of variation seen in our sample. Between 1990 and

2007, the cross-CZ interquartile range of the increase in imports per worker averaged approximately $1,100 per decade.[19]

In contrast to the impact of trade exposure on employment, the estimates do not detect a robust relationship between technology exposure and changes in the employment to population rate in column (2). The point estimate of -0.05 on the routine share measure is statistically insignificant and relatively small in magnitude. The estimate implies a reduction in the employment to population rate of approximately two-tenths of a percentage point per decade in the 75th percentile CZ relative to the 25th percentile CZ.[20]

Including both the trade and technology measures in the regression simultaneously has little substantive impact on the results (column 3). The point estimate on each measure rises in absolute magnitude (specifically, the trade measure increases from -0.70 to -0.83 and the routine share measure increases from -0.05 to -0.21) while statistical significance is unaffected. Notably, the fact that both measures become slightly more negative when the other is included implies that the conditional correlation between the (instrumented) trade and technology variables is negative—areas with high trade exposure have somewhat lower exposure to routine task displacement, and vice versa.

The next two panels of Table 1 present complementary estimates for unemployment and non-participation. As with the employment to population rate measure, both the unemployment and non-participation variables are constructed by dividing the count of workers in the relevant status (unemployed, not in the labor force) by CZ working-age population ages 16-64. A comparison of the point estimates for these three margins of adjustments thus provides an implicit decomposition of the disemployment effects of trade or technology into unemployment and non-participation components. Trade exposure significantly increases both unemployment and non-participation,with non-participation accounting for three quarters (0.65/0.83) of the trade-induced decline in employment to population. In the case of the computerization variable, the estimates suggests that any adverse employment effect, if present, accrues to non-participation rather than unemployment (all point estimates are, however, statistically insignificant).

Thus, an initial answer to the second question posed in the Introduction—do trade and technology have comparable impacts on aggregate employment, unemployment and non-participation–is

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[19]During the first decade of the sample, imports per worker rose by $1,320 in the 75th percentile CZ and $623 in the 25th percentile CZ, yielding an interquartile range of approximately $700. Between 2000 and 2007, imports per worker rose even more rapidly, with decadal-equivalent gains of $3,114 at the 75th percentile, $1,599 at the 25th percentile, and an interquartile range of approximately $1,515. Averaging over both decades yields a mean interquartile range of approximately $1,100. Notably, there is no evidence of CZ-level mean reversion in import exposure across decades, so the interquartile range of the exposure variable for the full period is extremely close to the sum of the interquartile ranges for the 1990s and 2000s.

[20]The cross-CZ interquartile range of the start-of-period routine share variable is 4.0 percentage points 1990 and 3.3 percentage points in 2000.

that they do not. Before considering why these causal effects may differ, however, we first drill down on the possible heterogeneity of impacts across demographic groups.

3.3 Differences in employment effects by demographic group

We next explore estimates comparable to those above for overall employment status performed separately for three different demographic breakdowns: males versus females; non-college versus college-educated adults; and adults ages 16 to 39 versus adults ages 40 to 64.[21] Table 2 contains estimates.

Focusing first on the trade exposure variable, a striking result is that the disemployment impact of trade shocks appears to be substantially more severe for non-college than college workers. A $1,000 increase in per-worker import exposure is estimated to reduce the non-college employment rate by 1.21 percentage points and the college employment rate by 0.53 percentage points. Perhaps surprisingly, however, the effects of trade shocks on employment are otherwise uniformly large and significant for both males and females and for both younger and older workers. Moreover, for all groups, the bulk of the reduction in employment to population is accounted for by reductions in labor force participation rather than increases in unemployment—though there is some suggestion that the non-participation effect is comparatively larger for older relative to younger workers.

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[21]We define non-college workers as those with a high school degree or lower educational attainment, and college workers as those with at least one year of college education.

Table 2. Effect of Exposure to Chinese Import Competition and Routine-Biased Technological Change on Employment Status among Working Age Population, 1990-2007: 2SLS Estimates.
Dep Var: 10-Year Equiv. Changes in Share of Working Age Population in Indicated Employment Status (in %pts)

	Males (1)		Females (2)		Non-College (3)		College (4)		Age<40 (5)		Age>=40 (6)	
	Outcomes Measured Among											
A. Outcome: Share Employed												
(Δ Imports from China to US)/Worker	-0.71	**	-0.93	**	-1.21	**	-0.53	**	-0.82	**	-0.89	**
	(0.23)		(0.22)		(0.31)		(0.14)		(0.20)		(0.24)	
Share of Emp in Routine Occs	0.10		-0.49	*	-0.34		-0.29	~	-0.10		-0.42	~
	(0.33)		(0.20)		(0.32)		(0.16)		(0.27)		(0.23)	
B. Outcome: Share Unemployed												
(Δ Imports from China to US)/Worker	0.17	**	0.20	**	0.25	**	0.08	*	0.22	**	0.14	*
	(0.05)		(0.06)		(0.09)		(0.04)		(0.06)		(0.06)	
Share of Emp in Routine Occs	-0.04		0.03		0.02		-0.05		-0.03		0.03	
	(0.08)		(0.06)		(0.10)		(0.05)		(0.09)		(0.05)	
C. Outcome: Share Not in Labor Force												
(Δ Imports from China to US)/Worker	0.54	*	0.73	**	0.96	**	0.44	**	0.60	**	0.75	**
	(0.22)		(0.18)		(0.26)		(0.13)		(0.17)		(0.22)	
Share of Emp in Routine Occs	-0.05		0.46	**	0.32		0.33	*	0.13		0.39	*
	(0.27)		(0.15)		(0.24)		(0.13)		(0.19)		(0.20)	

Notes: N=1444 (722 commuting zones x 2 time periods). All regressions control for the start of period levels of share of employment in manufacturing, share of population that is college educated, share of population that is foreign born, employment rate among females, and Census division dummies. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

In contrast to the insignificant relationship between computerization and aggregate employment, unemployment and non-participation, we do find that CZs that were initially concentrated in routine-intensive occupations saw significant falls in the employment to population rate of females, and the implied effect is economically meaningful. The point estimate of -0.49 in column 2 implies that comparing a CZ at the 75th percentile and 25th percentile of exposure to task-replacing technical change, the more exposed CZ would see a relative decline in the female employment to population rate of 1.8 percentage points per decade.[22]

Notably, as with the estimates for the impact of trade shocks on employment, a large share of the decline in employment is absorbed by a corresponding increase in non-participation. Why do we not observe a stronger effect on the fraction of adults who are unemployed? One potential reason is that our outcome variables are measured at low frequency (10 and 7 years respectively for the first and second periods) and thus capture medium-run effects. If, as seems likely, trade or

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[22]The analogous point estimates for college-educated adults and adults ages 40+ are not significant at the $p \leq 0.05$ level, and the magnitudes of the estimated effects are smaller than for females.

technology-induced job displacement leads initially to unemployment followed in the longer term with re-employment or labor force exit, these dynamics will likely be less visible using low-frequency outcome measures.

The estimates in Table 2 again underscore that trade and technology are not a unified, monolithic force acting on the local labor market. Most notably, trade shocks appear to reduce employment disproportionately among non-college workers. Impacts are not limited to this group, however; we find significant trade-induced falls in employment rates among males and females, older and younger workers, and college as well as non-college workers. By contrast, the negative employment impacts of computerization are concentrated among females, with smaller and inconsistently signed effects for other demographic groups. Our next two analyses for occupational and sectoral impacts offer help to interpret these patterns.

3.4 Effects of trade and technology on occupations and tasks

We have so far focused on employment status as our sole outcome measure. We now complement this analysis by asking how trade and technology shocks alter the distribution of job tasks that workers supply, which we proxy using employment by occupation. We examine employment in three broad occupational categories that differ in their primary job task content. The first category includes managerial, professional and technical occupations, which are relatively specialized in abstract problem-solving and organizational tasks and employ comparatively highly educated and highly paid workers. The second broad job category includes production, clerical and administrative support, and sales occupations. These occupations are comparatively routine task-intensive and hence potentially subject to increasing substitution of computer capital for labor. The third category encompasses mechanics, craft and repair occupations, agricultural occupations and service occupations. These occupations employ primarily non-college labor and are intensive in manual job tasks that demand physical flexibility and adaptability, which have proven challenging to automate.[23]

To explore how trade and technology affect employment in these three task categories, we estimate a variant of equation (6) where the dependent variable is the change in the fraction of the working-age population employed in each occupational group. Because we have established above that trade and technology shocks reduce the employment to population ratio—thus making employment status endogenous—we normalize the employment-by-occupation counts by CZ *working age population* rather than by *labor force*. Hence, by construction, the sum of the estimated impacts of

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[23]The analysis in Autor and Dorn (forthcoming) offers summary information on task content by occupation that documents the logic of this categorization. See especially Table 2 of their paper.

each forcing variable (trade, technology) on employment in these three occupational categories will equal the complement of its effect on the employment to population ratio seen in Tables 1 and 2.

Table 3 presents estimates. The first column, which pools all demographic groups, finds substantial differences between the effects of trade and technology on occupations. Exogenous increases in trade exposure reduce employment across *all* three broad task categories, with the largest impact found in employment in routine task-intensive occupations (-0.48 percentage points for a $\$1,000$ rise in trade exposure), the second largest effect in manual task-intensive occupations (-0.22), and the smallest effect in abstract task-intensive occupations (-0.14, which is not significant).[24] By contrast, the estimated effect of computerization on employment is negative, significant and large for only one occupational category: routine task-intensive occupations. The point estimate of -0.48 implies a substantial 1.8 percentage point per decade differential decline in the share of working-age adults employed in this broad occupational category in the 75th percentile CZ relative to the 25th percentile CZ. Notably, the point estimates also suggest that employment in abstract and manual task-intensive experiences small offsetting *gains*, though these effects are not statistically significant.

In combination, this pattern of results confirms the well known result that computerization is associated with occupational polarization—that is, gains in the share of employment in relatively high-education, high-wage occupations and relatively low-education, low-wage occupations relative to the employment in middle-skill, routine task-intensive jobs. These estimates also offer two novel results. First, they suggest that computerization and trade do *not* have comparable polarizing effects; the technology effect is both more concentrated and more pronounced for routine task-intensive occupations. Second, whereas prior literature has focused exclusively on the polarization of occupational structures among *employed* workers, the combination of results in Tables 1 through 3 suggests that conditioning on employment misses an important margin of adjustment to capital-labor substitution, namely, non-employment.

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[24]Note that these three coefficients sum to -0.84, which is identical (up to rounding) to the negative estimated effect of trade on the employment to population rate in column 3 of Table 1.

Table 3. Effect of Exposure to Chinese Import Competition and Routine-Biased Technological Change on Employment by Occupation Group among Working Age Population, 1990-2007: 2SLS Estimates.
Dep Var: 10-Year Equiv. Changes in Share of Working Age Population Employed in Indicated Occupation Group (in %pts)

	Outcomes Measured Among						
	All	Males	Females	Non-Clg	College	Age<40	Age>=40
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Outcome: Share Employed in Managerial/Professional/Technical Occs							
Primary Task: Abstract							
(Δ Imports from China to US)/Worker	-0.14	-0.05	-0.22 *	-0.17 **	-0.16	-0.08	-0.24 *
	(0.09)	(0.11)	(0.10)	(0.04)	(0.11)	(0.10)	(0.09)
Share of Emp in Routine Occs	0.15	0.35 *	-0.05	-0.05	0.09	0.32 *	-0.11
	(0.12)	(0.16)	(0.09)	(0.05)	(0.11)	(0.15)	(0.11)
B. Outcome: Share Employed in Production/Clerical/Retail Sales Occs							
Primary Task: Routine							
(Δ Imports from China to US)/Worker	-0.48 **	-0.37 **	-0.61 **	-0.63 **	-0.32 **	-0.46 **	-0.52 **
	(0.08)	(0.08)	(0.11)	(0.11)	(0.07)	(0.08)	(0.11)
Share of Emp in Routine Occs	-0.36 **	-0.32 **	-0.44 **	-0.37 *	-0.32 **	-0.37 **	-0.43 **
	(0.13)	(0.12)	(0.13)	(0.18)	(0.09)	(0.14)	(0.11)
C. Outcome: Share Employed in Craft/Mechanics/Agricultural/Service Occs							
Primary Task: Manual							
(Δ Imports from China to US)/Worker	-0.22 **	-0.29 **	-0.11	-0.42 *	-0.05	-0.29 **	-0.14 ~
	(0.08)	(0.11)	(0.07)	(0.21)	(0.05)	(0.09)	(0.08)
Share of Emp in Routine Occs	0.01	0.07	0.00	0.09	-0.06 ~	-0.05	0.12 ~
	(0.06)	(0.11)	(0.05)	(0.14)	(0.04)	(0.09)	(0.07)

Notes: N=1444 (722 commuting zones x 2 time periods). All regressions control for the start of period levels of share of employment in manufacturing, share of population that is college educated, share of population that is foreign born, employment rate among females, and Census division dummies. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Following the format of Table 2, the next six columns of Table 3 present estimates of the impacts of trade and technology on job tasks by demographic subgroup: males and females, college and non-college adults, and younger and older adults. Across all demographic groups, trade shocks uniformly have the greatest (negative) impact on employment in routine task-intensive occupations, with the largest impacts found for females and non-college adults. Trade shocks also substantially reduce employment in manual task-intensive occupations among males, non-college workers, and younger workers, and reduce employment in abstract-intensive occupations among females, non-college adults and older adults. These results shed light on our earlier finding that non-college adults suffer disproportionate employment losses from trade shocks. While one might have speculated that this is because they are concentrated in production occupations, the Table 3 results suggest otherwise.

Though non-college employment falls most in routine task-intensive occupations—which, logically, include many production positions—it also drops significantly in manual and abstract task-intensive occupations. In fact, net employment losses in these two job categories are essentially equal to the loss in the routine task-intensive categories. Thus, non-college adults in all occupations groups appear exposed to trade shocks.

In contrast to the broad-based disemployment impacts of trade shocks, the Table 3 estimates indicate that the disemployment effects of computerization are almost entirely confined to routine-task intensive occupations, and, moreover, that these effects are closely comparable across all demographic groups. How can this fact be reconciled with the earlier finding that computerization significantly reduces the employment to population rate of females, and to a lesser degree, older adults but not males and younger adults? The key difference lies in the abstract task-intensive occupation category. Males and younger adults show sharp offsetting gains in employment in abstract task-intensive occupations that almost entirely offset their losses in routine task-intensive occupations. Demographic groups that do not make these gains—females in particular—experience declining overall employment.

3.5 Sectoral impacts

We expect the effects of international trade on domestic labor market to be most concentrated in the manufacturing sector. Should we expect the same for computerization? On the one hand, earlier literature finds substantial impacts of the adoption of computer capital on skilled labor demand in manufacturing, and offers some evidence that this relationship started a decade earlier in manufacturing than non-manufacturing (Berman, Bound and Griliches, 1992; Autor, Katz and Krueger, 1998). Conversely, computerization is now ubiquitous in the workplace, and is now the backbone of most information-intensive activities. Thus, we might expect any employment effects to be as large or larger outside of manufacturing.

We explore these relationships in Table 4, by estimating variant of equation (6) for the effect of trade and technology exposure on the share of working age population employed in six sector-occupation cells: manufacturing and non-manufacturing × abstract, routine and manual-intensive occupations. As in prior tables, our outcome variables are measured as ten-year equivalent changes in the percentage of working-age population employed in each cell, with non-employment constituting a residual category. Thus, the sum of the trade or technology effect on the fraction of working-age adults employed in these six sector-occupation cells will equal its effect on the employment to population rate. One difference between these estimates and the earlier specifications is that we

construct separate CZ-level routine-share variables for the manufacturing and non-manufacturing sectors.[25]

Consistent with expectations trade shocks have disproportionate effects on employment in manufacturing. A $1,000$ per worker increase in trade exposure reduces manufacturing employment by 0.50 percentage points. Sixty percent of this impact is due to a fall in routine task-intensive employment, with the remainder due to reduced employment in abstract task-intensive occupations. Notably, the effect of trade shocks are not limited to manufacturing. Consistent with the results in ADH, we estimate a smaller but non-trivial contemporaneous reduction in non-manufacturing. While the point estimate of -0.20 is not statistically significant, this reflects the countervailing effects across occupational categories within non-manufacturing. Employment in manual task-intensive occupations falls by a significant -0.18 percentage points and in routine task-intensive occupations and by a marginally significant -0.09 percentage points while rising slightly by 0.06 percentage points in abstract task-intensive occupations. As discussed in ADH, this pattern likely reflects demand spillovers from manufacturing to non-manufacturing. As manufacturing employment contracts, demand from both businesses and consumers for locally produced services such as trucking, construction, food away from home and entertainment is likely to fall. Since these services make intensive use of manual tasks, it's not surprising that local employment in service-intensive occupations declines along with manufacturing employment.

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[25]As it turns out, introducing this additional degree of freedom is likely to be substantively important because the cross-CZ correlation between the manufacturing and non-manufacturing routine share variables is surprisingly low: 0.18 in 1990 and 0.13 in 2000 (weighted by CZ population).

Table 4. Effect of Exposure to Chinese Import Competition and Routine-Biased Technological Change on Employment in Manufacturing and Non-Manufacturing, 1990-2007: 2SLS Estimates.

Dep Var: 10-Year Equiv. Changes in Share of Working Age Population Employed in Indicated Sector-Occupation Cell (in %pts)

	A. Manufacturing Sector				B. Non-Manufacturing Sector			
	All Occs	Mgmt/ Prof/ Tech	Prodn/ Cleric/ Retail	All Other Occs	All Occs	Mgmt/ Prof/ Tech	Prodn/ Cleric/ Retail	All Other Occs
Primary Task	All	Abstract	Routine	Manual	All	Abstract	Routine	Manual
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	A. Regression Results							
(Δ Imports from China to	-0.504 **	-0.196 **	-0.290 **	-0.019	-0.203	0.064	-0.092 ~	-0.176 *
	(0.077)	(0.065)	(0.055)	(0.020)	(0.189)	(0.107)	(0.050)	(0.085)
Share of Mfg Emp in Routine Occs	0.016	0.022	-0.029	0.023				
	(0.081)	(0.021)	(0.054)	(0.018)				
Share of Non-Mfg Emp in Routine					0.063	0.141	-0.131 ~	0.053
					(0.177)	(0.086)	(0.072)	(0.055)
	B1. Predicted Effects 1990-2000, 75th vs 25th Percentile of Exposure							
Imports from China	-0.35	-0.14	-0.20	-0.01	-0.14	0.04	-0.06	-0.12
Routine Emp Share	0.08	0.10	-0.14	0.11	0.30	0.66	-0.62	0.25
	B2. Predicted Effects 2000-2007, 75th vs 25th Percentile of Exposure							
Imports from China	-0.76	-0.30	-0.44	-0.03	-0.31	0.10	-0.14	-0.27
Routine Emp Share	0.08	0.12	-0.15	0.12	0.27	0.61	-0.57	0.23

Notes: N=1444 (722 commuting zones x 2 time periods). All task values are standardized to a cross-commuting zone mean of zero and standard deviation of 1 in 1990. All regressions control for the start of period levels of share of employment in manufacturing, share of population that is college educated and foreign born, female employment rate, offshorability index of occupations, and Census division dummies. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

The second and third rows of the table present an equally striking set of results the impacts of exposure to technology. We detect no statistically or economically significant effect of our measure of susceptibility to computerization on employment in manufacturing, either overall or by occupational category. By contrast, computerization clearly predicts employment polarization in non-manufacturing, implying employment reductions in routine task-intensive occupations and offsetting gains in both abstract and manual-task intensive occupations. While neither of the latter two point estimates is statistically significant, it is noteworthy the net effect of computerization on employment in non-manufacturing is estimated to be weakly positive.

The lower two panels summarize the magnitudes of these effects by computing the interquartile range of effect sizes for both the trade and technology measures in the two decades of our sample. The employment effect of the trade shock doubles between the first and second decades of our sample,

reflecting the very rapid rise in Chinese import penetration in the U.S. market following China's accession to the WTO in 2001. Employment impacts are concentrated in routine task-intensive occupations and, to a lesser degree abstract task-intensive occupations in manufacturing, and in routine and manual task-intensive occupations in non-manufacturing. By contrast, the impact of the computerization variable is stable across periods. It implies no net effect on the employment to population rate but a substantial impact on employment polarization.

These results pose one puzzle. Given dramatic advances in computer-aided manufacturing in recent decades as well as the high levels of manufacturing investment in computer capital, it seems paradoxical that we estimate that computerization has had no effect on the composition of employment in manufacturing. One potential resolution may be that this effect was evident in a period before our sample begins. To investigate this possibility, we extend the sample backward by one additional decade to the 1980s. While we can measure technology exposure for the 1980s, a corresponding analysis for exposure to Chinese trade competition it is not practical because large-scale trade with China only commenced in the 1990s.[26] Table 5 presents these results.

Consistent with our conjecture, we find strong evidence in the left-hand panel of the table that computerization led to employment polarization in manufacturing in the 1980s, characterized by a strong decline in routine occupation employment and little changes in abstract and manual employment. The impact of the computer exposure measure on routine task intensive employment becomes weaker in each of the subsequent decades, and is no longer statistically significant in the 2000s. Thus, our estimates indicate that computerization has had substantial impacts on job task composition in manufacturing, but that this impact was felt with greatest force in the 1980s and and 1990s and appears to have had little further effect in the 2000s.[27] The slowing impact of technology on manufacturing employment contrasts with the rapidly growing impact of exposure to Chinese trade competition that was already illustrated by the results of panels B1 and B2 in Table 4.

The righthand panel of Table 5 finally offers an equally striking, and perhaps more unexpected, result: opposite to the declining secular effect of computerization on job polarization in manufacturing, the polarizing impact of computerization in non-manufacturing accelerates across decades. The significant point estimate of -0.8 for the decade of the 1980s more than doubles in the 1990s,

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[26]Furthermore, harmonized trade data is only available for the 1990s. ADH show that the local labor markets with differential exposure to China after 1990 did not have different employment trends in the 1980s.

[27]Further analysis (not shown in the table) provides insight into why this effect may be attenuating with time. When we divide routine task-intensive occupations in manufacturing into two subgroups, production occupations and clerical and sales occupations, we find that the entire attenuating effect is due to the falling impact of computerization on production employment, which declined from -0.094 in the 1980s to -0.068 in the 1990s to $+0.017$ in the 2000s. By contrast, the negative effect of computerization on employment in clerical and sales occupations is negative, significant, and stable in magnitude across all three decades.

and then rises by a further fifty percent in the 2000s. In net, these results suggest that the primary impact of technological change on employment has shifted from automation of routine production tasks in manufacturing to computerization of routine information-processing tasks which are more concentrated in the service sector.

Table 5. Effect of Exposure to Chinese Import Competition and Routinization on Employment by Sector and Occupation Group, 1980-2007: 2SLS Estimates.

Dep Var: 10-Year Equiv. Changes in Share of Working Age Population Employed in Sector-Occupation Cell (in %pts)

	A. Manufacturing Sector			B. Non-Manufacturing Sector		
	Mgmt/ Prof/ Tech	Prodn/ Cleric/ Retail	All Other Occs	Mgmt/ Prof/ Tech	Prodn/ Cleric/ Retail	All Other Occs
Primary Task	Abstract (1)	Routine (2)	Manual (3)	Abstract (1)	Routine (2)	Manual (3)
	1980 - 1990					
Share of Mfg Emp in Routine Occs	0.003 (0.011)	-0.130 ** (0.037)	-0.019 (0.014)	0.258 ** (0.027)	-0.077 ** (0.021)	0.068 ** (0.020)
(Δ Imports from China to US)/Worker	n/a	n/a	n/a	n/a	n/a	n/a
	1990 - 2000					
Share of Mfg Emp in Routine Occs	-0.024 (0.018)	-0.095 * (0.039)	0.021 ~ (0.012)	0.065 (0.061)	-0.183 ** (0.041)	0.108 ** (0.034)
(Δ Imports from China to US)/Worker	-0.164 ~ (0.086)	-0.141 (0.128)	0.016 (0.036)	-0.104 (0.134)	-0.206 * (0.098)	-0.295 ~ (0.155)
	2000 - 2007					
Share of Mfg Emp in Routine Occs	-0.026 (0.029)	-0.021 (0.047)	0.026 ~ (0.015)	0.100 (0.067)	-0.282 ** (0.057)	0.057 (0.098)
(Δ Imports from China to US)/Worker	-0.254 * (0.104)	-0.188 ** (0.045)	0.024 (0.019)	0.135 * (0.058)	-0.008 (0.087)	0.150 ~ (0.090)

Notes: N=722 commuting zones. All regressions control for start of period share of employment in manufacturing and Census division dummies. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

4 Conclusions

There is a wide agreement among economists that technological change and expanding international trade have led to changing skill demands and growing inequality or polarization of labor market outcomes in the U.S. and in other rich countries. While this paper confirms that both forces have shaped employment patterns in U.S. local labor markets in the last three decades, it also highlights

important differences in the impact of technology and trade on labor markets. We start by observing that local labor market exposure to technological change, as measured by specialization in routine task-intensive production and clerical occupations, is largely uncorrelated with local labor market exposure to trade competition from China, thus allowing us to observe separate impacts of trade and technology.

Local labor markets with greater exposure to trade competition experience differential declines in manufacturing employment. This employment decline is not limited to production jobs but instead affects all occupation groups. Employment losses are largest among workers without college education, for whom we also observe employment declines outside the manufacturing sector which may stem from local demand spillovers. While the differential effect of trade on manufacturing employment shifts the distribution of employment between sectors, exposure to technological change primarily affects the employment composition within sectors. In particular, we find that susceptibility to technological change predicts declining employment in routine-task intensive occupations both in the manufacturing and non-manufacturing sectors. For most demographic groups, these declines in routine employment are largely offset by increasing employment in abstract- or manual-task intensive occupations. One exception is women, for whom the reduction in routine occupation employment translates to an overall decline in employment.

Concurrent with the rapid growth of U.S. imports from China, the effect of trade competition on the manufacturing sector has become stronger over time, while the effect of technological change on employment shifts in the manufacturing sector has subsided. Conversely, the impact of technology on the non-manufacturing sector is growing as technological change seems to be shifting from automation of production in manufacturing to computerization of information processing in knowledge-intensive industries.

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