Untangling Trade and Technology:
Evidence from Local Labor Markets*

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Abstract

We analyze in a common framework 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 exposes them to rising import competition from China have experienced significant employment reductions particularly in the manufacturing sector and among non-college-educated workers. These employment losses are not limited to manual 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.

Keywords: Technological Change, Trade Flows, Import Competition, Skill Demand, Job Tasks, Local Labor Markets

JEL Classifications: F16, J21, J23, O33

1 Introduction

Many economists view trade and technology as two of the paramount forces shaping labor markets in the United States and other advanced countries. New technologies augment human and physical capital (Autor and Acemoglu, 2010) and enable firms to automate routine tasks previously performed by middle-rank workers (Autor and Dorn, forthcoming), both of which contribute to a rise in the relative demand for more-skilled labor (Katz and Autor, 1999). For its part, trade with low-wage countries depresses wages and employment in the industries (Artuc, Chaudhuri, and McLaren, 2010), occupations (Ebenstein, Harrison, McMillan, and Phillips, forthcoming), and regions (Autor, Dorn, and Hanson, forthcoming) that are exposed to import competition. What the literature has not yet established is the degree to which trade and technology should be seen as distinct shocks or, rather, are better described as varied facets of a common phenomenon. The aim of this paper is to jointly analyze the impacts of trade and technology on U.S. employment levels and job composition, juxtaposing their effects across local labor markets, over time, between sectors and occupations, and among workers of different education, age and sex categories. Our analysis reveals a surprising degree of divergence between the labor market consequences of these two phenomena–both across industrial, occupational, geographic and demographic groups, and over time as the trajectory of these forces has evolved.

It is natural to suspect that trade and technology could play mutually reinforcing roles in shaping labor-market developments in rich countries. An obvious association between the two arises from their concurrence. At the same time that the United States and many European countries have experienced growing income inequality and increasing employment polarization,[1] these economies have been exposed to both rapid technological change (e.g., the computer revolution) and growing international trade (e.g., the rise of China). A second line of thought linking trade and technology appeals to their interdependence. As falling trade costs permit firms to perform some production tasks offshore, the factors that remain at home become more productive (Grossman and Rossi-Hansberg, 2008). Reduced trade barriers may thus cause simultaneous growth in productivity and trade. Offshoring conjoins trade and technology in another manner, as well. When firms relocate production stages within an industry to other countries, the average factor intensity of the stages that remain at home is likely to change (Feenstra and Hanson, 1999). Standard measures of TFP typically do not account for shifts in the composition of activities performed inside industries, such that trade-induced changes in the composition of production may be confounded with TFP growth.

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

A final strand of reasoning that links trade and technology recognizes that many of the job tasks that are suitable for automation are also suitable for offshoring (Blinder, 2009).[2] Looking forward, it is not unreasonable to suppose that some of the low-skill work that cannot presently be automated in rich countries may soon be headed for the developing world.

In this paper, we assess the extent to which the labor market impacts of trade and technology coincide, and proceed to paint a detailed picture of the differential effects of trade and technology on overall employment, unemployment, and non-participation, on production versus non-production employment, on job polarization in manufacturing and nonmanufacturing, and on the time path of trade versus technology impacts overall and by sector. Focusing on changes in employment structure within 722 consistently defined, fully inclusive Commuting Zones (CZs) that approximate local labor markets in the United States, we analyze five core 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 local labor markets largely 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, e.g., males versus females, college versus non-college workers, older versus young workers? Fourth, are the same broad sets of occupations or workplace tasks—abstract, routine, manual—displaced or augmented by technology and trade? Finally, while the effects of international trade on domestic labor markets 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?

Critical inputs into our analysis are measures of local labor market exposure to technological change and to 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 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, variation in industry specialization across CZs observed in 1950 can account for the differential pace at which these markets reacted to

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[2]The reasoning here is that tasks that follow explicit codifiable procedures (what Autor, Levy and Murnane, 2003, call "routine" tasks) are 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. However, there are many tasks that are offshorable but not routine in the sense above (for example, interpreting medical x-rays) and other tasks that are codifiable but not clearly offshorable (e.g., adding vast arrays of numbers for actuarial analysis, or, to borrow an example from popular culture, the job that Homer Simpson performs as Nuclear Safety Inspector at the Springfield Nuclear Power Plant).

the precipitous decline in the price of computing power after 1980 by adopting workplace computing and reducing employment in routine task-intensive occupations.

On the trade front, we follow Autor, Dorn and Hanson (forthcoming, 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 barriers to trade. These forces have catapulted China's U.S. import presence—the share of Chinese imports in total U.S. expenditure on goods—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. product demand, we exploit the contemporaneous growth of Chinese exports by industry to other high-income countries. This identification strategy posits that growth in Chinese imports within a given industry (e.g., footwear, luggage, toys) that occurs simultaneously in the U.S. and other high-income countries is primarily driven by the surge in Chinese productivity that has accompanied its transition to a market economy (Brand, Van Biesebroeck, and Zhang, 2012; Hsieh and Ossa, 2012) and by reduced trade barriers resulting from China joining the World Trade Organization (Pierce and Schott, 2012). We then project these industry-level import shocks to the level of local labor markets by interacting them with variation in CZs' 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 the change in import exposure across local labor markets. As a case in point, the CZ containing Providence, Rhode Island—a traditional manufacturing hub—saw estimated increases in Chinese import exposure (that is, competing Chinese manufactures that would potentially be produced in Providence if not imported) of $2,330 per worker between 1991 and 2000, and an additional $3,490 per worker between 2000 and 2007. In contrast, the CZ containing New Orleans, Louisiana–which lacks industries that compete directly with China—saw comparatively small increases of $170 and $490 per worker during these same intervals.

Our paper builds on two broad and active literatures. The first explores the impact of trade and technical change on skill demands[3] while the second studies how these forces shape labor-market outcomes at the sub-national (i.e., local labor market) level.[4] This paper contributes to these bodies of work along two dimensions. 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

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[3]See, e.g., Doms, Dunne, and Troske (1997), Beaudry, Doms, and Lewis (2010), Firpo, Fortin, and Lemieux (2012), and other literature cited in Autor and Dorn (forthcoming).

[4]See, e.g., Borjas and Ramey (1995), Michaels (2008), McLaren and Hakobyan (2010), Kovak (forthcoming), Topalova (2010), and other literature cited Autor, Dorn and Hanson (forthcoming).

tends to focus on either trade or technology as candidate explanatory variables but rarely places the two on equivalent empirical footing.[5] An additional 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 margins include employment to population, unemployment and non-participation, as well as shifts in employment across broad occupational categories that differ in their intensity of abstract, routine and manual task input. Further, we consider these outcomes separately by demographic groups comprised by gender, education and age, and sector (manufacturing, non-manufacturing). In combination, we believe these analyses provide valuable evidence on how the distinctive impacts of trade and technology on rich country (or, more specifically, U.S.) labor markets can be characterized and interpreted.

In brief, we find that the local labor markets that are most exposed to technological change, as measured by specialization in routine task-intensive production and clerical occupations, are largely distinct from the markets most exposed to trade competition from China. Equally distinct are the consequences of trade and technology exposure for local labor market outcomes. Trade competition leads to sharp declines in local manufacturing employment, with corresponding growth in local unemployment and non-employment, particularly among workers without college education. In contrast, exposure to technological change has largely neutral effects on overall employment, yet leads to substantial polarization of occupational composition within sectors: employment in routine task-intensive production and clerical occupations declines in both manufacturing and non-manufacturing sectors, but these losses are largely offset by employment growth in abstract and manual-task-intensive occupations.

The time path of these relationships offers insights into the evolving magnitude and sectoral impacts of trade and technology. 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. Conversely, the effect of technological change on employment composition inside of manufacturing has decelerated, with the largest impacts detected in the 1980s and the smallest impacts found in the 2000s. Outside of manufacturing, however, the impact of automation accelerates during the three decades of our sample, suggesting that computerization of information processing activities in knowledge-intensive industries continues to intensify.

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[5]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 local labor market outcomes.

2 Measurement

2.1 Local labor markets

Our analysis requires a time-consistent definition of regional economies in the U.S. We approximate local labor markets using the construct of Commuting Zones (CZs) developed by Tolbert and Sizer (1996), who analyzed 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 both urban and rural areas, 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 we examine.[6]

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^A_k are, respectively, the routine, manual and abstract task inputs in each occupation k in 1980.[7] 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 a simple binary approach to distinguish 'routine' and 'non-routine' occupations. We classify as

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[6]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. Autor and Dorn (forthcoming) and Autor, Dorn and Hanson (forthcoming) also use Commuting Zones as a local labor market construct.

[7]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.

routine occupations those that fall in the top-third of the employment-weighted distribution of the RTI measure in 1980. 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 CZ j at time t, and $1[\cdot]$ 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 75/25 percentile range is 6 percentage points.

To isolate the long-run, quasi-fixed component of the routine occupation share that is determined prior to the onset of the era of rapid computerization, we exploit historical cross-CZ differences in industry specialization as instruments for the observed level in each decade. Our instrumental variables approach is as follows: let $E_{ij,1950}$ equal the employment share of industry $i \in 1, ..., I$ in CZ 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 CZ j.[8] The product of these two measures provides a predicted value for the routine employment share in each CZ, which depends only on the local industry mix in 1950 and the occupational structure of industries *nationally* in 1950:

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

Because the instrument is determined three decades prior to the onset of rapid computerization in the 1980s, we expect it to be correlated with the long-run component of the routine occupation share but uncorrelated with contemporaneous innovations to this share.[9]

2.3 Exposure to international trade

Following ADH, we examine changes in exposure to international trade for U.S. CZs associated with the growth in U.S. imports from China. The focus on China is a natural one: rising trade with China is responsible for much of the expansion in U.S. imports from low-income countries

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[8]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 CZs to be part of the state that contains the largest share of their population.

[9]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.

since the early 1990s. China's export surge is a consequence of its 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).[10] 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 157 WTO members (Pierce and Schott, 2012).

How can examining trade exposure in Commuting Zones be justified in terms of trade theory? 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. This approach is valid for identifying the labor-market consequences of trade insofar as (i) CZs differ in their pattern of industry specialization, and (ii) frictions in labor markets allow regional differences in wages, unemployment, and labor-force non-participation to persist over the medium run. ADH (forthcoming) find strong evidence that greater exposure to trade with China affects local labor market outcomes across CZs.

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 each 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.

In equation (4), 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

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[10]While China overwhelmingly 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), for instance, lowered U.S. barriers to imports to a country in which U.S. firms already had extensive supply networks. Finding exogenous sources of variation in Mexico's export growth, however, is tricky. Whereas China has had dramatic productivity growth in manufacturing—making internal supply shocks an important source of its export growth— Mexico has not (Hsieh and Klenow, 2012). The expansion of U.S. trade with Mexico is thus primarily driven by changes in U.S. bilateral trade policy which could be influenced by economic conditions in U.S. industries. Arguably, such simultaneity concerns are less an issue with regards to U.S. trade with China because of China's phenomenal productivity surge, which has been due in large part to how far inside the global technology frontier the country remained at the end of the Maoist era. 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.

two sources: differential concentration of employment in manufacturing versus non-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 this case, OLS estimates of the relationship between increased imports from China and changes in 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 the constraints associated with central planning, and accession to the WTO. This approach requires that import demand shocks in high-income countries are not the primary cause of China's export surge.

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.[11] 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

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[11]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. 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.

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.[12]

3 Results

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 routinization? Autor, Dorn, and Hanson (2013) provide a summary answer to this question. To set the stage for our empirical analysis, we briefly discuss their main findings. The CZs with the highest employment shares in routine task-intensive occupations constitute a mixture of manufacturing-intensive locations (in particular, locations around the Great Lakes and in the Southeast) and human-capital-intensive large cities, including New York, Chicago, Dallas, and Los Angeles. 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.

Trade-exposed CZs, by contrast, are the subset of manufacturing-intensive regions specialized in labor-intensive manufacturing, such as furniture, rubber products, toys, apparel, footwear and leather goods. Because CZs with high routine-task intensity include a broad collection of manufacturing and service centers whereas CZs with high trade exposure constitute a relatively narrow set of specialized industry clusters, the potential overlap among these two sets of regions is limited. Moreover, the geography of trade exposure is relatively concentrated. A substantial fraction of the most trade-exposed CZs are located in a small number of states, including Tennessee, Missouri, Arkansas, Mississippi, Alabama, Georgia, North Carolina, and Indiana, whereas routine task-intensive CZs are dispersed throughout the U.S. A simple population-weighted correlation between technology exposure in (2) and trade exposure in (4) 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.[13]

A concise 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

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[12]ADH (forthcoming) 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.

[13]The unweighted correlations are 0.21 and 0.31 in 1990 and 2000 respectively. The difference between the weighted and unweighted correlations almost surely reflects the fact that rural areas are typically neither manufacturing intensive nor concentrated in information-intensive or production-intensive occupations, both of which have high routine task content. Absenting weighting, these sparsely populated rural areas increase the correlation substantially.

largely disjoint. This feature of the data facilitates the identification of separate effects of trade and technology on local labor markets.

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 CZ i in U.S. Census division k during decade t.[14] 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 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. Most estimates stack two sets of first differences, 1990–2000 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 in (5) and the routine-share measure instrumented by CZs' historical industry structures in (3).

The first panel of Table 1 presents estimates of the impact of trade and technology exposure on the employment-to-population ratio. We start with the impact of trade exposure in column 1, which replicates regression results in ADH. 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

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

increase in imports per worker averaged approximately $1,100 per decade.[15]

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. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

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 overall 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.[16]

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[15]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.

[16]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.

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, 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 adjustment 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. In the case of the routinization 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). Again, the column (3) regressions that simultaneously include the variables measuring exposure to trade and technology yield results that are not materially different.

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 in the negative. Greater trade exposure results in significant losses of employment in local labor markets whereas greater exposure to routinization does not. Before considering why these 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 younger adults (ages 16 to 39) versus older adults (ages 40 to 64).[17] Table 2 presents estimates.

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[17]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.

Focusing first on the trade-exposure variable, a striking but not altogether unsurprising 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. More notable, perhaps, is that 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 the non-participation effect is larger for older relative to younger workers.

In contrast to the insignificant relationship between routinization and aggregate employment, unemployment and non-participation, we do find that CZs that were initially specialized 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. The effects of exposure to routinization also appear larger for older versus younger workers, though this difference is less precisely estimated.

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 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 further underscore that trade and technology are not a unified, monolithic force acting on the local labor market. Trade shocks appear to reduce employment among all groups of workers that we considered, with a disproportionately large effect among non-college workers. By contrast, negative employment impacts of routinization are concentrated among females and to some extent among older workers, 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.

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)

	*Outcomes Measured Among*											
	Males		Females		Non-College		College		Age<40		Age>=40	
	(1)		(2)		(3)		(4)		(5)		(6)	
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. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

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.[18]

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. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

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. Table 3 presents estimates.[19] 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

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[18]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.

[19]Note that non-employment (unemployment and non-participation) constitutes a fourth outcome category. The impact of trade or technology on this category is simply the negative of its effect on employment in the three occupational groups considered in Table 3 (see panel A of Table 2).

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).[20] By contrast, the estimated effect of routinization 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. The point estimates also suggest that employment in abstract and manual-task-intensive occupations experiences small offsetting *gains*, though these effects are not statistically significant.

In combination, the pattern of results supports the well-known finding that computerization is associated with occupational polarization—that is, gains in the share of employment in relatively high-education, abstract-task-intensive occupations and relatively low-education, manual-task-intensive occupations relative to the employment in middle-skill, routine task-intensive jobs. These estimates also offer two novel insights. First, exposure to trade and to technology have in common that their largest negative effects are on the middle category of routine task-intensive occupations. And second, exposure to trade and to technology differ in that trade has negative employment effects throughout the task distribution whereas technology does not.

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-task-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 occupation groups appear exposed to trade shocks.

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[20]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.

These findings are helpful for reconciling alternative views of offshoring that have emerged in the trade literature. Older approaches to offshoring (e.g., Feenstra and Hanson, 1999) emphasize variation in factor intensity across manufacturing stages to explain the fraction of production moved offshore whereas newer approaches to offshoring (e.g., Grossman and Rossi-Hansberg, 2008) focus on the inherent offshorability of tasks, abstracting away from factor intensity. Our results suggest there is a role for both channels: factor intensity matters (as shown by non-college workers being the skill group most impacted by trade) but so does the nature of the task (as shown by routine occupations being most affected by trade).

In contrast to the broad-based disemployment impacts of trade shocks, the Table 3 estimates indicate that the disemployment effects of technology exposure 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 technology exposure significantly reduces the employment-to-population rate of females, and to a lesser degree, older adults but not of males or 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 technology? 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 serves as 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 a 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 sectors crossed with abstract, routine and manual-task-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 ratio. 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.[21]

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. Chg in Share of Working Age Pop Employed in Indicated Sector-Occupation Cell (in %pts)

Primary Task	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
	All	Abstract	Routine	Manual	All	Abstract	Routine	Manual
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
A. Regression Results								
(Δ Imports from China to US)/Worker	-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 Occs					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 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.

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 is not limited to manufacturing. Consistent with the results

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[21]Introducing this additional degree of freedom is likely to be 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).

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. 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 construction, entertainment, food away from home, and retail trade is likely to fall. The consequence is reduced employment in various routine-task and manual-task activities outside the sector, as shown in the last two columns of Table 4.

The second and third rows of the table present an equally striking set of results for the impacts of exposure to technology. Local labor markets with a routine task-intensive manufacturing sector experience a slight shift of employment from routine to abstract and manual occupations, though none of these effects nor the overall effect of employment in manufacturing is statistically significant. By contrast, routinization more clearly predicts employment polarization in non-manufacturing, with reduced employment 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 that the net effect of routinization on employment in non-manufacturing appears 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, in abstract-task-intensive occupations in manufacturing, and in routine and manual-task-intensive occupations in non-manufacturing. By contrast, the impact of routinization 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 little 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.[22] Table 5 presents these results.

Consistent with our conjecture, we find strong evidence in the left-hand panel of the table that routinization led to significant 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 technology 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 suggest that computerization *did* have substantial impacts on job task composition in manufacturing, but that this impact was felt with greatest force in the 1980s and 1990s, and had little further effect in the 2000s. 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 routinization on production employment, which declined from a coefficient of -0.094 in the 1980s to -0.068 in the 1990s to $+0.017$ in the 2000s. By contrast, the negative effect of routinization on employment in clerical and sales occupations is negative, significant, and stable in magnitude across all three decades. The slowing impact of technology on manufacturing employment contrasts with the rapidly growing impact of exposure to Chinese trade competition, illustrated in Table 4.

The right-hand panel of Table 5 finally offers an equally striking, and perhaps more unexpected, result: opposite to the declining secular effect of routinization on job polarization in manufacturing, the impact of technology on routine-task employment 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, and almost quadruples by 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.

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

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 Sectorial 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 Sectorial 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 Sectorial 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, its main contribution is to highlight important differences in the impact of technology and trade on labor markets. The impacts of trade and technology can be observed separately because 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.

Local labor markets with greater exposure to trade competition experience differential declines in manufacturing employment, with corresponding growth in unemployment and non-employment. The employment decline is not limited to production jobs but instead affects all major occupation groups. Employment losses are particularly large among workers without college education, for whom we also observe employment declines outside the manufacturing sector which may stem from local demand spillovers. While trade exposure reduces overall employment and shifts the distribution of employment between sectors, exposure to technological change has substantially different impacts, characterized by neutral effects on overall employment and substantial shifts in occupational composition within sectors. In particular, we find that susceptibility to technological change predicts declining employment in routine task-intensive production and clerical 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 which tend to comprise the highest and lowest paid jobs in the economy. One exception is among 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 composition 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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