The China Syndrome: Local Labor Market Effects of Import Competition in the United States.*

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Abstract

We analyze the effect of rising Chinese import competition between 1990 and 2007 on local U.S. labor markets, exploiting cross-market variation in import exposure stemming from initial differences in industry specialization while instrumenting for imports using changes in Chinese imports by industry to other high-income countries. Rising exposure increases unemployment, lowers labor force participation, and reduces wages in local labor markets. Conservatively, it explains one-quarter of the contemporaneous aggregate decline in U.S. manufacturing employment. Transfer benefits payments for unemployment, disability, retirement, and healthcare also rise sharply in exposed labor markets. The deadweight loss of financing these transfers is one to two-thirds as large as U.S. gains from trade with China.

Keywords: Trade Flows, Import Competition, Local Labor Markets, China

JEL Classifications: F16, H53, J23, J31

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1 Introduction

The past two decades have seen a fruitful debate on the impact of international trade on U.S. labor markets (Feenstra, 2010). Beginning in the 1990s, the literature developed rapidly as economists sought to understand the forces behind rising U.S. wage inequality. While in the 1980s, trade in the form of foreign outsourcing was associated with modest increases in the wage premium for skilled manufacturing labor (Feenstra and Hanson, 1999), the evidence suggests that other shocks, including skill biased technical change, played a more important role in the evolution of the U.S. wage structure in that decade (Katz and Autor, 1999).[1]

One factor limiting trade's impact on U.S. labor is that historically, imports from low-wage countries have been small (Krugman, 2000). Though freer trade with countries at any income level may affect wages and employment, trade theory identifies low-wage countries as a likely source of disruption to high-wage labor markets (Krugman, 2008). In 1991, low-income countries accounted for just 2.9% of US manufacturing imports (Table 1).[2] However, owing largely to China's spectacular growth, the situation has changed markedly. In 2000, the low-income-country share of U.S. imports reached 5.9% and climbed to 11.7% by 2007, with China accounting for 91.5% of this import growth over the period. The share of total U.S. spending on Chinese goods rose from 0.6% in 1991 to 4.6% in 2007 (Figure 1), with an inflection in 2001 when China joined the World Trade Organization.[3] Increased exposure to trade with China and other developing economies suggests that the labor-market consequences of trade may be larger today than 20 years ago. Yet, skepticism about the importance of trade for U.S. labor markets persists. Lawrence (2008) and Edwards and Lawrence (2010), for instance, dismiss a significant role for trade in U.S. wage changes after 1990.

In this paper, we relate changes in labor market outcomes from 1990 to 2007 across U.S. local labor markets to changes in exposure to Chinese import competition. We treat local labor markets as sub-economies subject to differential trade shocks according to initial patterns of industry specialization.[4] Commuting zones (CZs), which encompass all metropolitan and non-metropolitan areas in the United States, are logical geographic units for defining local labor markets (Tolbert and Sizer, 1996; Autor and Dorn, 2011). They differ in their exposure to import competition as a result

[1] The significance of technical change for the U.S. wage structure is a source of continuing debate. See Lemieux (2006), Autor, Katz, and Kearney (2008), and Autor and Dorn (2011) for recent work.

[2] We classify countries as low income according to the World Bank definition in 1989, as listed in the online Data Appendix.

[3] In Figure 1, we define import penetration as U.S. imports from China divided by total U.S. expenditure on goods, measured as U.S. gross output plus U.S. imports minus U.S. exports.

[4] In related work, Borjas and Ramey (1995) examine how imports of durable manufactures affect wages across US cities, and Michaels (2008) considers whether improvements in U.S. transportation lead to factor price equalization among rural U.S. counties. Our approach is also related to the literature on the effects of immigration on native wages and employment across US regions. See, e.g., Borjas, Freeman, and Katz (1997), Borjas (1999), and Card (2001).

of regional variation in the importance of different manufacturing industries for local employment. In 1990, the share of regional employment hours worked in manufacturing ranged from 12% for CZs in the bottom tercile to 27% for CZs in the top tercile. Variation in the overall employment share of manufacturing, however, only explains about a quarter of the variation in the measure of local-labor-market import exposure that we will define below. The main source of variation in exposure is within-manufacturing specialization in industries subject to different degrees of import competition. In particular, there is differentiation according to local-labor-market reliance on labor-intensive industries, in which China's comparative advantage is pronounced (Amiti and Freund, 2010). By 2007, China accounted for over 40% of US imports in four four-digit SIC industries (luggage, rubber and plastic footwear, games and toys, and die-cut paperboard) and over 30% in 28 other industries, including apparel, textiles, furniture, leather goods, electrical appliances, and jewelry.

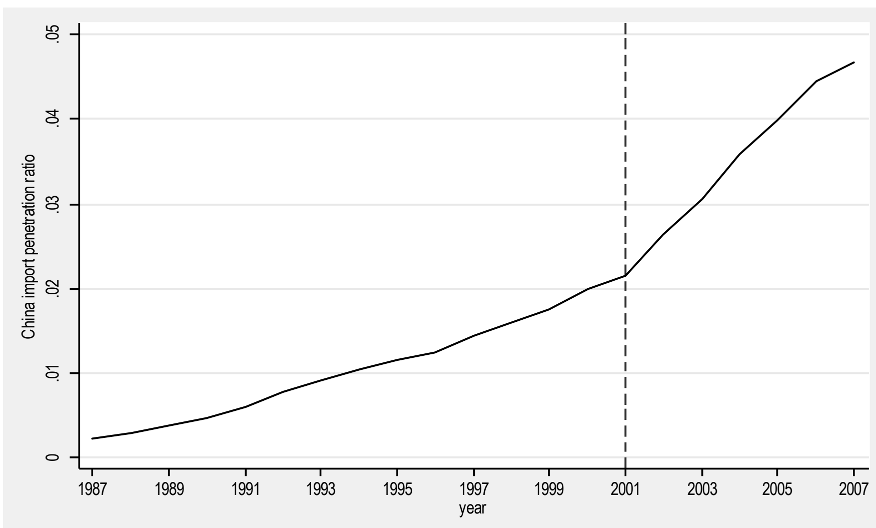


Figure 1.
Import Penetration Ratio for U.S. Imports from China.

The growth in low-income country exports over the time period we examine is driven largely by China's transition to a market-oriented economy, which has involved over 150 million workers migrating from rural areas to cities (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 (Blonigen and Ma, 2010).[5] China's transition has produced a large positive shock to its export supply, with the shock

[5]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. 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

concentrated in labor-intensive goods. Abetting this shock is China's accession to the WTO, which gives the country most-favored nation status among the 153 WTO members (Branstetter and Lardy, 2006). Thus, China's export growth is the product of internal productivity growth, associated with the dismantling of central planning, a latent comparative advantage in labor-intensive sectors, and global changes in trade policy toward China, facilitated by the lowering of its own trade barriers. In light of the 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.[6] As alternative estimation strategies, we measure CZ exposure to import competition using either the imputed labor content of U.S. net imports from China or U.S. import growth from China as predicted by the gravity model of trade. These three approaches yield similar results.

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. One solution to the degrees-of-freedom problem is to exploit the general equilibrium relationship between changes in product prices and changes in factor prices, which allows one to estimate changes in wages for skilled and unskilled labor mandated by industry trade shocks (e.g., Leamer, 1993; Feenstra and Hanson, 1999; Harrigan, 2000). This approach is well-grounded in trade theory but is silent on non-wage outcomes, such as employment status or receipt of government transfers.

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. We relate changes in exposure to low-income-country imports to changes in CZ wages, employment levels, industry employment shares, unemployment and labor-force participation rates, and take-up of unemployment, disability, welfare, and other publicly funded benefits, where we allow impacts to vary by age, gender, and education. Our local labor market approach to analyzing the impacts of trade exposure follows the approach used in recent work by Kovak (2011), Topolva (2010), and Chiquiar (2008), who study the affect of trade liberalizations on wages, poverty, and migration in local and regional labor markets in Brazil, India, and Mexico, respectively.

An alternative solution to the degrees-of-freedom problem in estimating the effects of trade shocks is to treat the industry or occupation as the unit of analysis. This approach is taken in recent work focusing on U.S. imports from low-income countries, including Bernard, Jensen, and Schott (2006),

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.

[6]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. See also Auer and Fischer (2008).

who find that over 1977-1997, manufacturing plants more exposed to low-wage-country imports grew more slowly and were more likely to exit, and Liu and Trefler (2008), who estimate that over 1996-2006, U.S. outsourcing of services to China and India had minimal effects on changes in occupation, employment, or earnings for U.S. workers. Ebenstein, Harrison, McMillan, and Phillips (2010), who like Liu and Trefler (2008) use data from the CPS, find larger effects of trade on wages, with wages growing more slowly in occupations more exposed to import penetration and to U.S. multinationals moving production offshore.[7] Our approach is complementary to this strand of literature. In examining regions rather than occupations we adopt a broader definition of skill (i.e., education rather than occupation), but also are able to examine a broader range of outcomes.

If labor is highly mobile across regions, trade may affect workers without its consequences being identifiable at the regional level. The literature on regional adjustment to labor-market shocks suggests that mobility responses to innovations in labor demand shocks across U.S. cities and states are slow and incomplete (Topel, 1986; Blanchard and Katz, 1992; Glaeser and Gyourko, 2005).[8] Mobility is lowest for non-college workers, who are over-represented in manufacturing (Bound and Holzer, 2000; Notowidigdo, 2010). It is therefore plausible that the effects of trade shocks on regional labor markets will be evident over the medium term; indeed, our analysis does not find significant population adjustments for local labor markets with substantial exposure to imports.

Our results suggest that the predominant focus of the previous literature on wages misses important aspects of labor market adjustments to trade. We find that increased exposure to low-income-country imports is associated with rising unemployment, decreased labor-force participation, and increased use of disability and other transfer benefits, as well as with lower wages, in affected local labor markets. Comparing two CZs over the period of 2000 through 2007, one at the 25th percentile and the other at the 75th percentile of exposure to Chinese import growth, the CZ at the 75th percentile would be expected to experience a differential 4.5 percent fall in the number of manufacturing employees, a 0.8 percentage point fall in the employment to population rate, a 0.8 percent fall in mean log weekly earnings, and increases in per capita unemployment, disability, and income assistance transfer benefits on the order of 2 to 3.5 percent. These results indicate that federally funded transfer programs, such as Social Security Disability Insurance (SSDI), implicitly insure U.S. workers against trade-related employment shocks. Import exposure also predicts a large but impre-

[7] Related literature examines wage outcomes of trade shocks at the plant level. See Verhoogen (2008) on Mexico, Amiti and Davis (2009) on Indonesia, and Hummels, Jorgensen, Munch, and Xiang (2010) on Denmark. Harrison, McLaren, and McMillan (2010) provide a survey of recent literature on trade and labor markets.

[8] Bertrand (2004) finds that increased exposure to imports makes workers' wages more sensitive to unemployment rates, suggesting that trade may reduce labor-market frictions. Artuc, Chaudhuri, and McLaren (2010) explicitly allow for costs to worker mobility between sectors, and find that such costs are large empirically.

cisely measured increase in benefits from Trade Adjustment Assistance (TAA), which is the primary federal program that provides financial support to workers who lose their jobs as a result of foreign trade. TAA grants are however temporary, whereas most workers who take-up disability receive SSDI benefits until retirement or death (Autor and Duggan, 2006). For regions affected by Chinese imports, the estimated dollar increase in per capita SSDI payments is more than thirty times as large as the estimated dollar increase in TAA payments.

To motivate the analysis, we begin in Section 2 by using a standard model of trade to derive product demand shocks facing local labor markets in the U.S. resulting from export growth in China. Section 3 provides a brief discussion of data sources and measurement. Section 4 provides our primary OLS and 2SLS estimates of the impact of trade shocks on regional employment in manufacturing. Section 5 analyzes the consequences of these shocks for regional labor market aggregates, including unemployment, labor force non-participation, population flows, and earnings levels. Section 6 expands the inquiry to broader measures of economic adjustment: household income and receipt of transfer benefits from federal and state governments. Section 7 integrates U.S. exports to China and the factor content of trade into the local labor market analysis. In Section 8, we provide a rough comparison of the potential consumer gains from trade with China and to the deadweight losses associated with trade-induced increases in the use of public transfer benefits. These deadweight losses equal, in the medium run, about one to two thirds of the consumer gains from trade. Section 9 concludes.

2 Theoretical motivation and empirical approach

How does import competition from China affect the demand for labor in U.S. regions? The most direct channel is through changes in the demand for goods produced by local labor markets. In this section, we use the Eaton and Kortum (2002) model of trade to consider how growth in U.S. imports from China—driven by changes in China's productivity and trade costs—affects the demand for goods produced by U.S. regional economies. These product demand shocks motivate our empirical measure of exposure to import competition as well as our identification strategy.

2.1 Shocks to regional markets

Let the demand for labor in industry j by region i be given by $L_{ij} = L^d(w_{ij}, Q_{ij})$, where w_{ij} is unit production costs and Q_{ij} is output. For region i, sales to destination market n in industry j are a function of its technological capability (T_{ij}), unit production costs (w_{ij}), and bilateral trade costs

(τ_{nij}), as well as expenditure in destination market n for goods of industry j (X_{nj}). Technological capability, T_{ij}, is a parameter that determines the position of the distribution of firm productivities in an industry and region. Using the solution to the Eaton and Kortum (2002) model, region i's sales in industry j to destination market n can be written as

$$X_{nij} = \frac{T_{ij}(w_{ij}\tau_{nij})^{-\theta}}{\Phi_{nj}} X_{nj}, \tag{1}$$

where θ describes the dispersion in productivity among firms and $\Phi_{nj} \equiv \sum_h T_{hj}(w_{hj}\tau_{nhj})^{-\theta}$ describes the "toughness" of competition in destination market n in industry j, reflecting production and trade costs in locations that supply market n. Region i will capture a larger share of market n's purchases in industry j when it has high productivity, low production costs, and low trade costs relative to other suppliers. Define $A_{ij} \equiv T_{ij} w_{ij}^{-\theta}$ to be the cost-adjusted productivity of region i in industry j. Summing over destination markets for region i, its total output in industry j is

$$Q_{ij} = A_{ij} \sum_n \frac{X_{nj}\tau_{nij}^{-\theta}}{\Phi_{nj}}. \tag{2}$$

China will be among the countries with which each U.S. region competes in serving destination markets. When China's productivity expands or its foreign trade costs fall, it increases the value of Φ_{nj} in each destination market, diverting product demand away from U.S. regions that also serve these markets. To show this formally, consider the change in Q_{ij} that would result were China to experience exogenous productivity growth (i.e., an increase in T_{cj}, where c indexes China) or a reduction in trade costs, due, say, to China's accession to the WTO. The direct effect of changes in China's productivity and trade costs on Q_{ij} is

$$\hat{Q_{ij}} = -\sum_n \frac{X_{nij}}{Q_{ij}} \frac{X_{ncj}}{X_{nj}} (\hat{A}_{cj} - \theta \hat{\tau}_{ncj}) \tag{3}$$

where $\hat{x} \equiv d \ln x$, X_{nij}/Q_{ij} is the share of exports to destination market n in region i's output in industry j, and X_{ncj}/X_{nj} is the share of imports from China in spending by destination market n in industry j. Equation (3) implies that the fall in region i's output in industry j is larger the higher is cost-adjusted productivity growth in China ($\hat{A}_{cj}$) and the larger is the reduction in trade costs facing China ($\hat{\tau}_{ncj}$), where the impact of these shocks is larger the more dependent region i is on market n and the more important China is as a source of supply to market n. In applying equation (3), we will primarily focus on competition that CZs face from China in the U.S. market, thus limiting the summation above to $n = u$, that is, to outputs produced and consumed in the United States.

Later in the analysis, we will relax this restriction, allowing China to affect U.S. regions through its impact on the toughness of competition facing U.S. industries in foreign markets.

In general equilibrium, changes in China's productivity and trade costs may also cause wages and other factor prices to change in the countries with which China competes. These changes in factor prices, in turn, may cause changes in aggregate spending by countries, as the effects of shocks to China reverberate through the global economy (Hsieh and Ossa, 2011). Equation (3) thus shows only the *direct* effect of shocks to Chinese productivity and trade costs on the demand for output in region i, ignoring the indirect effects of these changes on factor prices and spending in region i and in other regions and countries. Our empirical analysis does not assume that these general equilibrium impacts are zero, however. Instead, we use equation (3) to generate a measure of regional labor markets' exposure to shocks to Chinese productivity and trade costs, and then we analyze how regional labor markets adjust to these shocks along numerous margins.

2.2 Empirical approach

To consider the effects of shocks to China's productivity and trade costs on aggregate sales by region i, we sum equation (3) across industries to obtain:

$$\hat{Q}_i = -\sum_j \frac{Q_{ij}}{Q_i} \frac{X_{uij}}{Q_{ij}} \frac{X_{ucj}}{X_{uj}} (\hat{A}_{cj} - \theta\hat{\tau}_{cj}) = -\sum_j \frac{X_{uij}}{X_{uj}} \frac{X_{ucj}(\hat{A}_{cj} - \theta\hat{\tau}_{cj}).}{Q_i}. \tag{4}$$

This expression motivates our measure of exposure to import competition in U.S. local labor markets. It says that region i is more exposed to import competition from China when it accounts for a larger share of U.S. sales (X_{uij}/X_{uj}) in industries in which productivity and trade cost-driven growth in U.S. imports from China ($X_{ucj}(\hat{A}_{cj} - \theta\hat{\tau}_{cj})$) is large relative to its total output (Q_i).

To bring this expression to the data, we employ proxies for variables that are not observed. Because we lack data on output in local labor markets, we proxy for total regional output (Q_i) using total regional employment (E_i), and we proxy for industry level output by region using industry employment (E_{ij}). Similarly, because we lack data on the specific destination markets to which U.S. regions export, we focus on sales by each region on the U.S. market, where we proxy for the share of a region in U.S. output in an industry (X_{uij}/X_{uj}) with a region's share of U.S. national employment in the industry (E_{ij}/E_{uj}).

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:

$$\Delta IPW_{uit} = \sum_j \frac{E_{ijt}}{E_{ujt}} \frac{\Delta M_{ucjt}}{E_{it}}. \tag{5}$$

In this expression, E_{it} is equal to start of period employment (year t) in region i and ΔM_{ucjt} is equal to the observed change in U.S. imports from China in industry j between the start and end of the relevant time period. It bears note that the distribution of imports over CZs does not attempt to approximate actual shipments of goods to different locations in the U.S. Instead, it measures the *potential* exposure to import competition that local labor markets face due to their industry specialization.[9]

A concern for our subsequent estimation is that realized industry imports in equation (5) may be correlated with industry labor demand shocks. To identify the causal effect of rising Chinese import exposure (stemming from Chinese TFP gains and falling trade barriers) 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. Specifically, we exploit the exogenous component of Chinese imports that stems from the rising competitiveness of Chinese manufacturers (a supply shock from the U.S. producer perspective) spurred by China's lowering of trade barriers, dismantling of central planning, and accession to the World Trade Organization.

To identify this 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.[10] 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:

$$\Delta IPW_{oit} = \sum_j \frac{E_{ijt-1}}{E_{ujt-1}} \cdot \frac{\Delta M_{ocjt}}{E_{it-1}}. \tag{6}$$

This expression for *non*-U.S. exposure to Chinese imports differs from the expression in equation (5) 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

[9]Kovak (2011) derives a comparable equation relating changes in regional goods prices to regional wages in a model where regions hold comparative advantage in specific outputs due to their differential access to industry-specific factors. Our approach takes regional specialization as fixed (or predetermined) and does not model underlying industry production technologies. We instead use envelope conditions to derive changes in regional demand mandated by the rising productivity of a competing producer.

[10]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.

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.

This instrumental variable strategy will identify the Chinese productivity and trade-shock component of U.S. import growth if, plausibly, the common within-industry component of rising Chinese imports to the U.S. and other high-income countries stems from China's rising comparative advantage and (or) falling trade costs in these sectors. Changes in U.S. labor demand may arise in part from internal shocks to product demand or technology. If these shocks are correlated across countries, internal labor demand factors may not be fully purged by the instrument. Correlated product demand shocks are likely to bias our estimates *against* finding an adverse effect of Chinese import exposure on U.S. manufacturing. This attenuation bias would arise because positive domestic demand shifts for specific goods will typically contribute to both rising Chinese imports and rising U.S. employment in the relevant sectors.[11] The effects of correlated technology shocks are more difficult to gauge. However, our alternative gravity-based estimation approach, described below, implicitly controls for changes in U.S. industry productivity.

Equation (5) 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-manufacturing activities, and specialization in import-intensive industries within local manufacturing. Differences in manufacturing employment shares are not a dominating source of variation, however; the start-of-period manufacturing employment share explains less than 25% of the variation in ΔIPW_{uit} in a bivariate regression. In our main specifications, we will 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.[12]

In the Theory Appendix, we describe a second approach to measuring supply-drive growth in U.S. imports from China, $X_{ucj}(\hat{A}_{cj} - \theta\hat{\tau}_{cj})$. Using bilateral trade data at the industry level, we estimate

[11] In the case of consumer electronics, rising Chinese imports to the U.S. and other high-income countries may stem from a mixture of increased domestic demand (e.g., for mobile phones) and improving Chinese TFP (so that components are sourced from China rather than, say, Japan). For this industry, we are likely to understate the impact that rising Chinese imports would have had on U.S. manufacturing had they arisen solely from shifts in Chinese supply. Consistent with this logic, we find in unreported results that when we exclude the computer industry from our measure of imports, then the estimated impact of import exposure on manufacturing employment becomes larger.

[12] Concretely, consider two CZs, each with a 20 percent manufacturing employment share in 1990, one of which manufactures luggage (SIC 3161) and the other small firearms (SIC 3484). Between 1990 and 2000, the luggage manufacturing industry experienced an increase in Chinese imports of \$101,000 per worker . Imports of Chinese small arms fell by \$1,300 per U.S. worker in the decade. The ΔIPW_{ujt} metric will therefore imply that the former CZ experienced a substantial increase in Chinese import exposure during the 1990s while the latter CZ did not.

a modified gravity model of trade for the period 1990 through 2007 that includes fixed effects at the importer and product level. We show that the residuals from this regression approximate the percentage growth in imports from China due to changes in China's productivity and foreign trade costs relative to to the United States. Thus, in this alternative approach we measure changes in China's comparative advantage vis-a-vis the U.S. In the empirical estimation, shown in section 7, we obtain qualitatively similar results using either imports per worker from equation (5), with the instrument defined as in equation (6), or using the gravity-based approach. As a third approach, also presented in section 7, we replace the change in imports per worker as defined in equation (5) with the change in the imputed labor content of U.S. net imports from China, an approach motivated by analyses of the labor market consequences of trade based on the Heckscher-Ohlin model (Deardorff and Staiger, 1988; Borjas, Freeman, and Katz, 1997; Burstein and Vogel, 2011). This strategy again yields results that are comparable to our benchmark estimates.

3 Data sources and measurement

This section provides summary information on our data construction and measurement, with further details given in the online Data Appendix.

Table 1. Value of Trade with China for the U.S. and Other Selected High-Income Countries and Value of Imports from all other Source Countries, 1991/1992-2007.

	I. Trade with China (in BN 2007 US$)		II. Imports from Other Countries (in BN 2007 US$)		
	Imports from China (1)	Exports to China (2)	Imports from Other Low-Inc. (3)	Imports from Mexico/Cafta (4)	Imports from Rest of World (5)
			A. United States		
1991/92	26.3	7.5	7.7	38.5	905.8
2000	121.6	23.0	22.8	151.6	1865.5
2007	330.0	57.4	45.4	183.0	2365.9
Growth 1991-07	1156%	663%	491%	375%	161%
			B. 8 Other Developed Countries		
1991/92	28.2	19.4	9.2	2.8	1708.8
2000	94.3	68.2	13.7	5.3	1979.8
2007	262.8	196.9	31.0	11.6	3339.3
Growth 1991-07	832%	914%	236%	316%	95%

Notes: Trade data is reported for the years 1991, 2000, and 2007, except for exports to China which are first available in 1992. The set of "Other Developed Countries" in Panel B comprises Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Column 3 covers imports from all countries that have been classified as low-income by the World Bank in 1989, except for China. Column 4 covers imports from Mexico and the Central American and Carribean countries covered by the CAFTA-DR free trade agreement. Column 5 covers imports from all other countries (primarily from developed countries).

We use data from the UN Comrade Database on U.S. imports at the six-digit HS product level. Due to lags in countries adopting the HS classification, 1991 is the first year for which we can obtain data across many high-income economies. The first column in Panel A of Table 1 shows the value of annual U.S. imports from China for the years 1991, 2000, and 2007 (with all values in 2007 USD). During the sixteen year period from 1991 to 2007, this import value increased by a factor of 11.5, from 26 billion dollars to 330 billion dollars. For comparison, the second column of Panel A provides the value of annual U.S. exports to China in 1992, 2000, and 2007. The volume of U.S. exports was substantially smaller than the volume of imports throughout these years, and the growth of imports outpaced the growth of exports. The primary change in U.S.-China trade during our sample period is thus the dramatic increase of U.S. imports.

The third and fourth columns of Panel A summarize the value of imports from Mexico and Central America, and from a set of 51 low income countries that are mostly located in Africa and Asia.[13] While imports from these countries grew considerably over time, the expansion was much less dramatic than in the case of Chinese imports. Panel B summarizes trade flows from the same exporters to a group of eight high-income countries located in Europe, Asia, and the Pacific (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). Like the U.S., these countries experienced a dramatic increase in imports from China between 1991 and 2007, and a more modest growth of imports from Mexico and Central America, and from other low-income countries. We focus on these high-income countries as they are the rich nations for which disaggregated HS trade data are available back to 1991.

To assess the effect of imports of Chinese goods on local labor markets, we need to define 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).

It is plausible that the effects of Chinese imports will vary across local labor markets in the U.S. because there is substantial geographic variation in industry specialization. Local economies that are specialized in industries whose outputs compete with Chinese imports should react more strongly to the growth of these imports. Our measure for the exposure of local labor markets to Chinese imports in equation (5) combines trade data with information on local industry employment. Information on industry employment structure by CZs, including employment in 397 manufacturing industries, is derived from the County Business Patterns data (see the Data Appendix).

[13] Mexico/CAFTA includes Mexico, the Dominican Republic and all Central American countries except Belize and Panama. Other low-income countries include those the World Bank defined as low income in 1989, except China.

Panel A of Appendix Table 1 shows descriptive statistics for ΔIPW_{ujt} by time period.[14] In the median commuting zone, the 10-year equivalent growth of Chinese imports amounted to $890 dollars per worker during 1990 through 2000, and to $2,110 dollars per worker during 2000 through 2007, reflecting an acceleration of import growth over time. Appendix Table 1 also documents the considerable geographic variation in the exposure of local labor markets to Chinese import shocks. In both time periods, CZs at the 75th percentile of the import exposure variable experienced an increase in import exposure per worker that was roughly twice as large as that faced by CZs at the 25th percentile. Panel B of the table summarizes changes in import exposure per worker among the 40 most populous CZs in the United States. These rankings provide evidence for considerable variation of trade exposure within U.S. regions. For instance, the state of California contained three CZs in the top quartile of exposure in the 1990s (San Jose, San Diego, and Los Angeles) but also two CZs in the bottom quartile (Sacramento and Fresno). Relative trade exposure is generally persistent across the two time periods, with San Jose and Providence being the most exposed and Washington DC, New Orleans, and Orlando being the least exposed large CZs in both periods.

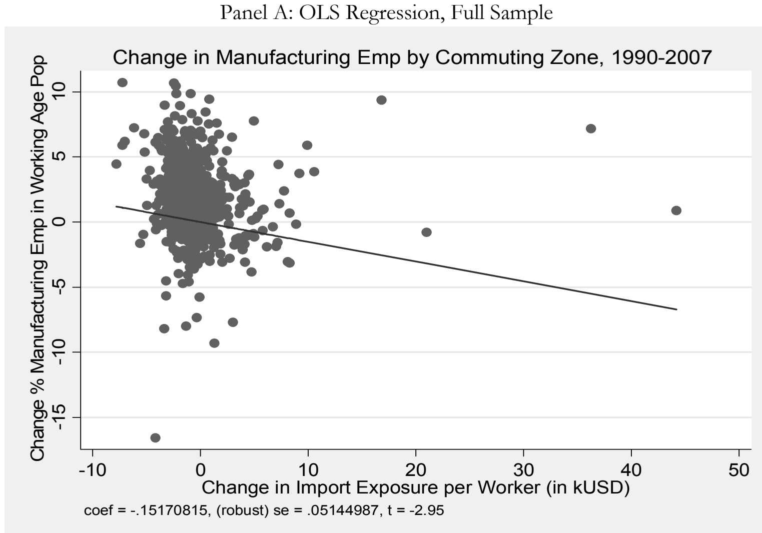
Most of the empirical analysis studies changes in CZ's population, employment and wage structure by education, age, and gender. These variables are constructed based on data from the Census Integrated Public Use Micro Samples (Ruggles et al. 2004) for the years 1970, 1980, 1990 and 2000, and the American Community Survey (ACS) for 2006 through 2008.[15] We map these data to CZs using the matching strategy that is described in detail in Dorn (2009) and that has previously been applied by Autor and Dorn (2009, 2011) and Smith (2010). We also use data on federal and state transfer payments to CZ residents. These data were obtained from the Bureau of Economic Analysis and the Social Security Administration (see the online Data Appendix for details). Appendix Table 2 provides means and standard deviations for the main variables.

[14] In order to put the two periods on a comparable decadal scale, trade growth during 1991 to 2000 and during 2000 to 2007 has been multiplied with the factors 10/9 and 10/7, respectively.

[15] We use the combined ACS 2006 to 2008 file instead of the ACS 2007 because it provides a larger sample size. The analysis implicitly treats the 2006 to 2008 data as referring to the year 2007.

4 The impact of trade shocks on manufacturing employment

Panel A: OLS Regression, Full Sample



Panel B: OLS Regression, Trimmed Sample

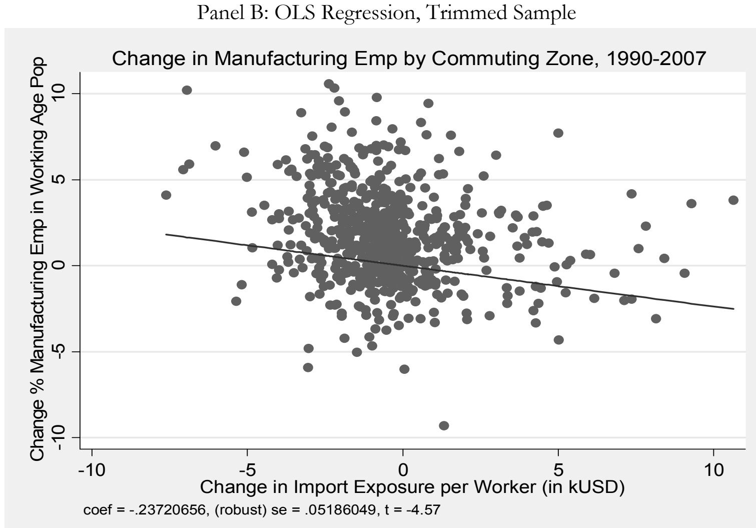


Figure 2.
Change in Import Exposure per Worker and Decline of Manufacturing Employment: Added Variable Plots of OLS Estimates.

Notes: N=722 in Panel A and N=707 in Panel B (covering 100% and 99.1% of U.S. population, respectively). The added variable plots control for the start of period share of employment in manufacturing industries. The regression in Panel B omits 15 commuting zones whose change in import exposure or change in manufacturing emplyoment share deviates from the respective sample medians by more than 5 standard deviations. Regression models are weighted by start of period commuting zone share of national population.

Prior to our statistical analysis of the impact of trade shocks on manufacturing employment in local labor markets, we plot in Figure 2 the relationship between changes in manufacturing employment as a share of overall working age population within CZs and changes in Chinese import exposure per worker during 1990-2007. The plotted regression models control for CZs' start-of-period share of employment in manufacturing so that the import exposure variable captures variation in CZs' manufacturing industry mix holding constant the manufacturing share. Figure 2a shows that in the full sample of 722 CZs, there is a pronounced negative relationship between changes in Chinese import exposure and changes in manufacturing employment within local labor markets. The regression model depicted in Figure 2a weights CZs according to their share in national population in 1990. Nevertheless, the figure reveals that there are a few small CZs with unusually large values of import exposure growth that affect the regression estimates substantially. Figure 2b plots the same bivariate relationship for a trimmed sample that suppresses the 15 CZs whose variable values differ from the sample medians by more than 5 standard deviations. In the trimmed sample, which covers 99.1% of U.S. mainland population, the negative relationship between changes in Chinese import exposure and changes in local manufacturing employment is larger and clearly visible in the figure, indicating that a rise of $1,000 per worker in a commuting zone's exposure to Chinese imports is associated with a decline in manufacturing employment of approximately one fourth of a percentage point of working age population. The mean increase in Chinese import exposure during 1990-2007 was about $3,300 per worker. In the estimation, we will use the full sample, addressing outliers stemming from measurement error through instrumentation.

Our instrumental variable strategy, as outlined in section 2.2, identifies the component of U.S. import growth that is due to Chinese productivity and trade costs. The identifying assumption underlying this 2SLS strategy is that the common within-industry component of rising Chinese imports to the U.S. and other high-income countries stems from China's rising comparative advantage and falling trade costs in these sectors. Figure 3 sketches the estimation strategy. Panel A reveals the substantial predictive power of the high-income country instrument for observed changes in import exposure. A $1,000 predicted increase in import exposure per CZ worker corresponds to a $815 increase in observed exposure per CZ worker. Panel B of Figure 3 plots a reduced form (OLS) regression of the change in manufacturing employment on the instrument. This figure shows a substantial reduction in manufacturing employment in the CZs facing large increases in Chinese import exposure.

We explore the robustness and interpretation of this result in subsequent tables. Before doing so, it is worth remarking on two reasons why the 2SLS point estimate in Figure 3 exceeds the corresponding OLS point estimate in Figure 2. A first is that the 2SLS model isolates the components of variation in imports that are due to Chinese *productivity and trade-cost* shocks, which are expected to reduce employment in import-competing U.S. industries. By contrast, the OLS model uses import variation stemming from both Chinese supply shocks and U.S. demand shocks, the latter of which may positively affect U.S. manufacturing employment. We would therefore expect the OLS estimates to be biased towards zero by simultaneity. The second factor affecting the comparison is that the 2SLS model should reduce attenuation bias due to measurement error in the CZ employment variables that are used for the construction of the endogenous variable. Indeed, the first stage plot in Figure 3a shows that two CZs with highest values of ΔIPW_{uct}, whose largest towns are Murray KY and Olney IL, respectively, do not have correspondingly large values for the predicted exposure instrument. With the influence of these outliers reduced, the data indicate a steeper relationship between Chinese import exposure and CZ manufacturing employment.[16]

4.1 2SLS estimates

Table 2 presents detailed estimates of the relationship between Chinese import exposure and U.S. manufacturing employment. Using the full sample of 722 CZs and weighting each observation by start of period CZ population, we fit models of the following form:

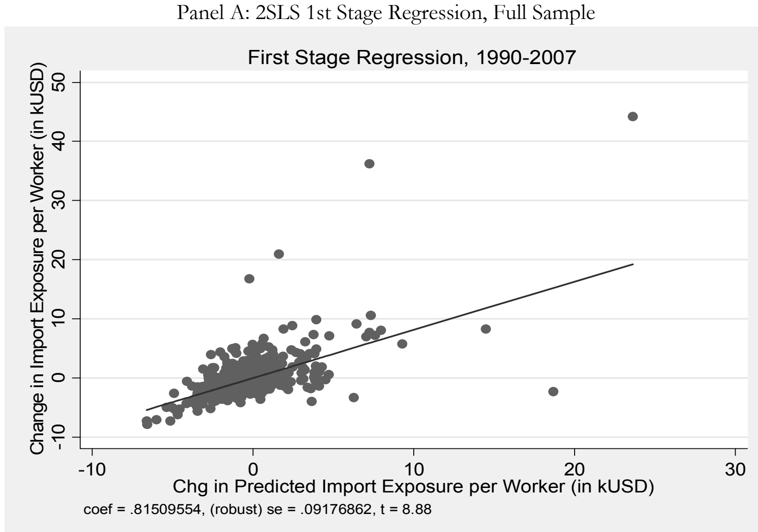
$$\Delta E^m_{it} = \gamma_t + \beta_1 \Delta IPW_{uit} + X'_{it}\beta_2 + e_{ct}, \tag{7}$$

where ΔE^m_{it} is the decadal change in the manufacturing employment share of the working age population in commuting zone i. When estimating this model for the long interval between 1990 and 2007, we stack the 10-year equivalent first differences for the two periods, 1990 to 2000 and 2000 to 2007, and include separate time dummies for each decade (in the vector γ_t). The change in import exposure ΔIPW_{uit} is instrumented by the variable ΔIPW_{oit} as described above. Because the model is estimated in first differences, the decade-specific models are equivalent to fixed effects regressions, while the stacked first difference models are similar to a three-period fixed effects model with slightly less restrictive assumptions made on the error term.[17] Additionally, the vector X_{it} contains a rich set of controls for CZs' start-of-decade labor force and demographic composition (detailed below), which might independently affect manufacturing employment. Standard errors are clustered at the state level to account for spatial correlations across CZs.

[16] We also experimented with using CZs' start of period employment shares, rather than their lagged values, when constructing the instrument. In these models, the outliers visible in Figure 2 were present in both the endogenous variable and the instrument. This suggests that measurement error in employment generates the large outliers in the endogenous variable, and that the instrument corrects this issue because the measurement error in employment is not strongly serially correlated over a 10-year interval.

[17] Estimating (7) as a fixed-effects regression assumes that the errors are serially uncorrelated, while the first-differenced specification is more efficient if the errors are a random walk (Wooldridge 2002). Since we use Newey-West standard errors in all models are clustered on U.S. state, our estimates should be robust to either error structure.

Panel A: 2SLS 1st Stage Regression, Full Sample



Panel B: OLS Reduced Form Regression, Full Sample

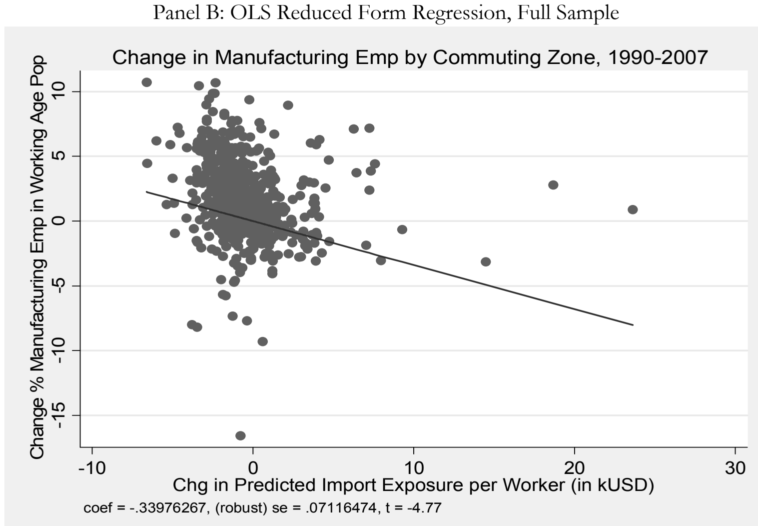


Figure 3.
Change in Import Exposure per Worker and Decline of Manufacturing Employment: Added Variable Plots 2SLS and Reduced Form Estimates

Notes: N=722. Regression models are weighted by start of period commuting zone share of national population.

The first two columns of Table 2 estimate equation (7) separately for the 1990-2000 and 2000-2007 periods, and the third column provides stacked first differences estimates. The estimated coefficient of the import exposure variable is of a similar in magnitude in both time periods and all three models, underscoring the stability of the statistical relationships.

Table 2. Imports from China and Change of Manufacturing Employment in Commuting Zones, 1970-2007: 2SLS Estimates.
Dependent Variable: 10 x Annual Change in Manufacturing Emp/Working Age Pop (in %pts)

	I. 1990-2007			II. 1970-1990 (Pre-Exposure)		
	1990-2000	2000-2007	1990-2007	1970-1980	1980-1990	1970-1990
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ Current Period Imports from China to US)/Worker	-0.89 **	-0.72 **	-0.75 **			
	(0.18)	(0.06)	(0.07)			
(Δ Future Period Imports from China to US)/Worker				0.43 **	-0.13	0.15
				(0.15)	(0.13)	(0.09)

Notes: N=722, except N=1444 in stacked first difference models of columns 3 and 6. The variable 'future period imports' is defined as the average of the growth of a CZ's import exposure during the periods 1990-2000 and 2000-2007. All regressions include a constant and the models in columns 3 and 6 include a time dummy. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Over the time period that we examine, U.S. manufacturing experienced a secular decline. One concern for our analysis is that increased imports from China could be a symptom of this decline rather than a cause. To verify that our results capture the period-specific effects of exposure to China trade, and not some long-run common causal factor behind both the fall in manufacturing employment and the rise in Chinese imports, in the fourth to sixth columns we conduct a falsification exercise by regressing *past* changes in the manufacturing employment share on *future* changes in import exposure. Column 4 shows the correlation between changes in manufacturing employment in the 1970s and the change in future import exposure averaged over the 1990s and 2000s, column 5 shows the corresponding correlation for the 1980s, and column 6 provides the results of the stacked first differences model. These correlations are inconsistently signed and generally small in value. There is a weak negative relationship between the change in manufacturing employment and future import exposure in the 1980s; in the prior decade, this relationship is positive. We thus see little evidence that manufacturing declines forecast future increases in imports from China.

In Table 3, we augment the stacked first difference model for the period 1990-2007. In the second column, we add a control for the share of manufacturing in a CZ's start-of-period employment. This specification further addresses the concern that the China exposure variable may in part be picking up an overall trend decline in U.S. manufacturing rather than the component that is due specifically to differences across manufacturing industries in their exposure to rising Chinese competition. The coefficient estimates in column 2 imply that a CZ with a one percentage point higher initial manufacturing share experiences a differential manufacturing employment share decline of 0.04 percentage points over the subsequent decade. Not surprisingly, this specification yields smaller coefficient estimates than the regression model in column 1 that does not directly control for the initial manufacturing share of local labor markets. Nevertheless, the estimated impact of import competition on manufacturing employment remains highly significant. The point estimate in column 2 of Table 3 implies that the share of manufacturing employees in the working age population of a CZ at the 75th percentile of import exposure declined by -0.65 percentage points more than in a CZ at the 25th percentile between 2000 and 2007.[18]

Column 3 augments the regression model with geographic dummies for the nine Census divisions. These dummies, which absorb region-specific trends in the manufacturing employment share, moderately decrease the estimated effect of import exposure on manufacturing employment. Column 4 additionally controls for the start-of-period share of a CZ's population that has a college education, the share of population that is foreign born, and the share of working age women that are employed. These controls leave the main result unaffected.

Column 5 introduces two variables that capture the susceptibility of a CZ's occupations to substitution by technology or task offshoring. Both of these variables are based on occupational task data are are described in detail in Autor and Dorn (2011). Routine occupations are a set of jobs whose tasks follow a set of precisely prescribed rules and procedures which makes them readily codifiable. This category includes white collar positions whose primary job tasks involve routine information processing (e.g., accountants and secretaries), and blue collar production occupations that primarily involve repetitive production and monitoring tasks. If CZs that have a large start-of-period employment share in routine occupations experience strong displacement of manufacturing jobs due to automation, one would expect a negative relationship between the routine share variable and the change in manufacturing share. Indeed, the estimates in column 5 suggest that the population share in manufacturing falls by about 0.23 percentage points for each additional percentage point of initial employment in routine occupations.

The offshorability index used in column 5 measures the average degree to which the occupations in a commuting zone are potentially offshorable because they require neither proximity to a specific work-site nor face-to-face contact with U.S. based workers. If offshoring of occupations were a major driver for the decline in manufacturing within CZs, one would expect a negative relationship between the offshorability index and the change of the manufacturing employment share. The estimate in column 5 does not however find a negative or statistically significant association between occupational offshorability and declines in manufacturing employment.

[18] According to Appendix Table 1, the 10-year growth in import exposure for CZs at the 75th and 25th percentile is 3.11 and 1.60, respectively. The difference in growth of exposure during the period 2000-2007 is $(3.11-1.60)\times 0.7 = 1.06$ where 0.7 rescales the 10-year growth to the 7-year period. The predicted differential change between the CZs at the 75th and 25th percentile of import exposure is therefore $1.06 \times -0.610 = -0.65$.

Table 3. Imports from China and Change of Manufacturing Employment in Commuting Zones, 1990-2007: 2SLS Estimates.
Dependent Var: 10 x Annual Change in Manufacturing Emp/Working Age Pop (in %pts)

	I. 1990-2007 Stacked First Differences					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ Imports from China to US)/Worker	-0.746 **	-0.610 **	-0.538 **	-0.508 **	-0.562 **	-0.596 **
	(0.068)	(0.094)	(0.091)	(0.081)	(0.096)	(0.099)
Percentage of employment in manufacturing$_{-1}$		-0.035	-0.052 **	-0.061 **	-0.056 **	-0.040 **
		(0.022)	(0.020)	(0.017)	(0.016)	(0.013)
Percentage of college-educated population$_{-1}$				-0.008		0.013
				(0.016)		(0.012)
Percentage of foreign-born population$_{-1}$				-0.007		0.030 **
				(0.008)		(0.011)
Percentage of employment among women$_{-1}$				-0.054 *		-0.006
				(0.025)		(0.024)
Percentage of employment in routine occupations$_{-1}$					-0.230 **	-0.245 **
					(0.063)	(0.064)
Average offshorability index of occupations$_{-1}$					0.244	-0.059
					(0.252)	(0.237)
Census division dummies	No	No	Yes	Yes	Yes	Yes
	II. 2SLS First Stage Estimates					
(Δ Imports from China to OTH)/Worker	0.792 **	0.664 **	0.652 **	0.635 **	0.638 **	0.631 **
	(0.079)	(0.086)	(0.090)	(0.090)	(0.087)	(0.087)
R^2	0.54	0.57	0.58	0.58	0.58	0.58

Notes: N=1444 (722 commuting zones x 2 time periods). All regression include a constant and a dummy for the 2000-2007 period. First stage estimates in Panel B also include the control variables that are indicated in the corresponding columns of Panel A. Routine occupations are defined such that they account for 1/3 of U.S. employment in 1980. The outsourcability index variable is standardized to mean of 0 and standard deviation of 10 in 1980. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

The fully augmented model in column 6 indicates a significant and sizable negative impact of increasing import exposure on manufacturing employment. The decline in manufacturing is also larger in CZs with a greater initial manufacturing employment share, and in local labor markets where employment is concentrated in routine-task intensive occupations, and is smaller where there is a larger initial foreign born population. The import exposure measure continues to have a large and robust effect on manufacturing employment in this specification. We build the remainder of the empirical analysis on the more detailed specification in column 6 that exploits geographic variation in import exposure conditional on initial manufacturing share, Census division dummies, and control variables for basic aspects of initial population and labor force composition.

One concern about our 2SLS estimates is that in some sectors, import demand shocks may be correlated across countries, undermining the validity of our instrument. To address this concern, in unreported results we have experimented with dropping industries that one may consider suspect. During the 2000s, many rich countries experienced housing booms, associated with easy credit, which may have contributed to similar increases in the demand for construction materials. Using the specification in column 6 of Table 3 while dropping the steel, flat glass, and cement industries—inputs in relatively high demand by construction industries—has minimal effect on the coefficient estimate for import exposure, reducing it from -0.60 to -0.57. Computers are another sector in which demand shocks may be correlated, owing to common innovations in the use of information technology. Dropping computers raises the coefficient estimate on import exposure to -0.68. Finally, one may worry that the results are being driven by a handful of consumer goods industries in which China has assumed a commanding role. Dropping apparel, footwear, and textiles, for which China is by far and away the world's dominate exporter, reduces the import exposure coefficient modestly to -0.51. In all cases, coefficient estimates remain highly significant. The results thus appear robust to excluding important individual industries from the estimation.

How do OLS and 2SLS estimates compare for our preferred specification in column 6 of Table 3? The OLS estimate for this specification, as seen in column 1 of panel A in Appendix Table 4, is -0.171. OLS is subject to both measurement error in CZ employment levels and simultaneity associated with U.S. industry import demand shocks. It is possible to partially separate the importance of these two sources of bias, both of which tend to push coefficient estimates toward zero. If we measure the change in import exposure per worker using lagged employment levels (as we do in constructing the instrument in equation (6)), instead of beginning of period employment (as we do in equation (5)), the OLS coefficient estimate increases in magnitude from -0.171 to -0.273. It thus appears that addressing measurement concerns regarding CZ employment may account for one-quarter of the difference between OLS and 2SLS estimates, with the remaining difference (from -0.273 versus -0.596) associated with the correction for endogeneity.

4.2 Benchmarking the impact of China trade exposure on U.S. manufacturing

To gauge the economic magnitude of these effects, we compare the estimated trade-induced reduction in manufacturing employment with the observed decline during 1991 to 2007. Our most conservative specification in Table 3 (column 6) implies that a $1,000 per worker increase in import exposure reduces manufacturing employment per working age population by 0.596 percentage points. Appendix Table 2 shows that Chinese import exposure rose by $1,140 per worker between 1991 and 2000 and by an additional $2,630 per worker between 2000 and 2007. Applying these values to the Table 3 estimates, we calculate that rising Chinese import exposure reduced U.S. manufacturing employment per population by 0.68 percentage points in the first decade of our sample and 1.57 percentage points in the second decade of our sample. In comparison, U.S. manufacturing employment per population fell by 2.07 percentage points between 1991 and 2000 and by 2.73 percentage points between 2000 and 2007 (Appendix Table 2). Hence, we estimate that rising exposure to Chinese import competition explains 33 percent of the U.S. manufacturing employment decline between 1991 and 2000, 57 percent of the decline between 2000 and 2007, and 47 percent of the decline for the full 1991 through 2007 period.

One sense in which these benchmarks may overstate the contribution of rising Chinese imports to declining U.S. manufacturing employment is that our 2SLS point estimates measure the causal effect of Chinese *supply shocks* on U.S. manufacturing whereas the import per worker measure that we employ in the calculation above refers to the *total change* in Chinese imports per worker, which includes both supply and demand forces. If plausibly the demand-driven component of Chinese imports has a less negative effect on U.S. manufacturing employment than the supply-driven component, our benchmark may overstate the cumulative adverse effect of rising Chinese import competition on U.S. manufacturing employment.

To isolate the share of variation in the China import measure that is driven by supply shocks, we perform in the Theory Appendix a simple decomposition in which we use the relationship between OLS and 2SLS estimates to calculate the share of the variance in imports per worker that stems from the exogenous supply-driven component isolated by our instrument, with the remainder attributed to demand forces. This calculation implies that approximately half (48%) of the observed variation in rising Chinese import exposure can be attributed to the supply-driven component. Thus, we more conservatively estimate that Chinese import competition explains 16 percent of the U.S. manufacturing employment decline between 1991 and 2000, 28 percent of the decline between 2000 and 2007, and 23 percent of the decline over the full period.

4.3 The importance of non-China trade

The focus of our study on Chinese imports is motivated by the observation that China accounts for a very large portion of the dramatic recent increase in U.S. imports from low-income countries (Table 1). Moreover, it is plausible that much of China's recent trade expansion has been driven by internal productivity growth and reductions in trade barriers rather than by labor demand shocks in the U.S. To consider Chinese imports alongside those of other countries, Appendix Table 3 compares the impact of growing exposure to Chinese imports to the effect of exposure to imports from other source countries. The first column repeats our baseline estimates from Tables 2 and 3. The second column shows that the effect of imports from all low-income countries (China included) is nearly identical to the effect of imports from China, suggesting that imports from other low-income countries may have a similar impact on U.S. manufacturing as Chinese imports. Because the real dollar growth in imports from other low-income countries is an order of magnitude smaller than the growth in imports from China, their inclusion leaves our substantive conclusions regarding economic magnitudes unaffected.

Columns 3 and 4 of the table contain estimates of the impact on U.S. manufacturing employment of imports from Mexico and Central America. Column 3, which calculates import exposure by adding imports from Mexico and Central America to those of China, produces nearly identical 2SLS estimates to China's imports alone, reinforcing the idea that trade with China is the driving force behind supply-driven U.S. imports from lower wage countries. Column 4, which considers imports from Mexico and Central America separately from China, produces coefficient estimates that are more erratic. A problem for this analysis is that Mexico's U.S. export growth is more associated with its idiosyncratic relationship with the United States than with an across the board export boom, as has occurred in China.[19] Indeed, the OLS estimates in panel A show a *positive* relationship between increasing exposure to imports from Mexico and Central America and growth of manufacturing employment in the U.S. These results are consistent with the interpretation that Mexican exports are driven by rising U.S. product demand rather than changing conditions in Mexico.

For the same reason, Mexican and Central American exports to other high income countries are unlikely to be a strong predictor of exports to the U.S. As seen in panel B of Appendix Table 3, the first-stage results for U.S. imports from Mexico and Central America are relatively weak. The second stage point estimates, while negative, have large standard errors and hence should be treated with some skepticism. In related work that uses data for 1990 and 2000, McLaren and Haboyan (2010) fail to find significant effects of NAFTA on local U.S. labor markets (though they do detect effects on industry wage growth). The 2SLS estimates in columns 5 for the impact of all other middle-income and high-income country imports on U.S. manufacturing find small and inconsistently signed effects.

The results of this section suggest that the exposure of CZs to growing imports from China is quantitatively an important determinant of the decline in the share of manufacturing employment in the working age population that we estimate in Tables 2 and 3. We now expand our focus beyond manufacturing to study the impacts of China trade shocks on broader labor market outcomes.

[19]Unlike China, Mexico has experienced little productivity growth following its market opening which began in the 1980s (Hanson, 2010). Increased exports to the U.S. from Mexico appear largely driven by bilateral trade liberalization through NAFTA rather than through multilateral trade liberalization under the WTO (Romalis, 2007).

5 Beyond manufacturing: Trade shocks and local labor markets

Prior research on the labor market impacts of international trade has primarily focused on employment and wage effects in manufacturing industries or occupations. This approach is satisfactory if labor markets are geographically integrated, fully competitive, and in continuous equilibrium such that a shock to any one manufacturing sector affects the aggregate labor market through only two channels: (1) directly, via a change in employment in the affected sector; and (2) indirectly, to the degree that the sector affects aggregate labor demand. This latter channel will in turn move the competitive wage rate faced by all other sectors, spurring further employment adjustments economy-wide. If these rather stringent conditions are not satisfied, shocks to local manufacturing employment may also differentially affect employment, unemployment, and wages in the surrounding local labor market. We explore the relevance of these local labor market effects in this section, focusing on impacts in the aggregate labor market and in non-manufacturing specifically.

5.1 Population shifts

We begin in Table 4 by assessing the degree to which import shocks to local manufacturing cause reallocation of workers across CZs. If this mobility response is large, this would suggest that we are unlikely to find indirect effects of trade on *local* labor markets since initial local impacts will rapidly diffuse across regions. We find no robust evidence, however, that shocks to local manufacturing lead to substantial changes in population. The regressions in Table 4 are analogous to our earlier models for the manufacturing employment share except that our dependent variable is the log of the working age population ages 16 through 64 in the CZ, calculated using Census IPUMS data for 1990 and 2000 and American Community Survey for 2006 through 2008.

The first set of specifications in panel A, which includes no control variables except a constant and a time dummy for the 2000-2007 time period, finds a significant negative relationship between exogenous increases in Chinese import exposure and CZ-level population growth. A $1,000 per worker increase in trade exposure predicts a decline of 1.03 log points in a CZ's working-age population, which is concentrated among non-college workers according to columns 2 and 3. This pattern appears to be driven by regional population trends. In specifications that add Census division dummies (panel B)—which are equivalent to trends in our first-difference model—and in specifications that further include the full set of controls from Table 3, we find no significant effect of import shocks on local population size. This null is found for the overall working age population (column 1), for college and non-college adults (columns 2 and 3), and for age groups 16 through 34, 35 through 49, and 50 through 64 (columns 4 through 6). In moving from panel A to C, the point estimates on import exposure fall while the standard errors rise. These estimates suggest that the effect of trade exposure shocks on population flows is small, though the imprecision of these estimates does not preclude more substantial responses.

Table 4. Imports from China and Change of Working Age Population in Commuting Zones, 1990-2007: 2SLS Estimates.
Dependent Variables: 10-Year Equivalent Log Changes in Headcounts (in log pts)

	I. By Education Level					II. By Age Group			
	All		College	Non-College		Age 16-34	Age 35-49	Age 50-64	
	(1)		(2)	(3)		(4)	(5)	(6)	
	A. No Census Division Dummies or Other Controls								
(Δ Imports from China to US)/Worker	-1.031	*	-0.360	-1.097	*	-1.299	-0.615	-1.127	**
	(0.503)		(0.660)	(0.488)		(0.826)	(0.572)	(0.422)	
R^2	.		0.03	0.00		0.17	0.59	0.22	
	B. Controlling for Census Division Dummies								
(Δ Imports from China to US)/Worker	-0.355		0.147	-0.240		-0.408	-0.045	-0.549	
	(0.513)		(0.619)	(0.519)		(0.953)	(0.474)	(0.450)	
R^2	0.36		0.29	0.45		0.42	0.68	0.46	
	C. Full Controls								
(Δ Imports from China to US)/Worker	-0.050		-0.026	-0.047		-0.138	0.367	-0.138	
	(0.746)		(0.685)	(0.823)		(1.190)	(0.560)	(0.651)	
R^2	0.42		0.35	0.52		0.44	0.75	0.60	

Notes: N=1444 (722 commuting zones x 2 time periods). All regression include a constant and a dummy for the 2000-2007 period. Models in Panel B and C also include Census Division dummies while Panel C adds the full vector of control variables from column 6 of Table 3. 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 lack of a significant effect of trade exposure on population flows is consistent with several interpretations. One is that shocks to manufacturing from China trade are too small to affect outcomes in the broader CZ. A second is that goods markets are sufficiently well integrated nationally such that local labor markets adjust to adverse shocks without a mobility response. This would occur, for example, in a Heckscher-Ohlin setting if local labor markets operated within a single cone of diversification. In that case, factor price equalization would pin down the wage of labor in all markets, and local factor prices would be independent of local factor demands and supplies. A third possibility is that population adjustments to local economic shocks are sluggish because mobility is costly or because factors other than labor (including government transfer benefits or house prices) bear part of the incidence of labor demand shocks (Katz and Blanchard, 1991; Glaeser and Gyourko, 2005; Notowidigdo, 2010). In this third case, we would expect to see local labor markets adjust along margins other than inter-sectoral or geographic mobility. Our evidence below is most consistent with the third interpretation.

5.2 Employment effects in local labor markets

In Table 5, we explore the effect of import exposure on manufacturing and non-manufacturing employment, unemployment, and labor force participation among working age adults. The sum of the first two coefficients in panel A implies that a $1,000 per worker increase in a CZ's import exposure reduces its employment to population rate by 0.77 percentage points. About three-quarters of that decline is due to the loss in manufacturing employment, but there is also a small, though not statistically significant, reduction in non-manufacturing employment. Columns 3 and 4 of panel A show that one-quarter of the reduction in the employment to population ratio is accounted for by a rise in the unemployment to population rate (0.22 percentage points) while the remaining three-quarters accrue to labor force non-participation (0.55 percentage points).[20]

One mechanism that accommodates the rise in labor force non-participation following a rise in import exposure is enrollment in the Social Security Disability Insurance (SSDI) program, which provides transfer benefits and Medicare coverage to working age adults who are able to establish that their disabilities preclude gainful employment. The estimate in column 5 of Table 5 suggests that approximately 10 percent (0.076/0.77) of those who lose employment following an import shock obtain federal disability insurance benefits. While this is a large fraction, it is not implausible. At present, 4.6 percent of adults age 25 to 64 receive SSDI benefits, and SSDI applications and awards are elastic to adverse labor market shocks (Autor and Duggan, 2003 and 2006).

Subsequent panels of Table 5 report changes in employment status separately by age, education, and gender. A $1,000 import exposure shock results in a fairly uniform reduction in the employment-to-population ratio among all three age brackets considered in Table 5 (ages 16-34, 35-49, and 50-64), though the employment losses are more concentrated in manufacturing among the young and relatively more concentrated in non-manufacturing among the old. For the oldest group, 84 percent of the decline in employment is accounted for by a rise in non-participation, relative to 71 percent among the prime age group and 68 percent among the younger group. It is likely that the increase in disability rolls reported in column 5 is strongly concentrated among the older groups of workers, though we cannot directly test this assumption since the SSDI data are not available to us separately by age group at the detailed geographic level.

[20] Note that our unemployment measure is the ratio of unemployed to the working age population, not the ratio of unemployed to total labor force participants. We denominate by working age population to put the labor force metrics in common units. In particular: $-\Delta EMP/POP = \Delta UNEMP/POP + \Delta NILF/POP$.

Table 5. Imports from China and Employment Status of Working Age Population within Commuting Zones, 1990-2007: 2SLS Estimates.
Dep Vars: 10-Year Equivalent Changes in Population Shares by Employment Status (in %pts)

	I. Overall and by Age Group					II. By Education and Gender			
	Mfg Emp/ Pop (1)	Non-Mfg Emp/ Pop (2)	Unemp/ Pop (3)	NILF/ Pop (4)	SSDI/ Pop (5)	Mfg Emp/ Pop (6)	Non-Mfg Emp/ Pop (7)	Unemp/ Pop (8)	NILF/ Pop (9)
	A. Entire Working Age Population					C1. College Education			
(Δ Imports from China to US)/Worker	-0.596 **	-0.178	0.221 **	0.553 **	0.076 **	-0.592 **	0.168	0.119 **	0.304 **
	(0.099)	(0.137)	(0.058)	(0.150)	(0.028)	(0.125)	(0.122)	(0.039)	(0.113)
	B1. Age 16-34					C2. No College Education			
(Δ Imports from China to US)/Worker	-0.686 **	-0.155	0.271 **	0.569 **	n/a	-0.581 **	-0.531 **	0.282 **	0.831 **
	(0.129)	(0.145)	(0.074)	(0.128)		(0.095)	(0.203)	(0.085)	(0.211)
	B2. Age 35-49					D1. Males			
(Δ Imports from China to US)/Worker	-0.637 **	-0.162	0.236 **	0.563 **	n/a	-0.625 **	-0.140	0.224 **	0.541 **
	(0.119)	(0.119)	(0.076)	(0.157)		(0.124)	(0.151)	(0.062)	(0.159)
	B3. Age 50-64					D2. Females			
(Δ Imports from China to US)/Worker	-0.353 **	-0.295	0.105 **	0.542 **	n/a	-0.555 **	-0.218	0.217 **	0.556 **
	(0.079)	(0.195)	(0.035)	(0.199)		(0.088)	(0.133)	(0.060)	(0.149)

Notes: N=1444 (722 commuting zones x 2 time periods). All statistics are based on working age individuals (age 16 to 64). The effect of import exposure on the overall employment/population ratio can be computed as the sum of the coefficients for manufacturing and non-manufacturing employment; this effect is highly statistically significant ($p \leq 0.01$) in the full sample and in all reported subsamples. The number of recipients of SSDI benefits is not available separately by age, gender, or education. All regressions include the full vector of control variables from column 6 of Table 3. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

While import shocks reduce employment and raise unemployment and non-participation among both college and non-college adults, these effects tend to be much larger for non-college adults. In particular, rising import exposure is associated with a loss in non-manufacturing jobs only among adults with low educational attainment. A possible explanation for this result is that the decline of manufacturing industries decreases the demand for non-traded services that are typically provided by low-skilled workers, such as janitorial services, food services, or construction. Overall, a $1,000 import exposure shock reduces the employment to population rate of college and non-college adults by 0.42 and 1.11 percentage points, respectively. For either group, only about one-fourth of this reduction is accounted for by rising unemployment, with the remainder accruing to labor force non-participation. The patterns of declining employment and increasing unemployment and non-participation are similar for males and females.

5.3 Wage effects

In Table 6, we analyze effects of import exposure shocks on CZ mean log wage levels. Our estimation approach follows the models above except that our dependent variable is the mean log weekly earnings in a CZ.[21] Because the outcome is only available for the employed, and bearing in mind

[21] We use the log weekly wage as the outcome variable because it measures the net effect of changes in hours worked and wages paid per hour.

that we have already established that import exposure shocks reduce employment, the wage estimates must be interpreted with caution. If, plausibly, workers with lower ability and earnings are more likely to lose employment in the face of an adverse shock, the observed change in wages in a CZ will understate the composition-constant change in wages. This is likely to be relevant for workers with lower education levels, among whom job losses are concentrated.

Table 6. Imports from China and Wage Changes within Commuting Zones, 1990-2007: 2SLS Estimates.
Dep Var: 10-Year Equivalent Change in Avg Log Weekly Wage (in log pts)

	All Workers (1)		Males (2)		Females (3)	
			A. All Education Levels			
(Δ Imports from China to US)/Worker	-0.759	**	-0.892	**	-0.614	**
	(0.253)		(0.294)		(0.237)	
R^2	0.56		0.44		0.69	
			B. College Education			
(Δ Imports from China to US)/Worker	-0.757	*	-0.991	**	-0.525	~
	(0.308)		(0.374)		(0.279)	
R^2	0.52		0.39		0.63	
			C. No College Education			
(Δ Imports from China to US)/Worker	-0.814	**	-0.703	**	-1.116	**
	(0.236)		(0.250)		(0.278)	
R^2	0.52		0.45		0.59	

Notes: N=1444 (722 commuting zones x 2 time periods). All regressions include the full vector of control variables from column 6 of Table 3. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Despite the potential for upward bias, Table 6 finds a significant negative effect of import exposure on average weekly earnings within CZs. A \$1,000 per worker increase in a CZ's exposure to Chinese imports during a decade is estimated to reduce mean weekly earnings by -0.76 log points. Point estimates for wage impacts are largely comparable across gender and education groups, though they are somewhat larger overall for males than for females, with the largest declines found among college males and non-college females. We do not, however, have sufficient precision to reject the null hypothesis that the wage impacts are uniform across demographic groups.

In Table 7, we explore wage effects separately for workers employed in manufacturing and non-manufacturing. To aid interpretation, the upper panel of the table assesses the effect of import exposure on employment counts in both sectors. Consistent with Table 3, which explores the impact of import exposure on the *share* of the working age population employed in manufacturing, Table 7 confirms that import exposure reduces head-counts in manufacturing. A \$1,000 rise in a CZ's import exposure reduces the number of manufacturing workers in the CZ by -4.23 log points, where this effect is comparable for college and non-college workers. The estimated employment effect outside of manufacturing is statistically insignificant and, for college workers, small in magnitude.

Table 7. Comparing Employment and Wage Changes in Manufacturing and outside Manufacturing, 1990-2007: 2SLS Estimates.
Dep Vars: 10-Year Equiv. Changes in Log Workers (in Log Pts) and Avg Log Weekly Wages (in %)

	I. Manufacturing Sector			II. Other Sectors		
	All Workers (1)	College (2)	Non-College (3)	All Workers (4)	College (5)	Non-College (6)
	A. Log Change in Number of Workers					
(Δ Imports from China to US)/Worker	-4.231 **	-3.992 **	-4.493 **	-0.274	0.291	-1.037
	(1.047)	(1.181)	(1.243)	(0.651)	(0.590)	(0.764)
R^2	0.31	0.30	0.34	0.35	0.29	0.53
	B. Change in Average Log Wage					
(Δ Imports from China to US)/Worker	0.150	0.458	-0.101	-0.761 **	-0.743 *	-0.822 **
	(0.482)	(0.340)	(0.369)	(0.260)	(0.297)	(0.246)
R^2	0.22	0.21	0.33	0.60	0.54	0.51

Notes: N=1444 (722 commuting zones x 2 time periods). All regressions include the full vector of control variables from column 6 of Table 3. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

The effect of import exposure on mean wages found in panel B in Table 7 is the complement of the employment effects estimated in panel A. Although import exposure reduces manufacturing employment, it appears to have no significant effects on mean manufacturing wages in CZs. This finding mirrors the outcomes of industry-level studies such as Edwards and Lawrence (2010) or Ebenstein et al. (2010), which observe no negative wage effects of imports on U.S. workers in import-competing manufacturing industries.[22] One explanation of this pattern is that the most productive workers retain their jobs in manufacturing, thus biasing the estimates against finding a reduction in manufacturing wages. An alternative possibility, suggested by Bloom, Draca and van Reenen (2009), is that manufacturing plants react to import competition by accelerating technological and organizational innovations that increase productivity and may raise wages.

Conversely, Chinese import exposure significantly reduces earnings in sectors outside manufacturing. Non-manufacturing wages fall by 0.76 log points for a \$1,000 increase in Chinese import exposure per worker. This result is consistent with the hypothesis that a negative shock to local manufacturing reduces the demand for local non-traded services while increasing the available supply of workers, thus creating downward pressure on wages in the sector.

The results of this section demonstrate that an increase in the exposure of local U.S. labor markets to Chinese imports stemming from rising Chinese comparative advantage leads to a significant decline

[22] An exception to this generalization is McLaren and Hakobyan (2010), who find a wage impact on U.S. industries exposed to increased competition from Mexico by NAFTA.

in employment and wages in these local markets. While we cannot directly observe the causal channels by which these effects operate, the estimates suggest a variety of partial and incomplete labor market adjustments. Because CZ employment falls following a shock to local manufacturing, we conclude that labor and product markets are not sufficiently integrated to diffuse the shock across the broader regional or national labor market. The fact that manufacturing wages do not fall along with employment may indicate that manufacturing wages are downwardly rigid or that our wage estimates are biased towards zero by shifts in employment composition. That wages fall in non-manufacturing suggests that this sector is subject to a combination of negative demand shocks—working through reduced demand for non-traded services—and positive shocks to sectoral labor supply, as workers leaving manufacturing seek jobs outside of that the sector. Overall, our results suggest that general equilibrium effects operate within but not across local labor markets: an adverse demand shock to manufacturing reduces wages in other sectors locally and is not dissipated either within or across sectors in the greater (non-local) labor market.

6 Public transfer payments and household incomes

The decline in employment and wages in CZs with growing import exposure is likely to generate an increase in residents' demand for public transfer payments. This conjecture is reinforced by the finding in Table 5 that CZs facing increased import exposure experience a rise in federal disability program (SSDI) recipients. Table 8 studies how a variety of public transfer benefits respond to changes in import exposure. We use data from the BEA Regional Economic Accounts (REA) and from the Social Security Administration's *Annual Statistical Supplement* to measure transfer payments per capita. Table 8 reports the estimated effect of changes in import exposure on the dollar and log change in individual transfers per capita for total transfers and for major subcategories.

The effect of import exposure on transfer payments to CZs is sizable. We estimate that a $1,000 increase in Chinese import exposure leads to a rise in transfer payments of $58 per capita (1.01 log points in the logarithmic specification). Logically, the largest *proportionate* increase is found for Trade Adjustment Assistance (TAA), which is targeted specifically at individuals who lose employment due to foreign competition.[23] Other transfers that are elastic to import exposure are Unemployment Insurance benefits, Social Security Disability Insurance (SSDI) benefits, federal income assistance benefits from SSI (Supplemental Security Income), TANF (Temporary Assistance

[23]TAA payments are observed at the state level and assigned to CZs in proportion to unemployment payments. Columns 2 and 3 in panel A of Table 8 imply that the growth of TAA benefits is more concentrated in states with a high import exposure than is the growth of unemployment benefits, consistent with TAA benefits primarily responding to import shocks and unemployment benefits also responding to other labor demand shocks.

for Needy Families), and SNAP (Supplemental Nutrition Assistance), which are summed in column 7, and education and training assistance, which comprises means-tested education subsidies.

Table 8. Imports from China and Change of Government Transfer Receipts in Commuting Zones, 1990-2007: 2SLS Estimates.
Dep Vars: 10-Year Equivalent Log and Dollar Change of Annual Transfer Receipts per Capita (in log pts and US$)

	Total Individ Transfers (1)	TAA Benefits (2)	Unemp-loyment Benefits (3)	SSA Re-tirement Benefits (4)	SSA Disabili-ty Ben. (5)	Medical Benefits (6)	Federal Income Assist. (7)	Other Income Assist. (8)	Educ/ Training Assist. (9)
	A. Log Change of Transfer Receipts per Capita								
(Δ Imports from China to US)/Worker	1.01 **	14.41 ~	3.46 ~	0.72 ~	1.96 **	0.54	3.04 **	1.08	2.78 *
	(0.33)	(7.59)	(1.87)	(0.38)	(0.69)	(0.49)	(0.96)	(2.20)	(1.32)
R^2	0.57	0.28	0.48	0.36	0.32	0.27	0.54	0.37	0.33
	B. Dollar Change of Transfer Receipts per Capita								
(Δ Imports from China to US)/Worker	57.73 **	0.23	3.42	10.00 ~	8.40 **	18.27	7.20 **	4.13	3.71 **
	(18.41)	(0.17)	(2.26)	(5.45)	(2.21)	(11.84)	(2.35)	(4.44)	(1.44)
R^2	0.75	0.28	0.41	0.47	0.63	0.66	0.53	0.30	0.37

Notes: N=1444 (722 commuting zones x 2 time periods), except N=1436 in column 2, panel A. Results for TAA benefits in column 2 are based on state-level data that is allocated to commuting zones in proportion to unemployment benefits. Unemployment benefits in column 3 include state benefits and federal unemployment benefits for civilian federal employees, railroad employees, and veterans. Medical benefits in column 6 consist mainly of Medicare and Medicaid. Federal income assistance in column 7 comprises the SSI, AFDC/TANF, and SNAP programs while other income assistance in column 8 consists mainly of general assistance. Education and training assistance in column 9 includes such benefits as interest payments on guaranteed student loans, Pell grants, and Job Corps benefits. The transfer categories displayed in colums 2 to 9 account for 96% of total individual transfer receipts. All regressions include the full vector of control variables from column 6 of Table 3. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \le 0.10$, * $p \le 0.05$, ** $p \le 0.01$.

These transfer programs differ substantially in expenditure levels per capita (Appendix Table 2). For example, the in-kind medical transfer benefit programs, which include Medicare and Medicaid, spent about $2,500 per adult in 2007, whereas the Social Security retirement and disability insurance programs transferred about $1,400 and $300 per adult, respectively. Meanwhile, the three federal income assistance programs combined, SSI, TANF, and SNAP, transferred about as much income as SSDI. By contrast, average TAA payments amounted to a mere $2 per adult which is less than 0.05 percentage points of total transfers from governments to individuals according to the REA data. The large relative growth of TAA payments in CZs with growing import exposure thus translates to just a small increase of $0.23 in per adult in benefits for every $1,000 of growth in a CZ's per-worker exposure to Chinese imports. Unemployment benefits also contribute only modestly to the overall increase in transfers. In contrast, the increase in federal transfer spending on SSDI payments is large and significant, equal to about $8 per $1,000 growth of export exposure. In-kind medical benefits rise by a substantial $18 per capita, while federal and other income assistance and retirement benefits account for an additional $11 and $10 in per-adult transfer spending. Not all of these effects are precisely measured, however.

Overall, Table 8 suggests that through its effects on employment and earnings, rising import exposure spurs a substantial increase in government transfer payments to citizens in the form of increased disability, medical, income assistance, and unemployment benefit payments. These transfer payments vastly exceed the expenses of the TAA program, which specifically targets workers who lose employment due to import competition. The transfers should not for the most part be counted as economic losses, of course, since they primarily reflect income redistribution among citizens via taxation and transfers. However, applying a typical estimate of the deadweight loss of taxation of around 40 cents on the dollar (Gruber, 2010), the real cost of the transfers spurred by rising import exposure is non-trivial. In addition, the trade-induced rise in labor force non-participation documented above should also be counted as a deadweight loss to the degree that workers' market wage (prior to the shock) exceeds their value of leisure.

Table 9. Imports from China and Change in Household Income, 1990-2007: 2SLS Estimates.
Dependent Variable: 10-Year Equivalent Relative Growth and Absolute Dollar Change of Average and Median Annual Household Income per Working-Age Adult (in %pts and US$)

	Average HH Income/Adult by Source				Median HH Inc./Ad.	
	Total (1)	Wage-Salary (2)	Business Invest (3)	SocSec +AFDC (4)	Total (5)	Wage-Salary (6)
	A. Relative Growth (%pts)					
(Δ Imports from China to US)/Worker	-1.48 **	-2.14 **	-0.51	2.12 **	-1.73 **	-2.32 **
	(0.36)	(0.59)	(0.74)	(0.58)	(0.38)	(0.51)
R^2	0.69	0.43	0.76	0.52	0.53	0.52
	B. Dollar Change					
(Δ Imports from China to US)/Worker	-492.6 **	-549.3 **	40.1	17.3 **	-439.9 **	-476.5 **
	(160.4)	(169.4)	(116.7)	(4.3)	(112.7)	(122.2)
R^2	0.63	0.40	0.72	0.51	0.49	0.48

Notes: N=1444 (722 commuting zones x 2 time periods). Per capita household income is defined as the sum of individual incomes of all working age household members (age 16-64), divided by the number of household members of that age group. Total income comprises wage and salary income; self-employment, business and investment income; social security and welfare income; and income from other non-specified sources. Social security and welfare income in column 4 includes social security retirement, disability, and supplementary income, aid to families with dependent children (AFDC), and general assistance. All regressions include the full vector of control variables from column 6 of Table 3. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Import exposure shocks may also cause substantial reductions in household income and therefore consumption. Table 9 shows that the combination of falling employment, declining wage levels, and growing transfer payments has measurable impacts on the level and composition of household income in local labor markets exposed to growing Chinese import competition. The estimates in Table 9, which are performed using data from the Census and American Community Survey (rather than the REA transfer data above), find that a \$1,000 increase in a CZ's import exposure leads to a fall in CZ average household wage and salary income per working age adult of 2.14 log points (column 2 of panel A) or about \$549 per working age adult and year (panel B).[24]

[24]These estimates use the combined wage and salary income of working-age adults ages 16-64 in each household

The effect of import competition on household incomes is statistically significant and economically large. To test its plausibility, we benchmarked it against our earlier estimates of the effect of rising import exposure on employment rates and weekly earnings among the employed. The estimates in the first two columns of Table 5 indicate that a $1,000 per worker increase in a CZ's import exposure reduces manufacturing and non-manufacturing employment per population rates by 0.60 and 0.18 percentage points, respectively. Average annual earnings in these sectors at the mid-point of our sample was $44,233 and $36,142 (in 2007 dollars), implying that a $1,000 increase in trade exposure lowered labor income per capita among adults by $331 through reduced employment, with four-fifths of that fall due to reduced manufacturing employment. Turning to wages, the estimates in Table 7 imply that a $1,000 per worker rise in trade exposure reduced weekly earnings by -0.76 log points among workers employed in non-manufacturing and (insignificantly) increased weekly earnings by 0.15 log points among workers in manufacturing. The average employment-to-population ratio in the manufacturing and non-manufacturing sectors was 10.5 percent and 59.2 percent at the mid-point of our sample (Appendix Table 2). We thus calculate a further reduction in labor earnings of $156 per capita accruing from reduced weekly earnings among the employed.[25] Combining the employment and earnings margins yields an estimated per adult reduction of $490 per $1,000 increase in trade exposure, which is very close to the per adult household impact estimate of $493 obtained in Table 9.

Also consistent with the estimates in Table 8, we find that rising transfer income offsets only a small part of the decline in household earnings. The estimates in column 4 show that a $1,000 increase in a CZ's import exposure generates a $17 increase in average household transfer income per working age adult from Social Security and AFDC. Other sources of transfer income, notably those that do not take the form of unrestricted cash benefits, cannot be observed in the Census data. However, given an increase in total government transfers of about $58 per person for a $1,000 increase in import exposure according to Table 8, it appears unlikely that the increase in households' transfer benefits comes anywhere close to offsetting the substantial decline in earnings.

7 Exports and the factor content of trade

So far, we have ignored competition from China in U.S. export markets. China's growth not only displaces U.S. producers in the U.S. market, it may also displace U.S. sales in the foreign markets

divided by the number of working-age adults. Households are weighted by their number of working-age adults.

[25] The per-capita earnings impact from reduced wages in non-manufacturing is $-0.0076 \times \$36,142 \times 0.592 = -\$163$, and the tiny countervailing effect from higher manufacturing wages is $0.0015 \times \$44,233 \times 0.105 = \$7$.

that U.S. industries serve. Following the logic of equation (1) and equation (5), we can show that the total exposure of U.S. region i to imports from China is,

$$\sum_j \frac{E_{ijt}}{E_{ujt}} \frac{\Delta M_{ucjt} + \sum_{o \neq c} \frac{X_{oujt}}{X_{ojt}} \Delta M_{ocjt}}{E_{it}}.$$

This expression differs from equation (5) due to the second summation term, which captures growth in third markets' imports from China (ΔM_{ocjt}) weighted by the initial share of spending in these markets on U.S. produced goods (X_{oujt}/X_{ojt}). We measure the spending shares using initial U.S. exports to a market divided by a market's imputed spending on industry output (calculated under the assumptions that preferences are Cobb-Douglas and that industry expenditure shares equal those in the U.S.). Although the United States is a large exporter, the large share of spending most countries devote to domestic goods means that the share of expenditures directed towards U.S. products is not large. As a consequence, allowing for U.S. exposure to China through third markets increases the mean change in China import exposure for CZs by only 21 percent.

Panel B of Table 10 reports regression results in which we replace the import exposure measure in equation (5) with domestic plus international import exposure to China. We adjust the instrument for import exposure in equation (6) in an analogous manner. The results are qualitatively similar to the baseline regressions in panel A and show similar patterns of statistical significance. The coefficients are smaller in absolute value, consistent with the scaling up of import exposure in the new measure. In column (1), the impact of a \$1,000 increase in import competition from China on the manufacturing employment to population share falls to -0.42, a decline of 30 percent relative to panel A. Other coefficients in panel B differ from those in panel A by similar magnitudes.

Another feature missing in our analysis is U.S. exports to China. There are two reasons for this exclusion. First, U.S. exports to China are unlikely to have a strong quantitative impact on U.S. manufacturing, as these exports are less than one-fifth as large as Chinese imports and have grown only half as rapidly as imports (Table 1).[26] The second issue concerns the linkage between empirics and theory. The model we describe in section 2 treats all products as final goods. In practice, many goods are manufactured in production chains in which firms produce inputs in one country, export the goods to a second country for further processing, and so on until the final product is delivered

[26] The large U.S.-China trade deficit suggests that the effects of greater China import exposure in some CZs are not offset by growth in U.S. exports to China in other CZs. Were trade balanced, greater imports from China in some industries would necessarily imply greater exports by the United States in other industries, meaning that our empirical approach would estimate the *relative* employment effects of import exposure on CZs but not *absolute* employment effects. The existence of the trade deficit suggests that are empirical approach does in fact identify absolute effects of import exposure on CZ employment.

to consumers (Hummels, Ishii, and Yi, 2001). In many industries, China is the final link in the production chain, owing to its comparative advantage in labor-intensive assembly, which tends to be the last stage of production (Feenstra and Hanson, 2005). Hence, goods leaving China are often on their way to consumers. China's place in global production suggests that although our model does not explicitly incorporate production chains, its characterization of how imports from China affect the demand for U.S. goods may not be a grave abuse of reality.[27]

Table 10. Adding Exposure to Indirect Import Competition or Exposure to Net Imports, 1990-2007:
2SLS and OLS Estimates.
Dependent Variables: 10-Year Equivalent Changes of Indicated Variables

	I. Employment/Pop				II. Log Wages				III. Transfers, Wage Inc			
									Log		Avg Log	
	Mfg		Non-Mfg		Mfg		Non-Mfg		Transfers		HH Wage Inc	
	(1)		(2)		(3)		(4)		(5)		(6)	
	A. Baseline Results. Instr.: Exposure to Imports from China (using Chn-OTH Trade)											
(Δ Imports from China to US)/Worker	-0.60	**	-0.18		0.15		-0.76	**	1.01	**	-2.14	**
	(0.10)		(0.14)		(0.48)		(0.26)		(0.33)		(0.59)	
	B. Instr.: Exposure to Domestic and Intl Imports from China (using Chn-OTH Trade)											
(Δ Domestic+International Exposure to Chn Imp)/W	-0.42	**	-0.10		0.11		-0.47	**	0.87	**	-1.75	**
	(0.05)		(0.10)		(0.33)		(0.18)		(0.22)		(0.43)	
	C. Instruments: Import and Export Exposure (using China-OTH Trade)											
(Δ Net Imports of US from China)/Worker	-0.45	**	-0.12		0.43		-0.50	~	0.71	*	-1.68	**
	(0.10)		(0.15)		(0.42)		(0.27)		(0.34)		(0.65)	
	D. Reduced Form OLS: Change in China-US Productivity Differential											
Δ Comparative Advantage China (Gravity Residual)	-0.29	**	-0.03		0.04		-0.26	~	0.53	**	-0.93	**
	(0.04)		(0.08)		(0.28)		(0.15)		(0.14)		(0.28)	
	E. Instr.: Factor Cont. of Trade Exp. based on I/O Tables (using Chn-OTH Trade)											
(Δ Factor Content of Net Imports from Chn)/Worker	-0.46	**	-0.14		0.53		-0.53	**	0.75	*	-1.56	**
	(0.08)		(0.13)		(0.40)		(0.20)		(0.30)		(0.50)	

Notes: N=1444 (722 commuting zones x 2 time periods). The estimates in Panel A correspond to the main results of the preceding Tables 5, 7, 8, and 9. The mean (and standard deviation) of the trade exposure variable is 1.88 (1.75) for the decadal growth in gross direct import exposure in Panel A; 2.28 (2.17) for the decadal growth in direct and indirect import exposure in Panel B; 1.56 (1.67) for decadal growth of U.S. net imports from China per worker in Panel C; 1.40 (1.79) for the decadal change of the comparative advantage measure in Panel D; and 1.89 (1.80) for the decadal growth in imput-output matrix-adjusted factor content of net imports per worker in Panel E. The first stage coefficient estimate is 0.61 (0.07) for the models in Panel B; 0.70 (s.e. 0.10) for the import instrument and -0.32 (0.08) for the export instrument in Panel C; and 0.69 (s.e. 0.07) for the import instrument and -0.29 (0.06) for the export instrument in Panel E. All regressions include the full vector of control variables from column 6 of Table 3. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

The same is unlikely to hold for U.S. exports to China. U.S. firms tend to occupy a position higher up in the production chain and U.S. products that are destined for China may be shipped through

[27]For a multi-stage version of Eaton and Kortum (2002), see Yi (2010). While China may be the last link in global production chains, its contribution to value added is not small. Roughly half of China's manufacturing exports are by "export processing" plants, which import most non-labor inputs and export most output. The other half of exports are by plants that produce a larger fraction of the inputs they consume and which sell a larger fraction of their output on the domestic market. Feenstra and Hanson (2005) estimate that over the period 1997-2002, value added in China was 36% of total output for export processing plants. Since the share of value added in output among other plants is almost certainly higher, the 36% figure is a lower bound for China's value added in its manufacturing shipments abroad. Koopmans et al. (2010) estimate that across all sectors in 2004, value added in China accounted for 63% of its gross exports.

third countries. Further, many of the goods U.S. firms do send to China are inputs for further processing that are ultimately bound not for China's consumers but for third markets. Thus, there is likely to be a greater disconnect between our model and actual trade for U.S. exports to China than for U.S. imports from China.

Despite these qualms, we add US-China exports to our analysis, extending our earlier approach. We construct *net*-imports from China by subtracting U.S. exports from U.S. imports by industry. These net imports are apportioned to geographic regions analogously to our prior import exposure measure (equation (5)):

$$\sum_j \frac{E_{ijt}}{E_{ujt}} \frac{\Delta M_{ucjt}}{E_{it}} - \sum_j \frac{E_{ijt}}{E_{ujt}} \frac{\Delta X_{cujt}}{E_{it}}.$$

We instrument for the net import measure using two variables: the potential import exposure index used in prior tables (equation 6) and an analogously constructed potential export exposure measure, built using observed exports to China by industry from the eight comparison countries previously used for the potential import exposure measure. As with the potential import exposure measure, potential U.S. export flows are allocated to CZs according to local industry employment shares.[28]

Panel C of Table 10 presents estimates. We find that a \$1,000 per worker increase in Chinese *net* import exposure reduces the manufacturing employment to population ratio by 0.45. This point estimate is about a quarter smaller and similarly precisely estimated to the estimate in panel A that uses gross rather than net import exposure. Columns 2 to 6 in panel C of Table 10 estimate the impacts of net import exposure on non-manufacturing employment, weekly earnings, transfer income, and household wage income per capita. The estimated effects of net imports on these outcomes are moderately smaller than our earlier estimates that use gross import exposure.

Another alternative to studying net import effects that circumvents the conceptual and measurement issues discussed above is to apply the gravity residual described in the Theory Appendix. The virtue of the gravity measure is that it captures changes in the productivity or transport costs of Chinese producers *relative* to U.S. producers. These relative changes are the force that gives rise to both Chinese imports and U.S. exports—in other words, net trade flows.[29] To interpret the scale of the gravity measure, note that a one unit increase in the gravity measure corresponds to a \$1,000

[28] The mean (and standard deviation) of the decadal growth in net import exposure is 1.56 (s.d. 1.67). The first stage coefficient estimates for the instrumental variables for $\Delta NIPW_{uit}$ are 0.70 (s.e. 0.10) for the import instrument and -0.32 (0.08) for the export instrument.

[29] If we estimate a 2SLS model with net imports as the endogenous variable and the gravity measure as the instrument, the first stage coefficient is 0.55 (s.e. 0.08) and the second stage coefficient is -0.53 (s.e. 0.09), similar to the coefficient of -0.60 in column 6 of Table 3. We do not tabulate this 2SLS model because we view the exclusion restriction as invalid: changes in the productivity of U.S. industries affect U.S. labor demand directly, through the US industry production function as well as indirectly, through general equilibrium effects related to trade competition.

per worker increase in a region's Chinese import exposure stemming from a rise in China's productivity or fall in China's trade costs. This is the same scaling used in our import exposure variable in panel A. The point estimates in panels A and D are thus comparable, though since the gravity residual corresponds to a logarithmic measure of productivity, it is appropriate to exponentiate this coefficient.

Following this logic, panel D of Table 10 estimates gravity-based models for the impact of Chinese trade exposure on the set of outcomes that have been studied in the previous panels of the table. These estimates are comparable to the 2SLS models in panel C, though the precision of the gravity estimates is typically greater. Column 1 finds that a \$1,000 per worker increase in net import exposure to Chinese trade resulting from rising relative Chinese productivity or falling transport costs reduces local U.S. manufacturing employment by three-tenths of one percentage point but has no effect on non-manufacturing employment. Estimated wage effects are insignificant, though the pattern of coefficients is comparable to the 2SLS estimates of panel A. We detect a significant positive effect of increased Chinese trade exposure on receipt of transfer benefits in CZs and a significant negative effect on household wage income of CZ residents.

As a final specification, we use the factor content of U.S. net imports from China to replace imports per worker. An earlier literature, based on Heckscher-Ohlin trade theory, models trade as affecting labor markets through the import of factor services embodied in goods (Deardorff and Staiger, 1988; Borjas, Freeman, and Katz, 1997). The validity of the factor content approach was, however, the subject of considerable debate in the trade and wages literature of the 1990s, as discussed in Krugman (2000), Leamer (2000) and Feenstra (2010). Recent theoretical work by Burstein and Vogel (2011) revives this approach, deriving the relationship between wages and the labor content of trade by comparing trade in labor services for one skill group against that in another.

Our data at the CZ level do not permit analysis of the relationship between the relative imports of labor services and relative wages by worker type. By way of comparison, however, it is informative to re-estimate our core regressions using the factor content of trade to measure import exposure in CZs. In panel E of Table 10, we report results in which we replace the change in imports per worker with the change in the net import of effective labor services, calculated as,

$$\sum_j \frac{E_{ijt}}{E_{ujt}} \frac{\tilde{E}_{uj0}}{V_{uj0}} \frac{\Delta M_{ucjt}}{E_{it}} - \sum_j \frac{E_{ijt}}{E_{ujt}} \frac{\tilde{E}_{uj0}}{V_{uj0}} \frac{\Delta X_{cujt}}{E_{it}}.$$

This measure of the labor content of U.S. net imports from China calculates CZ exposure to trade by imputing labor services embodied in net imports using net imports times employment per dollar of gross shipments in U.S. industries at the national level ($\tilde{E}_{uj0}/V_{uj0}$), where we measure $\tilde{E}_{uj0}$ based on the *direct plus indirect* employment of labor used to manufacture goods in an industry. That is, $\tilde{E}_{uj0}$ is the component for industry j of the vector $E(I-C)^{-1}$, where E is the vector of direct employment in each industry, C is the industry input-output matrix, and I is the identity matrix (where we use values from 1992 for each element). The implicit assumption is that the labor intensities of U.S. goods that are replaced by Chinese imports and of goods the U.S. exports to China are the same as average U.S. industry labor intensity. In reality, we expect that within industries, imports from China are likely to be products that are relatively labor intensive and exports to China are likely to be relatively capital intensive. Absent data on product mix within four digit industries across CZs, however, we are forced to treat industry labor intensity as being uniform among imports, exports, and domestic shipments. We instrument for the labor content of net imports from China in a manner analogous to our strategy for net imports in panel C.

The results in column 1 of panel E show that the net import of labor services of one U.S. worker displaces 0.66 workers in manufacturing, with the result precisely estimated.[30] These estimates are consistent with our findings for other measures of trade exposure: larger increases in the factor content of net imports yield lower wages in non-manufacturing, higher government transfers to households, and lower household wage and salary income.[31]

Taken together, the Table 10 results suggest that our focus on Chinese imports effectively exploits the economically consequential and well-identified variation in China trade exposure without compromising the substantive interpretation of the results.

8 Costs from adjustment to imports vs. gains from trade

What do our results imply about overall U.S. gains from trade with China? In theory, such gains are positive. Trade may lower incomes for workers exposed to import competition, but gains to consumers from increased product variety (Broda and Weinstein, 2006) and gains to firms from having inputs at lower cost and in greater variety should ensure that aggregate gains from trade are greater than zero. Trade may also induce firms to invest in innovation, contributing to productivity growth (Bloom, Draca, and Van Reenen, 2009). Our finding that increased exposure to import

[30] The factor content of net imports is normalized by CZ employment, whereas manufacturing employment in the dependent variable is normalized by CZ population. To place both on the same footing, we multiply the point estimate for factor contents by the inverse ratio of CZ employment to CZ population, which is equal to 0.70 at the mid-point of the sample. Hence, we calculate that the import of the labor services of one U.S. worker displaces $-0.46 \times (1/0.70) = 0.66$ U.S. manufacturing workers.

[31] The mean decadal change in the factor content measure is 1.89. Multiplying this by the point estimate of 0.46 yields an effect size of 0.87, as compared to an effect size of $1.88 \times 0.60 = 1.13$ for the import exposure measure.

competition is associated with lower manufacturing employment and lower wages in exposed local labor markets does not contradict this logic. It just highlights trade's distributional consequences.

To establish a benchmark for the gains from trade with China, we utilize the framework in Arkolakis, Costinot, and Rodriguez-Clare (2010), which yields a simple formula for the gains from trade that holds under a variety of trade models.[32] Consider an increase in U.S. trade barriers that drives U.S. imports from China to zero. The log change in income that would be needed to keep income constant given the resulting reduction in trade is

$$\left(\frac{\lambda}{\lambda'}\right)^{-1/\theta} - 1. \tag{8}$$

where λ is the initial share of U.S. expenditure on domestic goods, λ' is the share of expenditure after the change in trade barriers, and θ is the elasticity of trade with respect to trade costs, which recent literature suggests lies between -2.5 and -10 (Simonovska and Waugh, 2011). In 2007, one minus manufacturing imports as a share of U.S. gross output (an approximation of the share of domestic expenditure on domestic goods) was 93.9% and China accounted for 10.3% of U.S. manufacturing imports.[33] Assuming that domestic goods replace imports from China, the log change in income needed to offset the loss of gains from trade would be 0.0007 to 0.0027 (depending on the value of θ), equivalent to a change in income of \$32 to \$125 per capita.[34] If some of the lost imports from China are offset by an increase in imports from other countries, rather than U.S. production, the \$32-\$125 range may overstate the range of gains from trade with China.

One manner in which adjustment to import competition may partly offset these gains from trade is through the deadweight loss associated with individual take-up of government transfers. Such a loss is not a distributional consequence of trade but a loss in economic efficiency associated with U.S. benefit programs. The coefficient estimate on exposure to import competition in the regression for the change in transfers per capita in column 1 of Table 8 implies that annual per capita transfers increase by \$58 for every \$1,000 of additional import exposure per worker. When applying a confidence interval of plus and minus one standard error around that point estimate, the growth in exposure to Chinese imports over the period 1991 to 2007 is associated with an increase in

[32] Their approach, which applies to models that have CES import demand and a gravity equation for trade, allows for heterogeneity in firm productivity and for either perfect or imperfect competition. It assumes Dixit-Stiglitz preferences, linear cost functions, one factor of production, complete specialization, and iceberg transport costs.

[33] Ideally, one would measure the share of domestic expenditure on imports with imports of final goods as a share of GDP. However, observed imports are contaminated by the presence of intermediate inputs, and among these inputs are goods manufactured in the United States. Absent measures of final expenditure on the foreign content of goods, we follow Arkolakis, Costinot and Rodriguez-Clare (2010) in using imports over gross output to measure the share of domestic expenditure on foreign products.

[34] In 2007, U.S. income per capita was \$46,700.

annual transfers receipts of $114 to $218 per capita.[35] As in our benchmarks above for manufacturing employment, we scale this estimate downward by approximately half (52%) so our impact estimate only incorporates the variation in rising Chinese import exposure that we can confidently attribute to supply shocks. By this metric, we estimate the increase in annual per capita transfers attributable to rising Chinese import competition at $55 to $105.

Using Gruber's (2010) estimate that the deadweight loss from transfers is equal approximately to 40% of their value, the increase in transfers resulting from import exposure implies an increase in deadweight loss over 1991 to 2007 of $22 to $42 per capita, a range of values that is one to two-thirds as large as the gains from trade with China in 2007 that we computed above based on Arkolakis, Costinot, and Rodriguez-Clare (2010). This calculation excludes the trade-induced rise in labor force non-participation documented above, which should also be counted as a deadweight loss to the degree that workers' market wage (prior to the shock) exceeded their value of leisure. Of course, the deadweight loss from transfers is not permanent, whereas the gains from trade are. As affected workers retire or expire, the loss in economic efficiency from transfers they receive as a consequence of trade with China will dissipate. Nevertheless, it appears in the medium run that losses in economic efficiency from increased usage of public benefits may offset a substantial fraction of the gains from trade from China.

9 Conclusion

The value of annual U.S. goods imports from China has increased by a staggering 1,156% from 1991 to 2007. The rapid increase in U.S. exposure to trade with China and other developing economies over this period suggests that the labor-market consequences of trade may have increased considerably during the past 20 years. Previous research has studied the effects of imports on manufacturing firms or employees of manufacturing industries. By analyzing local labor markets that are subject to differential trade shocks according to initial patterns of industry specialization, this paper extends the analysis of the consequences of trade beyond wage and employment changes in manufacturing. Specifically, we relate changes in manufacturing and non-manufacturing employment, earnings, and transfer payments across U.S. local labor markets to changes in market exposure to Chinese import

[35] According to Appendix Table 2, the 10-year equivalent increase in import exposure (in 1000s of dollars) was 1.14 in the first and 2.63 in the second period of the analysis. A confidence interval of plus and minus one standard error around the point estimate of column 1 in Table 8 suggests that a $1000 increase in exposure is associated with a $39 to $76 growth in per-capita transfers, and thus predicts a 10-year equivalent growth of transfers by $45-$87 in the first and by $104-$201 in the second period. These ten-year equivalent changes correspond to a $41-$78 increase during the nine-year period 1991-2000 and a $73-$140 increase in the seven-year period 2000-2007 which leads to the prediction that over the full period, the increase in per-capita transfers would have been $114-$218 lower had Chinese imports remained at their near-zero level of 1991.

competition. While most observed trade flows into the U.S. are the result of both supply and demand factors, the growth of Chinese exports is largely the result of changes within China: rising productivity growth, a latent comparative advantage in labor-intensive sectors, and a lowering of trade barriers. In light of these factors, we instrument for the growth in U.S. imports from China using Chinese import growth in other high-income markets.

Our analysis finds that exposure to Chinese import competition affects local labor markets along numerous margins beyond its impact on manufacturing employment. Consistent with standard theory, growing Chinese imports reduces manufacturing employment in exposed local labor markets. More surprisingly, it also triggers a decline in wages that is primarily observed outside of the manufacturing sector. Reductions in both employment and wage levels lead to a steep drop in the average earnings of households.

We also find an important margin of adjustment to trade that the literature has largely overlooked: rising transfer payments through multiple federal and state programs. Comparing two CZs at the 75th and 25th percentiles of rising Chinese trade exposure over the period of 2000 through 2007, we find a differential increase in transfer payments of about $63 per capita in the more exposed CZ. The largest components of these transfers are federal disability, retirement and in-kind medical transfer payments. Unemployment insurance and income assistance programs play an important but secondary role. By contrast, the Trade Adjustment Assistance (TAA) program, which specifically provides benefits to workers who have been displaced due to trade shocks, accounts for a negligible part of the trade-induced increase in transfers.

Overall, our study suggests that the increase in U.S. imports of Chinese goods during the past two decades has had a large impact on employment and household incomes, benefits program enrollments, and transfer payments in local labor markets exposed to increased import competition. These effects extend outside manufacturing and imply changes in worker and household welfare.

References

Amiti, Mary, and Donald Davis. 2009. "Trade, Firms, and Wages: Theory and Evidence." NBER Working Paper No. 14106.

Amiti, Mary, and Caroline Freund. 2010. "An Anatomy of China's Export Growth." In Robert Feenstra and Shang-Jin Wei, eds., China's Growing Role in World Trade, Chicago: NBER and University of Chicago Press, 35-62.

Arkolakis, Costas, Arnaud Costinot, and Andres Rodriguez-Clare. 2010. "New Trade Models, Same Old Gains?" Mimeo, Yale University.

Artuc, Erhan, Shubham Chaudhuri, and John McLaren. 2010. "Trade Shocks and Labor Adjustment: A Structural Empirical Approach." *American Economic Review*, 100(3), 1008-1045.

Auer, Rafael, and Andreas Fischer. 2008. "The Effect of Trade with Low Income Countries on U.S. Industry." Mimeo, Swiss National Bank.

Autor, David H. and David Dorn. 2009. "This Job is "Getting Old": Measuring Changes in Job Opportunities using Occupational Age Structure." *American Economic Review Papers and Proceedings*, 99(2), 45-51.

Autor, David H. and David Dorn. 2011. "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market." Mimeo, June.

Autor, David H. and Mark Duggan. 2003. "The Rise in the Disability Rolls and the Decline in Unemployment." *Quarterly Journal of Economics*, 118(1), February, 157-206.

Autor, David H. and Mark Duggan. 2006. "The Growth in the Social Security Disability Rolls: A Fiscal Crisis Unfolding." *Journal of Economic Perspectives*, 20(3), Summer, 71-96.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. "Trends in U.S. Wage Inequality: Revising the Revisionists." *Review of Economics and Statistics*, 90(2), 300-323.

Bernard, Andrew B., J. Bradford Jensen and Peter K. Schott. 2006. "Survival of the Best Fit: Exposure to Low-Wage Countries and the (Uneven) Growth of U.S. Manufacturing Plants." *Journal of International Economics*, 68(1), 219-237.

Bertrand, Marianne. 2004. "From the Invisible Handshake to the Invisible Hand? How Import Competition Changes the Employment Relationship." *Journal of Labor Economics*, 22(4), 722-765.

Blanchard, Olivier Jean and Lawrence F. Katz. 1992. "Regional Evolutions." *Brookings Papers on Economic Activity*, 1992(1), 1-75.

Blonigen, Bruce., and Alyson C. Ma. 2010. "Please Pass the Catch-Up: The Relative Performance of Chinese and Foreign Firms in Chinese Exports." In Robert Feenstra and Shang-Jin Wei, eds., China's Growing Role in World Trade, Chicago: NBER and University of Chicago Press, 475-512.

Bloom, Nicholas, Mirko Draca, and John Van Reenen. 2009. "Trade Induced Technical Change? The Impact of Chinese Imports on Diffusion, Innovation, and Productivity." Mimeo, Stanford University.

Borjas, George J. 1999. "The Economic Analysis of Immigration." in Orley C. Ashenfelter and David Card, eds., Handbook of Labor Economics, Amsterdam: North-Holland, 1697-1760.

Borjas, George J., Richard B. Freeman, and Lawrence F. Katz. 1997. "How Much Do Immigration and Trade Affect Labor Market Outcomes?" *Brookings Papers on Economic Activity*, 1, 1-90.

Borjas, George J., and Valerie A. Ramey.1995. "Foreign Competition, Market Power, and Wage Inequality." *Quarterly Journal of Economics*, 110(4), 1075-1110.

Bound, John and Harry J. Holzer. 2000. "Demand Shifts, Population Adjustments, and Labor Market Outcomes during the 1980s." *Journal of Labor Economics*, 18(1), 20-54.

Branstetter, Lee, and Nicholas Lardy. 2006. "China's Embrace of Globalization." NBER Working Paper No. 12373.

Broda, Christian, David Weinstein. 2006. "Globalization and the Gains from Variety." *Quarterly Journal of Economics*, 121(2), 541-585.

Burstein, Ariel, and Jonathan Vogel. 2011. "Factor Prices and International Trade: A Unifying Perspective." NBER Working Paper No. 16904.

Card, David. 2001. "Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration." *Journal of Labor Economics*, 19(1), 22-64.

Chen YuYu, Ginger Zhe Jin, and Yang Yue. 2010. "Peer Migration in China." NBER Working Paper No. 15671.

Chiquiar, Daniel. 2008. "Globalization, Regional Wage Differentials, and the Stolper-Samuelson Theorem: Evidence from Mexico." *Journal of International Economics*, 74(1), 70-93.

Deardorff, Alan V., Robert W. Staiger. 1988. "An Interpretation of the Factor Content of Trade." *Journal of International Economics*, 24(1-2), 93-107.

Dorn, David. 2009. "Essays on Inequality, Spatial Interaction, and the Demand for Skills." Dissertation University of St. Gallen no. 3613, September.

Eaton, Jonathan, and Samuel Kortum. 2002. "Technology, Geography, and Trade." *Econometrica*, 70(5), 1741-1779.

Ebenstein, Avraham, Ann Harrison, Margaret McMillan, and Shannon Phillips. 2010. "Estimating the Impact of Trade and Offshoring on American Workers Using the Current Population Surveys." Mimeo, UC Berkeley.

Edwards, Lawrence, Robert Z. Lawrence. 2010. "US Trade and Wages: The Misleading Implications of Conventional Trade Theory." NBER Working Paper No. 16106.

Feenstra, Robert C. 2010. "Offshoring in the Global Economy: Microeconomic Structure and Macroeconomic Implications." Cambridge, MA: MIT Press.

Feenstra, Robert C., and Gordon H. Hanson. 1999. "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the U.S., 1979-1990." *Quarterly Journal of Economics*, 114(3), 907-940.

Feenstra, Robert C., and Gordon H. Hanson. 2005. "Ownership and Control in Outsourcing to China: Estimating the Property Rights Theory of the Firm. " *Quarterly Journal of Economics*, 120(2), 729-762.

Glaeser, Edward L. and Joseph Gyourko. 2005. "Urban Decline and Durable Housing." *Journal of Political Economy*, 113(2), 345-375.

Gruber, Jonathan. 2010. "Public Finance and Public Policy." 3rd edition, New York: Worth Publishers.

Harrigan, James. 2000. "International Trade and American Wages in General Equilibrium, 1967-1995." In Robert C. Feenstra, ed., *The Impact of International Trade on Wages.* Chicago: NBER and University of Chicago Press.

Hanson, Gordon. 2010. "Why Isn't Mexico Rich? " *Journal of Economic Literature*, 48(4), 987-1004.

Harrison, Ann, John McLaren, and Margaret McMillan. 2010. "Recent Findings on Trade and Inequality." NBER Working Paper No. 16425.

Harrison, Ann and Margaret McMillan. 2010. "Offshoring Jobs? Multinationals and U.S. Manufacturing Employment." *Review of Economics and Statistics*, forthcoming.

Holmes, Thomas J. and John J. Stevens. 2010. "An Alternative Theory of the Plant Size Distribution with an Application to Trade." Mimeo, University of Minnesota.

Hsieh, Chang-Tai, and Peter J. Klenow. 2009. "Misallocation and Manufacturing TFP in China and India." *Quarterly Journal of Economics*, 124(4): 1403-1448.

Hsieh, Chang-Tai, and Ralph Ossa. 2011. "A Global View of Productivity Growth in China." NBER Working Paper No. 16778.

Hummels, David, Jun Ishii, Kei-Mu Yi. 2001. "The Nature and Growth of Vertical Specialization in Trade." *Journal of International Economics*, 54(1): 75-96.

Hummels, David, Rasmus Jorgensen, Jakok Munch, and Chong Xiang. 2010. "The Wage and Employment Effects of Outsourcing: Evidence from Danish Matched Worker-Firm Data." Mimeo, Purdue University.

Katz, Lawrence F., and David Autor. 1999. "Changes in the Wage Structure and Earnings Inequality," in Orley Ashenfelter and David Card, eds., Handbook of Labor Economics, Vol. 3A, Amsterdam: Elsevier Science, 1463-1555.

Koopmans, Robert, William Powers, Zhi Wang, and Shang-Jin Wei. 2010. "Giving Credit where Credit Is Due: Tracing Value Added in Global Production Chains." NBER Working Paper No.

16426.

Kovak, Brian K. 2011. "Local Labor Market Effects of Trade Policy: Evidence from Brazilian Liberalization." Mimeo, Carnegie Mellon University.

Krugman, Paul. 2000. "Technology, trade and factor prices." *Journal of International Economics*, 50(1), 51-71.

Krugman, Paul. 2008. "Trade and Wages, Reconsidered." *Brookings Papers on Economic Activity*, 1, 103-154.

Lawrence, Robert Z. 2008. "Blue Collar Blues: Is Trade to Blame for Rising US Income Inequality?" Washington, DC: Peterson Institute for International Economics.

Leamer, Edward E. 1993. "Wage Effects of a U.S.-Mexico Free Trade Agreement." In P.M. Garber, ed., The Mexico-U.S. Free Trade Agreement, Cambridge, MA: MIT Press, 57-128.

Leamer, Edward E. 2000. "What's the Use of Factor Contents?" *Journal of International Economics*, 50(1), 17-49.

Lemieux, Thomas. 2006. "Increased Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill." *American Economic Review*, 96, 461-498.

Liu, Runjuan, and Daniel Trefler. 2008. "Mucho Ado about Nothing: American Jobs and the Rise of Service Outsourcing to China and India." NBER Working Paper No. 14061.

McLaren, John, and Shushanik Hakobyan. 2010. "Looking for Local Labor Market Effects of NAFTA." NBER Working Paper No. 16535.

Michaels, Guy. 2008. "The Effect of Trade on the Demand for Skill: Evidence from the Interstate Highway System." *The Review of Economics and Statistics*, 90(4), 683-701.

Notowidigdo, Matthew J. 2010. "The Incidence of Local Labor Demand Shocks." MIT working paper, January.

Pierce, Justin R. and Peter Schott. 2009. "A Concordance between Ten Digit Harmonized System Codes and SIC/NAICS Product Classes and Industries." NBER Working Paper No. 15548.

Romalis, John. 2007. "NAFTA's and CUSTA's Impact on International Trade." *Review of Economics and Statistics*, 89(3), 416-435.

Ruggles, Steven, Matthew Sobek, Trent Alexander, Catherine A. Fitch, Ronald Goeken, Patricia Kelly Hall, Miriam King, and Chad Ronnander. 2004. *Integrated Public Use Microdata Series: Version 3.0* [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor].

Simonovska, Ina, and Michael Waugh. 2011. "The Elasticity of Trade: Estimates and Evidence." NBER Working Paper No. 16795.

Smith, Christopher L. 2010. "The Polarization of the U.S. Adult Labor Market and its Effects on the Demand for Teenage Labor." Federal Reserve Board of Governors Working Paper, June.

Tolbert, Charles M. and Molly Sizer. 1996. "U.S. Commuting Zones and Labor Market Areas. A 1990 Update." Economic Research Service Staff Paper No. 9614.

Topalova, Petia. 2010. "Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India." *American Economic Journal: Applied Economics*, 2, 1-41.

Topel, Robert H. 1986. "Local Labor Markets." *Journal of Political Economy*, 94(3), 111-143.

United States Social Security Administration. Various years. *Annual Statistical Supplement to the Social Security Bulletin.* Washington, DC: U.S. Government Printing Office.

Verhoogen, Eric. 2008. "Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector." *Quarterly Journal of Economics*, 123(2), 489-530.

Wooldridge, Jeffrey M. 2002. *Econometric Analysis of Cross Section and Panel Data.* Cambridge, Massachusetts: MIT Press.

Yi, Kei-Mu. 2010. "Can Multistage Production Explain the Home Bias in Trade?" *American Economic Review*, 100(1), 364-393.

Appendix Tables

Appendix Table 1. Descriptive Statistics for Growth of Imports Exposure per Worker across C'Zones

Rank	I. 1990-2000		II. 2000-2007	
	A. Percentiles			
	90th percentile	2.05	90th percentile	4.30
	75th percentile	1.32	75th percentile	3.11
	50th percentile	0.89	50th percentile	2.11
	25th percentile	0.62	25th percentile	1.60
	10th percentile	0.38	10th percentile	1.03
	B. Largest and Smallest Values among the 40 Largest C'Zones			
1	San Jose, CA	3.15	San Jose, CA	7.32
2	Providence, RI	2.59	Providence, RI	4.99
3	Buffalo, NY	2.24	Los Angeles, CA	3.59
4	Boston, MA	1.55	San Diego, CA	3.08
5	Portland, OR	1.53	Portland, OR	2.96
6	San Diego, CA	1.52	Pittsburgh, PA	2.95
7	Newark, NJ	1.32	Chicago, IL	2.93
8	Los Angeles, CA	1.28	Milwaukee, WI	2.93
9	Bridgeport, CT	1.27	Boston, MA	2.79
10	Denver, CO	1.23	Dallas, TX	2.77
20	Forth Worth, TX	0.83	Columbus, OH	1.90
21	Phoenix, AZ	0.83	Phoenix, AZ	1.90
31	Atlanta, GA	0.61	Fresno, CA	1.56
32	Pittsburgh, PA	0.56	St. Louis, MO	1.53
33	Sacramento, CA	0.53	Tampa, FL	1.49
34	Kansas City, MO	0.51	Atlanta, GA	1.31
35	West Palm Beach, FL	0.48	Baltimore, MD	1.25
36	Fresno, CA	0.47	West Palm Beach, FL	1.22
37	Orlando, FL	0.46	Kansas City, MO	1.13
38	Houston, TX	0.45	Washington, DC	0.86
39	Washington, DC	0.21	New Orleans, LA	0.70
40	New Orleans, LA	0.19	Orlando, FL	0.59

Notes: The table reports 10-year equivalent values of (Δ Imports from China to US)/Worker in kUS$. The statistics in panel A are based on 722 commuting zones and weighted by start-of-period population size. The ranking in panel B is based on the 40 commuting zones with largest population in 1990, and indicates the largest city of each ranked commuting zone.

Appendix Table 2. Means and Standard Deviations of Commuting Zone Variables.

	I. Levels			II. 10-Year Equivalent Chg	
	1990/1991	2000	2007	1990-2000	2000-2007
	(1)	(2)	(3)	(4)	(5)
(Imports from China to US)/(Workers in 1990) (in kUS$)	0.29 (0.32)	1.32 (1.18)	3.58 (2.84)	1.14 (0.99)	n/a
(Imports from China to US)/(Workers in 2000) (in kUS$)	0.25 (0.27)	1.08 (0.90)	2.92 (2.13)	n/a	2.63 (2.01)
Percentage of working age pop employed in manufacturing	12.69 (4.80)	10.51 (4.45)	8.51 (3.60)	-2.07 (1.63)	-2.73 (1.80)
Percentage of working age pop employed in non-manufacturing	57.75 (5.91)	59.16 (5.24)	61.87 (4.95)	1.29 (2.38)	3.70 (2.71)
Percentage of working age pop unemployed	4.80 (0.99)	4.28 (0.93)	4.87 (0.90)	-0.51 (0.73)	0.85 (1.39)
Percentage of working age pop not in the labor force	24.76 (4.34)	26.05 (4.39)	24.75 (3.70)	1.29 (2.56)	-1.82 (2.57)
Percentage of working age pop receiving disability benefits	1.86 (0.63)	2.75 (1.04)	3.57 (1.41)	0.91 (6.38)	1.23 (0.71)
Average log weekly wage, manufacturing sector (in log pts)	655 (17)	666 (17)	671 (19)	11.4 (6.4)	7.8 (7.7)
Average log weekly wage, non-manufacturing sectors (in log pts)	637 (16)	650 (15)	653 (16)	12.5 (4.1)	3.5 (4.3)
Average individual transfers per capita (in US$)	3338 (692)	4297 (908)	5544 (1091)	1004.4 (334.0)	1844.0 (437.6)
Average retirement benefits per capita (in US$)	1121 (284)	1262 (310)	1398 (338)	150.5 (79.3)	206.2 (120.4)
Average disability benefits per capita (in US$)	136 (46)	213 (77)	300 (112)	78.2 (39.8)	128.3 (61.5)
Average medical benefits per capita (in US$)	1115 (371)	1789 (552)	2564 (679)	698.3 (231.9)	1142.8 (288.5)
Average federal income assistance per capita (in US$)	298 (136)	270 (134)	303 (129)	-24.8 (43.6)	52.2 (46.0)
Average unemployment benefits per capita (in US$)	106 (52)	86 (43)	108 (55)	-19.1 (29.4)	34.1 (41.0)
Average TAA benefits per capita (in US$)	0.6 (0.6)	1.1 (1.0)	2.2 (2.7)	0.5 (0.9)	1.6 (3.3)
Avg household income per working age adult (in US$)	32122 (6544)	38126 (7743)	37909 (7501)	5964 (2358)	-367 (2646)
Avg household wage and salary income per w. age adult (in US$)	23496 (4700)	27655 (5449)	28872 (6304)	4152 (1569)	1703 (2623)

Notes: N=722 commuting zones. Statistics in columns (1) and (3) are weighted by 1990 population, statistics in columns (2) and (4) are weighted by 2000 population, and statistics in column (5) are weighted by 2007 population. The first two rows of column (3) report import volumes for the year 1991, all other variables in column (3) are based on 1990 data. Information on employment composition, wages, and income in column (5) is derived from pooled 2006-2008 ACS data.

Appendix Table 3. Imports from Different Exporting Countries and Change of Manufacturing Employment in Commuting Zones, 1990-2007.
Dependent Variable: 10 x Annual Change in Share of Employment in Manufacturing (in %pts)

	Exporters									
	China		China+ other Low-Inc		China+ Mexico/Cafta		Mexico/ Cafta		All Other Exporters	
	(1)		(2)		(3)		(4)		(5)	
					A. OLS Estimates					
(Δ Imports from specified exporter to U.S.)/Worker	-0.171	**	-0.182	**	-0.034		0.297	**	0.021	**
	(0.028)		(0.026)		(0.031)		(0.050)		(0.005)	
					B. 2SLS Estimates					
					second stage estimates					
(Δ Imports from specified exporter to U.S.)/Worker	-0.596	**	-0.587	**	-0.602	**	-1.870	**	-0.031	~
	(0.099)		(0.096)		(0.110)		(0.682)		(0.018)	
					first stage estimates					
(Δ Imports from specified exporter to OTH)/Worker	0.631	**	0.621	**	0.632	**	1.146	*	0.420	**
	(0.087)		(0.078)		(0.093)		(0.514)		(0.047)	
t-statistic	7.3		7.9		6.8		2.2		8.9	
					C. Descriptive Statistics					
Mean and SD of (Δ Imports to U.S.)/Worker	1.88		2.13		2.76		0.88		9.04	
	(1.75)		(1.89)		(2.08)		(1.12)		(9.30)	

Notes: N=1444. The other ('OTH') countries that were used to construct the instrument include Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. "Low-Income" countries are defined according to the 1990 Worldbank classification (see Data Appendix); the exporters countries in column 5 comprise all countries except low-income countries and Mexico/Cafta. All regressions contain the full vector of control variables from column 6 of Table 3. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Theory appendix

Variance decomposition of Chinese imports into supply and demand components

To decompose the share of the variance in Chinese imports that is accounted for by supply versus demand-driven components, we rewrite the equation (7) above for the effect of import exposure on manufacturing employment (suppressing covariates) as:

$$\Delta E_{it}^{m} = \gamma_t + \beta \Delta IPW_{uit} + e_{ct}. \tag{9}$$

Estimated by OLS, this equation recovers:

$$\hat{\beta}_{OLS} = \sigma_{MI}/\sigma_I^2,$$

where σ_I^2 is the variance of the observed changes in Chinese import exposure per worker and σ_{MI} is the covariance of this measure with CZ-level changes in manufacturing employment. Similarly, 2SLS estimates of equation (9) recover

$$\hat{\beta}_{2SLS} = \sigma_{MI_{IV}} / \sigma^2_{I_{IV}},$$

where the subscript I_{IV} is the variation in the import exposure measure isolated by the instrumental variables estimator.

Because the instrumental variables estimator partitions the observed variation in ΔIPW into an exogenous component and a residual:

$$\Delta IPW = \Delta IPW_{IV} + \Delta IPW_e.$$

we can rewrite $\hat{\beta}_{OLS}$ as

$$\hat{\beta}_{OLS} = \frac{\sigma_{MI_{IV}} + \sigma_{MI_e}}{\sigma^2_{I_{IV}} + \sigma^2_{I_e}},$$

using the fact that ΔIPW_{IV} and ΔIPW_e are orthogonal by construction. Substituting, we obtain:

$$\hat{\beta}_{OLS} = \hat{\beta}_{IV} \times \frac{\sigma^2_{I_{IV}}}{\sigma^2_{I_{IV}} + \sigma^2_{I_e}} + \hat{\beta}_e \times \frac{\sigma^2_{I_e}}{\sigma^2_{I_{IV}} + \sigma^2_{I_e}}. \tag{10}$$

This equation highlights that the OLS estimate is a convex combination of the coefficient on the import-driven component, $\hat{\beta}_{IV}$, and the coefficient on the residual (demand-driven) component, where the weights given to the two components are equal to the fraction of the total variance in import exposure explained by each.

Equation (10) suggests that a logical quantity to use for benchmarking the total impact of supply-driven Chinese import shocks on U.S. employment is the product of $\hat{\beta}_{IV} \times \sigma^2_{I_{IV}} / \left(\sigma^2_{I_{IV}} + \sigma^2_{I_e}\right)$ and the observed change in Chinese import exposure ΔIPW. This quantity is equal to the causal effect of a supply-driven unit increase in Chinese import exposure scaled by the total change in exposure, discounted by the fraction of the variance in exposure that is not driven by the supply shock component.

The terms in (10) are obtained from the data: $\hat{\beta}_{OLS} = -0.397$, $\hat{\beta}_{2SLS} = -0.746$ (column 1 of Table 3), $\hat{\beta}_e = -0.029$, implying that $\sigma^2_{I_{IV}} / \left(\sigma^2_{I_{IV}} + \sigma^2_{I_e}\right) \simeq 0.48$. For our benchmarking exercise, we calculate the magnitude of the causal effect of the supply-driven component of Chinese import exposure as $\hat{\beta}_{IV} \times \Delta IPW \times 0.48$.

Estimating the gravity model

We measure productivity and trade cost-driven growth in U.S. imports from China, $(\hat{A}_{cj} - \theta\hat{\tau}_{cj}))$, as shown in equation (4), using regression output from the gravity model of trade. To begin, consider China's exports to country n in industry j:

$$X_{cnj} = \frac{T_{cj}(w_{cj}\tau_{cnj})^{-\theta}X_{nj}}{\Phi_{nj}}, \tag{11}$$

where X_{cnj} is exports by China to country n, X_{nj} is total expenditure by n, Φ_{nj} is a price index for n, T_{cj} is China's technological capability, w_{cj} is China's unit production costs, and τ_{cnj} is trade costs between China and country n, all for industry j. Analogously, exports by the US (country u) to n in industry j are,

$$X_{unj} = \frac{T_{uj}(w_{uj}\tau_{unj})^{-\theta}X_{nj}}{\Phi_{nj}}, \tag{12}$$

which together with (11) imply that

$$\ln(X_{cnj}) - \ln(X_{unj}) = \ln(z_{cj}) - \ln(z_{uj}) - \theta[\ln(\tau_{cnj}) - \ln(\tau_{unj})], \tag{13}$$

where $z_{cj} \equiv T_{cj}(w_{cj})^{-\theta}$ is China's cost-adjusted productivity, meaning that $\ln(z_{cj}) - \ln(z_{uj})$ captures China's comparative advantage vis-à-vis the US, which is constant across importing countries, n, for industry j. The term in the brackets on the right of (13) is the difference in trade costs to country n between the China and the U.S. Notice that by taking the difference between China and U.S. exports to country n, we remove non-trade-cost related demand-side factors in country n from the regression, thus isolating the effects of bilateral differences in productivity and trade costs on exports. Now consider the following regression, where we add a dimension for year (t):

$$\ln(X_{cnjt}) - \ln(X_{unjt}) = \alpha_j + \alpha_n + \epsilon_{njt}, \tag{14}$$

where α_j is an industry fixed effect (capturing China's initial comparative advantage vis-a-vis the U.S. in industry j) and α_n is an importer fixed effect (capturing the time invariant difference in trade costs between China and the US for country n in industry j). The residual from the regression in (14) is

$$\epsilon_{njt} = \left[\ln\left(\frac{z_{cjt}}{z_{ujt}}\right) - \alpha_j\right] + \left[-\theta\ln\left(\frac{\tau_{cnjt}}{\tau_{unjt}}\right) - \alpha_n\right]. \tag{15}$$

The first term on the right of (15) is China's differential comparative advantage relative to the U.S. for industry j in year t, which captures China's ability to compete against the United States in the U.S market and other foreign markets (holding trade costs constant). The industry fixed effect absorbs the mean difference in China and U.S. export capabilities. The second term on the right of (15) is China's differential trade cost relative to the U.S. in industry j and year t for country n. The importing country fixed effect absorbs the mean difference in China-U.S. trade costs, which are presumably driven largely by geography. Differential changes in trade costs are the sum of differential changes in transport costs (which Hummels (2007) suggests fluctuate during our sample period with no clear trend) and differential changes in trade barriers in importing countries, the primary component of which will relate to China's joining the WTO in 2001, when WTO members jointly and simultaneously lowered their trade barriers toward China. The residual in (15) therefore captures the upgrading in China's comparative advantage relative to the U.S. and China's differential improvement in access to foreign markets. These are precisely the components of China's export growth that matter for U.S. labor demand. As an alternative to the specification in equation (5), we use the following gravity-based measure of exposure to imports from China,

$$\Delta IPW_{git} = \sum_j \frac{E_{ijt-1}}{E_{ujt-1}} \cdot \frac{\Delta \bar{\epsilon}_{jt} M_{ucjt-1}}{E_{it-1}}. \tag{16}$$

where $\Delta \bar{\epsilon}_{jt}$ is the mean change in the residual in (15) for industry j across destination markets n between year t and year $t-1$ based on estimation of a gravity model of trade for China and U.S. four-digit SIC exports to high-income countries over the period 1991 to 2007. When the change in residual is multiplied by initial U.S. imports from China in industry j, M_{ucjt-1}, we obtain the change in U.S. imports from China predicted by China's changing comparative advantage and falling trade costs. Note that in (16) we use lagged values for employment shares, as in (6).

Data appendix

Matching trade data to industries

Data on international trade for 1991 to 2007 are from the UN Comrade Database (*http:// comtrade.un.org/db/default.aspx*), which gives bilateral imports for six-digit HS products. To concord these data to four-digit SIC industries, we proceed as follows. First, we take the crosswalk in Pierce and Schott (2009), which assigns 10-digit HS products to four-digit SIC industries (at which level each HS product maps into a single SIC industry) and aggregate up to the level of six-digit HS products and four-digit SIC industries (at which level some HS products map into multiple SIC industries). To perform the aggregation, we use data on US import values at the 10-digit HS level, averaged over 1995 to 2005. The crosswalk assigns HS codes to all but a small number of SIC industries. We therefore slightly aggregate the 4-digit SIC industries so that each of the resulting 397 manufacturing industries matches to at least one trade code, and none is immune to trade competition by construction. Details on our industry classification are available on request.

Second, we combine the crosswalk with six-digit HS Comrade data on imports for the United States (for which Comrade has six-digit HS trade data from 1991 to 2007) and for all other high-income countries that have data covering the sample period (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) and then aggregate up to four-digit SIC industries. For each importing region (the United States and the eight other high-income countries), we aggregate imports across four export country groups: China; other low-income countries; Mexico, Central America, and the Dominican Republic (which are the neighboring countries with which the United States has free trade agreements); and the rest of the World. All import amounts are inflated to 2007 US$ using the Personal Consumption Expenditure deflator.

Low-income countries are defined according to the World Bank definition in 1989. They are: Afghanistan, Albania, Angola, Armenia, Azerbaijan, Bangladesh, Benin, Bhutan, Burkina Faso, Burundi, Burma, Cambodia, Central African Republic, Chad, China, Comoros, Republic of the Congo, Equatorial Guinea, Eritrea, Ethiopia, The Gambia, Georgia, Ghana, Guinea, Guinea-Bissau, Guyana, Haiti, India, Kenya, Laos, Lesotho, Madagascar, Maldives, Mali, Malawi, Mauritania, Moldova, Mozambique, Nepal, Niger, Pakistan, Rwanda, Saint Vincent and the Grenadines, Samoa, Sao Tome and Principe, Sierra Leone, Somalia, Sri Lanka, Sudan, Togo, Uganda, Vietnam, and Yemen.

Measuring the industry structure of local labor markets

We derive the potential exposure of Commuting Zones (CZs) to import competition from detailed information on local industry employment structure in the years 1980, 1990 and 2000 that is taken from the County Business Patterns (CBP) data. CBP is an annual data series that provides information on employment, firm size distribution, and payroll by county and industry. It covers all U.S. employment except self-employed individuals, employees of private households, railroad employees, agricultural production employees, and most government employees. CBP data is extracted from the Business Register, a file of all known U.S. companies that is maintained by the U.S. Census Bureau, and is available for download at *http://www.census.gov/econ/cbp/index.html*.

The CBP does not disclose information on individual employers, and information on employment by county and industry is hence sometimes reported as an interval instead of an exact count. Moreover, some establishments are not identified at the most disaggregate level of the industry classification. The 1980 and 1990 data however always reports the exact number of firms in each of 13 establishment size classes for each county-industry cell. We impute employment by county by 4-digit SIC code using the following procedure: (i) Narrow the range of possible employment values in cells with bracketed employment counts using the minimum and maximum employment values that are consistent with a cell's firm size distribution, and with the employment count of the corresponding aggregate industry. (ii) Construct a sample with all non-empty county-level 4-digit industry cells, and regress the employment in these cells on the number of firms in each of the 13 establishment size classes. The starting value of employment for cells with bracketed employment counts is the midpoint of the bracket. The coefficients of the regression yield an estimate for the typical firm size within each firm size bracket. Replace employment counts in cells with bracketed values with the predicted values from the regression, and repeat the estimation and imputation until the coefficients of the establishment size variables converge. (iii) Use the establishment size information in 4-digit and corresponding 3-digit industries, and the coefficients from the preceding regression analysis to compute the employment in firms that are identified only by a 3-digit industry code in the data, and repeat the same step for higher levels of industry aggregation. (iv) If necessary, proportionally adjust estimated employment in 4-digit industries and in firms that lack a 4-digit code so that they sum up to the employment of the corresponding 3-digit code. Repeat this step for higher levels of industry aggregation. (v) Assign employment of firms that are only identified at the 2-digit industry level to 3-digit industries, proportional to observed 3-digit industry employment in the respective county. Repeat this step for assigning 3-digit employment to 4-digit industries.

The CBP 2000 reports employment by county and industry for 6-digit NAICS codes and the distribution of firm sizes over 9 establishment size classes. We impute suppressed employment counts using the same procedure as outlined for the CBP 1980 and 1990 above. In order to map NAICS to SIC codes, we construct a weighted crosswalk based on the Census "bridge" file (available for download at *http://www.census.gov/epcd/ec97brdg/*). This file reports the number of employees and firms in the 1997 Economic Census for each existing overlap between NAICS and SIC industry codes. Employment counts are reported in brackets for some 6-digit NAICS—4-digit SIC cells while exact firm counts are always available. We impute employment in these cells by multiplying the number of firms in the cell by the average firm size in the corresponding NAICS industry that we observe in the CBP 2000. If necessary, imputed employment counts are proportionally adjusted so that estimated employment in 6-digit NAICS industries correctly sums up to employment in associated 5-digit industries. The resulting weighted crosswalk reports which fraction of a 6-digit NAICS code matches to a given 4-digit SIC code. We use this crosswalk to map the information on employment by county by NAICS industry from the CBP 2000 to the corresponding SIC industries. Finally, we aggregate employment by county to the level of Commuting Zones.

Measuring labor supply and earnings

Our measures for labor supply, wages, household income, and population are based on data from the Census Integrated Public Use Micro Samples (Ruggles et al. 2004) for the years 1970, 1980, 1990 and 2000, and the American Community Survey (ACS) for 2006 through 2008. The 1980, 1990 and 2000 Census samples include 5 percent of the U.S. population, while the pooled ACS and 1970 Census samples include 3 and 1 percent of the population respectively. We map these data to CZs using the matching strategy that is described in detail in Dorn (2009) and that has previously been applied by Autor and Dorn (2009, 2011) and Smith (2010).

Our sample of workers consists of individuals who were between age 16 and 64 and who were working in the year preceding the survey. Residents of institutional group quarters such as prisons and psychiatric institutions are dropped along with unpaid family workers. Labor supply is measured by the product of weeks worked times usual number of hours per week. For individuals with missing hours or weeks, labor supply weights are imputed using the mean of workers in the same education-occupation cell, or, if the education-occupation cell is empty, the mean of workers in the same education cell. All calculations are weighted by the Census sampling weight multiplied with the labor supply weight.

The computation of wages excludes self-employed workers and individuals with missing wages, weeks or hours. Hourly wages are computed as yearly wage and salary income divided by the product of weeks worked and usual weekly hours. Top-coded yearly wages are multiplied by a factor of 1.5 and hourly wages are set not to exceed this value divided by 50 weeks times 35 hours. Hourly wages below the first percentile of the national hourly wage distribution are set to the value of the first percentile. Wages are inflated to the year 2007 using the Personal Consumption Expenditure Index.

Measuring government transfers

Our primary source for data on transfers are the Regional Economic Accounts (REA) of the Bureau of Economic Analysis (available for download at *http://www.bea.gov/regional/index.htm*). The REA data includes information on total receipts of transfers by individuals from governments at the county level. It also hierarchically disaggregates these transfers into different categories and subcategories of transfer payments. The largest transfer categories are medical benefits, retirement and disability benefits, and income maintenance benefits which together account for 93% of the national transfer sum in 2007.

The REA data provides the exact amount of annual transfers by county and transfer type unless the transfer sum is very small (i.e., positive amounts of transfers that are below 50,000 dollars in a given county and year). If county lacks precise transfer amounts in some transfer categories, we distribute its total transfer receipts over these transfer categories in proportion to their relative share of total transfers in the corresponding state. All transfer amounts are inflated to 2007 US$ using the Personal Consumption Expenditure deflator.

Our secondary source for transfer data is the Social Security Administration's *Annual Statistical Supplements* (various years), from which we obtained data on social security payments by county. This data source disaggregates Social Security payments into retirement and disability benefits, and it also reports the number of beneficiaries by county.