

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.

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 U.S. manufacturing imports (Table 1).² However, owing largely to China's spectacular economic 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 growth. 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 point in 2001 when China joined the World Trade Organization.³ Over the same period, the fraction of U.S. working age population employed in manufacturing fell by a third, from 12.6% to 8.4% (Figure 1).⁴ Amplifying China's potential impact on the U.S. labor market are sizable current-account imbalances in the two countries. In the 2000s, China's average current-account surplus was 5% of GDP, a figure equal to the contemporaneous average U.S. current-account *deficit*. U.S. industries have thus faced a major increase in import competition from China without an offsetting increase in demand for U.S. exports.

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. Commuting zones (CZs), which encompass all metropolitan and non-metropolitan areas

¹The significance of technical change for the U.S. wage structure is a source of continuing debate. See Lemieux (2006), Autor, Katz, and Kearney (2008), Acemoglu and Autor (2010), Beaudry, Doms, and Lewis (2010), Autor and Dorn (2011) and Firpo, Fortin, and Lemieux (2011) for recent work.

²We classify countries as low income using the World Bank definition in 1989, shown in the online Data Appendix.

³In 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.

⁴The data series for manufacturing/population in Figure 1 is based on the Current Population Survey for workers aged 16 to 64. While the reduction in manufacturing employment was rapid during the recessions in 1990-1991 and 2001, there were also declines during the expansions 1992-2000 and particularly 2002-2007. In previous expansion phases of the 1970s and 1980s, the manufacturing/population ratio had increased following a recession.

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 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 U.S. 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.

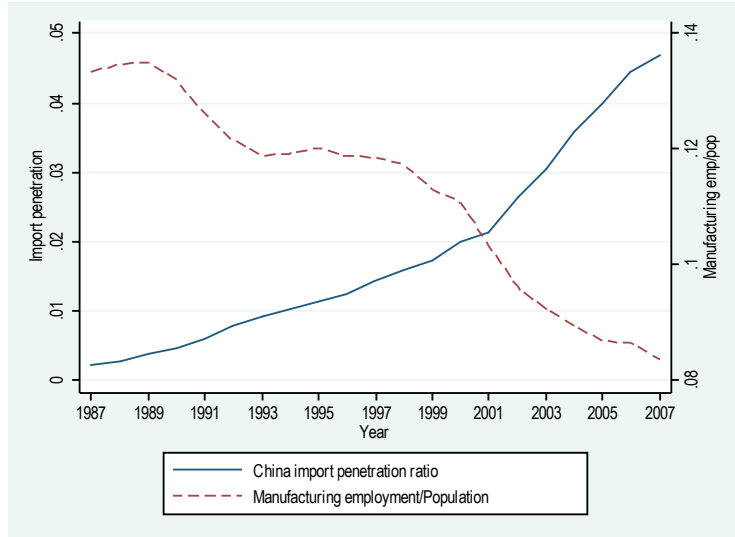


Figure 1.
Import Penetration Ratio for U.S. Imports from China (left scale), and Share of U.S. Working-Age Population Employed in Manufacturing (right scale).

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 rural-to-urban migration of over 150 million workers (Chen, Jin, and Yue, 2010), Chinese industries gaining access to long banned foreign technologies, capital goods, and intermediate inputs (Hsieh and Klenow, 2009), and multinational enterprises being permitted to operate in the country (Naughton, 2007).⁵ Compounding the positive effects of internal reforms on China's trade is the country's accession to the WTO,

⁵While 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

which gives it most-favored nation status among the 153 WTO members (Branstetter and Lardy, 2006). In light of the internal and global external factors driving China’s exports, we instrument for the growth in U.S. imports from China using Chinese import growth in other high-income markets.⁶ We also adopt several alternative estimation strategies, including measuring CZ exposure to import competition using the gravity model of trade. All approaches yield substantially 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 important early work by Borjas and Ramey (1995), who also emphasize the role of trade imbalances in mapping trade shocks to labor-market outcomes, as well as more recent work by Chiquiar (2008), Topalova (2005, 2010) and Kovak (2011), who study the effects of trade liberalizations on wages, poverty, and migration in local and regional labor markets in Mexico, India and Brazil, respectively.⁷

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), 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 Treffer (2008), who estimate that

American Free Trade Agreement (2005) each lowered U.S. barriers to imports. However, whereas China’s export growth appears driven by internal conditions and global changes in trade policy toward the country, export growth in Mexico and Central America appears more related to import demand associated with U.S. outsourcing to the region. Consequently, it is more difficult to find exogenous variation in U.S. imports from Mexico and Central America. In recent work, McLaren and Hakobyan (2010) do not detect substantial effects of NAFTA on local U.S. labor markets, though they do find effects on wage growth nationally in exposed industries.

⁶Our 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).

⁷See Michaels (2008) for work on how falling trade costs affect factor price equalization between regions.

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.⁸ Our approach is complementary to this strand of literature. In examining economic outcomes at the level of local labor markets, we are able to capture both the direct effect of trade shocks on employment and earnings at import-competing employers as well as net effects on employment, earnings, labor force participation, geographic mobility and take-up of public transfer benefits in the surrounding geographic area.

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 labor demand shocks across U.S. cities and states are slow and incomplete (Topel, 1986; Blanchard and Katz, 1992; Glaeser and Gyourko, 2005). 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. The sluggish response of regional labor supply to import exposure may be related to the costly mobility of labor between sectors, as documented by Artuc, Chaudhuri, and McLaren (2010) in the United States and Dix-Carneiro (2011) in Brazil, also in the context of adjustment to trade shocks.

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-

⁸Related 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.

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. Section 6 expands the inquiry to broader measures of economic adjustment. Section 7 considers alternative measures of trade exposure. In Section 8, we provide a rough estimate of the deadweight losses associated with trade-induced changes in transfer benefits and unemployment. Section 9 concludes.

2 Theoretical motivation and empirical approach

In this section, we consider theoretically how growth in U.S. imports from China 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

Suppose China experiences productivity growth due to its transition from central planning to a market economy or a reduction in its trade costs as a result of its accession to the WTO. How would such shocks affect the labor market of U.S. region i ? In an Online Theory Appendix, we develop a simple model of trade based on monopolistic competition (Helpman and Krugman, 1985) and variation in industry labor productivities across countries.⁹ We treat region i as a small open economy and derive how shocks in China affect region i 's employment and wages.¹⁰ In applying the monopolistic competition model, we assume that trade has a “gravity” structure (as in Arkolakis, Costinot, and Rodriguez-Clare, 2012), in which case one can map changes in *trade quantities* into

⁹We treat these productivities as given. Melitz (2003) and Eaton, Kortum, and Kramarz (2011) give microfoundations for differences in national industry productivities in trade models based on monopolistic competition.

¹⁰We also solve a two-country version of the model (implicitly, for China and the U.S. as a whole). For global general equilibrium analyses of trade and productivity growth in China, see Hsieh and Ossa (2010) and di Giovanni, Levchenko, and Zhang (2011).

labor-market outcomes. An alternative approach would be to use a Heckscher-Ohlin or a specific-factors model, as in Topalova (2005, 2010) or Kovak (2011), in which the mapping is strictly from *trade prices* to wages and employment. Given the absence of suitable U.S. industry import price data, the quantity-based approach is logical for our setting.

We assume that region i produces both traded goods and a homogeneous non-traded good, which could alternatively represent consumption of leisure. Traded goods are produced in sectors that each contain a large number of monopolistically competitive firms that manufacture differentiated product varieties.¹¹ For simplicity, we ignore migration in or out of region i , though in the empirical analysis we test for regional population shifts in response to trade shocks.¹² The labor-market outcomes of interest for region i are the change in the wage (\hat{W}_i), the change in employment in traded goods (\hat{L}_{Ti}), and the change in employment in non-traded goods (\hat{L}_{Ni}), where hats over variables denote log changes ($\hat{x} \equiv d \ln x$).¹³ Productivity growth or falling trade costs in China affect region i through two channels: (i) increased competition in the markets in which region i sells its output, captured by the change in China's export-supply capability in each industry j (\hat{A}_{Cj}), which we treat as exogenous and which is a function of changes in labor costs, trade costs, and the number of product varieties made in China, and (ii) increased demand for goods in China, captured by the change in expenditure in China on each industry j (\hat{E}_{Cj}), which we also treat as exogenous.

The impacts of export-supply and import-demand shocks in China on region i 's wages and employment are as follows,

$$\begin{aligned}\hat{W}_i &= \sum_j c_{ij} \frac{L_{ij}}{L_{Ni}} \left[\theta_{ijC} \hat{E}_{Cj} - \sum_k \theta_{ijk} \phi_{Cjk} \hat{A}_{Cj} \right], \\ \hat{L}_{Ti} &= \rho_i \sum_j c_{ij} \frac{L_{ij}}{L_{Ti}} \left[\theta_{ijC} \hat{E}_{Cj} - \sum_k \theta_{ijk} \phi_{Cjk} \hat{A}_{Cj} \right], \\ \hat{L}_{Ni} &= \rho_i \sum_j c_{ij} \frac{L_{ij}}{L_{Ni}} \left[-\theta_{ijC} \hat{E}_{Cj} + \sum_k \theta_{ijk} \phi_{Cjk} \hat{A}_{Cj} \right].\end{aligned}\tag{1}$$

Wage and employment outcomes are the sum of the increase in demand for region i 's exports to China, given by the change in expenditure in China (\hat{E}_{Cj}) times the initial share of output by region i that is shipped to China ($\theta_{ijC} \equiv X_{ijC}/X_{ij}$); and the decrease in demand for region i 's shipments to all markets in which it competes with China. The latter is given by the growth in China's export-supply capability (\hat{A}_{Cj}) times the initial share of output by region i that is shipped to each market k ($\theta_{ijk} \equiv X_{ijk}/X_{ij}$) and the initial share of imports from China in total purchases

¹¹We assume that labor is perfectly mobile between sectors. For analysis of imperfect sectoral labor mobility and trade, see Artuc, Chaudhuri, and McLaren (2010) and Dix-Carneiro (2011).

¹²Allowing for migration would dampen the effects of trade on wages and amplify its effect on employment.

¹³Wage changes are in nominal and not real terms.

by each market k ($\phi_{Cjk} \equiv M_{kjC}/E_{kj}$).¹⁴ These shocks are summed across sectors, weighted by the initial ratio of employment in industry j to total employment in non-traded or traded industries (L_{ij}/L_{Mi} , $M = N, T$) and a general-equilibrium scaling factor ($c_{ij} > 0$). The employment equations are scaled further by ρ_i , the share of the current-account deficit in total expenditure in region i .

In (1) positive shocks to China's export supply decrease region i 's wage and employment in traded goods and increase its employment in non-traded goods. Similarly, positive shocks to China's import demand increase region i 's wage and employment in traded goods and decrease its employment in non-traded goods. In the context of balanced trade, reduced labor demand in U.S. regions relatively exposed to import competition from China would be offset by labor demand growth in U.S. regions enjoying expanded export production for China, such that for the aggregate U.S. economy labor demand may be unchanged. However, with imbalanced trade this need not be the case. The import demand shock in China is a function of growth in its *expenditure*, not income. Because over the time period we examine China's income exceeds its expenditure, productivity growth in China need not result in commensurate increases in import demand and export supply. In (1) the impact of trade shocks on the division of employment between traded and non-traded sectors depends on $\rho_i \neq 0$, or trade imbalance. With balanced trade, reduced traded-sector labor demand from greater import competition is offset by increased traded-sector labor demand from greater export production. Trade shocks may cause wages in region i to change, and labor may shift between different traded-sector industries but will not reallocate employment between the traded and non-traded sectors. Imbalanced trade breaks this symmetry, allowing shocks to affect the size of the traded sector.

To use (1) for empirical analysis, we assume that the share of the trade imbalance in total expenditure (ρ_i) and the general equilibrium scaling factor (c_{ij}) are the same across U.S. regions (such that $\rho_i c_{ij} = \alpha$). Further, we begin by focusing on a single channel through which trade with China affects region i : greater import competition in the U.S. market, thus ignoring (temporarily) the effects of greater U.S. exports to China or greater import competition in the foreign markets that U.S. regions serve. We impose these restrictions for our base specifications because U.S. imports from China vastly exceed U.S. exports to China (suggesting the export channel is relatively small) and because the U.S. market accounts for the large majority of demand for most U.S. industries. With these restrictions in place, the change in employment for traded goods in region i becomes

$$\hat{L}_{Ti} = -\alpha \sum_j \frac{L_{ij}}{L_{Ti}} \frac{X_{ijU}}{X_{ij}} \frac{M_{CjU}}{E_{Uj}} \hat{A}_{Cj} \approx -\tilde{\alpha} \sum_j \frac{L_{ij}}{L_{Uj}} \frac{M_{CjU}}{L_{Ti}} \hat{A}_{Cj}, \quad (2)$$

¹⁴ As in Hsieh and Ossa (2010), log differentiation allows one to derive solutions for changes in wages and employment that are free of production parameters, which makes comparative advantage opaque in these equations. Implicitly, comparative advantage for region i is summarized by the output shares, θ_{ijk} .

with the change in the wage and the change in non-traded employment defined analogously.¹⁵ In (2), traded-sector employment in region i depends on growth in U.S. imports from China mandated by growth in China’s export-supply capability ($M_{CjU}\hat{A}_{Cj}$), scaled by region i ’s labor force (L_{Ti}), and weighted by the share of region i in U.S. employment in industry j (L_{ij}/L_{Uj}).

2.2 Empirical approach

Following (2), our main measure of local-labor-market exposure to import competition is the change in Chinese import exposure per worker in a region, where imports are apportioned to the region according to its share of national industry employment:

$$\Delta IPW_{uit} = \sum_j \frac{L_{ijt}}{L_{ujt}} \frac{\Delta M_{ucjt}}{L_{it}}. \quad (3)$$

In this expression, L_{it} is the start of period employment (year t) in region i and ΔM_{ucjt} is the observed change in U.S. imports from China in industry j between the start and end of the period.¹⁶

A concern for our subsequent estimation is that realized U.S. imports from China in (3) may be correlated with industry labor demand shocks. To identify the causal effect of rising Chinese import exposure (stemming from Chinese productivity 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. 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.¹⁷ 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:

¹⁵In deriving (2), we make use of the fact that in the monopolistic competition model (with a single factor of production) L_{ij}/X_{ij} equals a constant and we assume that the share of region i in total U.S. purchases in industry j (X_{ijU}/E_{Uj}) can be approximated by the share of region i in U.S. employment in industry j (L_{ij}/L_{Uj}), an assumption motivated by the lack of data on regional output or expenditure. Variation in capital or skill by industry would create noise in the instrument.

¹⁶Relative to (2), the quantity in (3) divides imports by total employment in the commuting zone (L_{it}) rather than traded sector employment (L_{Tit}). We renormalize in this manner to be consistent with our initial dependent variable, which is the change in manufacturing employment as a share of the labor force (rather than the log change in manufacturing employment).

¹⁷The 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.

$$\Delta IPW_{oit} = \sum_j \frac{L_{ijt-1}}{L_{ujt-1}} \cdot \frac{\Delta M_{ocjt}}{L_{it-1}}. \quad (4)$$

This expression for *non*-U.S. exposure to Chinese imports differs from the expression in equation (3) in two respects. First, in place of realized U.S. imports by industry (ΔM_{ucjt}), it uses realized imports from China to other high-income markets (ΔM_{ocjt}). Second, in place of start-of-period employment levels by industry and region, this expression uses employment levels from the *prior* decade. We use 10-year-lagged employment levels because, to the degree that contemporaneous employment by region is affected by anticipated China trade, the use of lagged employment to apportion predicted Chinese imports to regions will mitigate this simultaneity bias.

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.¹⁸ 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 (3) 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 the primary source of variation, however; in a bivariate regression, the start-of-period manufacturing employment share explains less than 25% of the variation in ΔIPW_{uit} . In our main specifications, we will control for the start-of-period manufacturing share within CZs so as to focus on variation in exposure to Chinese imports stemming

¹⁸In 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.

from differences in industry mix within local manufacturing sectors.

In the Theory Appendix, we describe a second approach to measuring supply-driven growth in U.S. imports from China, $M_{CjU}\hat{A}_{Cj}$. Using bilateral trade data at the industry level, we estimate 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 the United States. Thus, in this alternative approach we estimate changes in China’s comparative advantage vis-a-vis the U.S using changes in Chinese versus U.S. exports to third-party countries with which both countries trade. In the empirical estimation in section 7, we obtain qualitatively similar results using either imports per worker from equation (3), with the instrument defined as in equation (4), or using the gravity-based approach.

As additional approaches in section 7, we replace the change in imports per worker as defined in equation (3) with (i) the change in net imports (imports - exports) per worker (following equation (1)), (ii) the change in imports per worker incorporating imports in non-U.S. markets (also following (1)), (iii) 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), and (iv) the change in imports per worker net of imported intermediate inputs, the latter of which may have productivity enhancing effects on U.S. industries (Goldberg, Khandelwal, Pavcnik, and Topalova, 2010). These strategies again yield 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.

We use data from the UN Comtrade 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.

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	Exports to China	Imports from Other Low-Inc.	Imports from Mexico/Cafta	Imports from Rest of World
	(1)	(2)	(3)	(4)	(5)
<u>A. United States</u>					
1991/92	26.3	10.3	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%	456%	491%	375%	161%
<u>B. 8 Other Developed Countries</u>					
1991/92	28.2	26.6	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%	639%	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 Caribbean countries covered by the CAFTA-DR free trade agreement. Column 5 covers imports from all other countries (primarily from developed countries).

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.¹⁹ 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).

¹⁹Mexico/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.

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 (3) combines trade data with data 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 Online Data Appendix).

Panel A of Appendix Table 1 shows descriptive statistics for ΔIPW_{ujt} by time period.²⁰ 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 import exposure 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 CZs' population, employment and wage structure by education, age, and gender. These variables are constructed 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 2008.²¹ We map these data to CZs using the matching strategy detailed in Dorn (2009). This approach 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.

²⁰In 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.

²¹We pool the Census ACS 2006 through 2008 files to increase sample size and hence the measurement precision. We treat the 2006 through 2008 data as referring to the year 2007.

4 The impact of trade shocks on manufacturing employment

Our instrumental variable strategy, 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 strategy is that the common within-industry component of rising Chinese imports to the U.S. and other high-income countries is China's rising comparative advantage and falling trade costs.

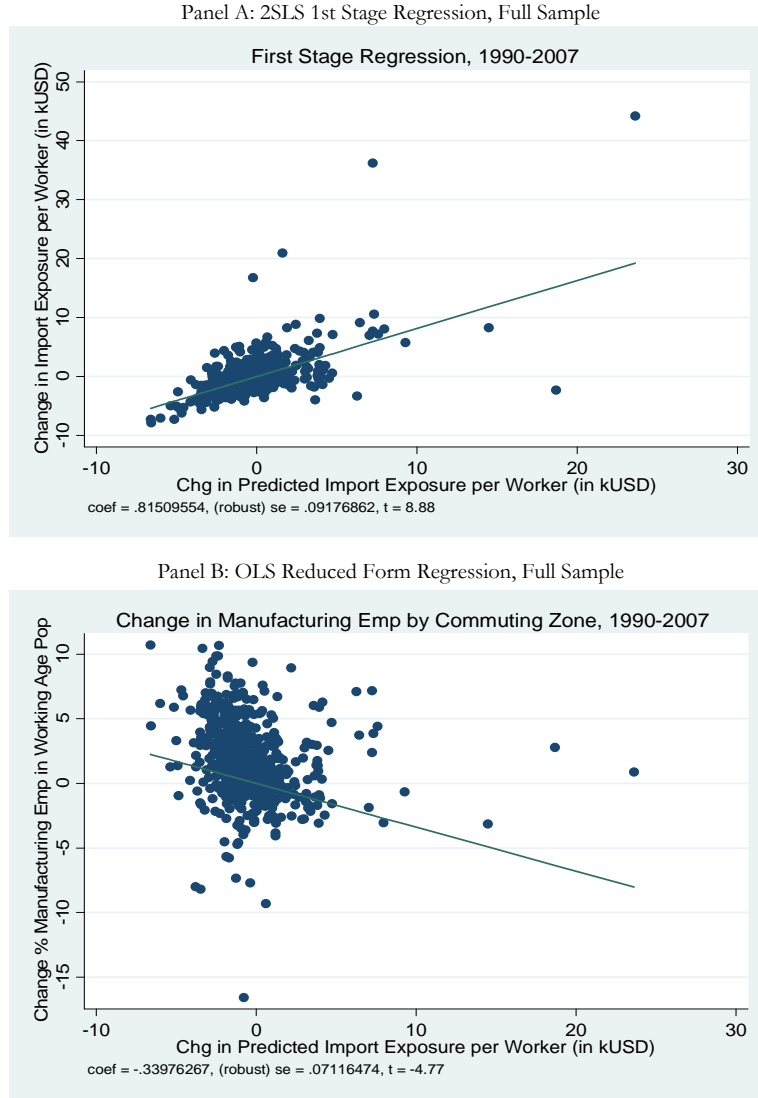


Figure 2.

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

Notes: N=722. The added variable plots control for the start of period share of employment in manufacturing industries. Regression models are weighted by start of period commuting zone share of national population.

Figure 2 sketches the estimation strategy. Panel A reveals the substantial predictive power of the high-income country instrument for changes in U.S. import exposure. A \$1,000 predicted increase

in import exposure per CZ worker corresponds to a \$815 increase in measured exposure per CZ worker.²² Panel B of Figure 2 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.²³ We explore the robustness and interpretation of this result in subsequent tables.

4.1 2SLS estimates

Table 2 presents initial 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:

$$\Delta L_{it}^m = \gamma_t + \beta_1 \Delta IPW_{uit} + X_{it}' \beta_2 + e_{ct}, \quad (5)$$

where ΔL_{it}^m 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.²⁴ Additionally, the vector X_{it} contains (in most specifications) a rich set of controls for CZs' start-of-decade labor force and demographic composition that might independently affect manufacturing employment. Standard errors are clustered at the state level to account for spatial correlations across CZs.

The first two columns of Table 2 estimate equation (5) separately for the 1990-2000 and 2000-2007 periods, and the third column provides stacked first differences estimates. The coefficient of -0.75 in column 3 indicates that a one-thousand dollar exogenous decadal rise in a CZ's import exposure

²²Predicted changes in U.S. imports are constructed by regressing observed changes in U.S. imports from China by industry ($n = 397$) between 1991 and 2007 on the corresponding changes in Chinese imports in eight other high-income countries, weighting industries by their U.S. employment in 1991. This estimation yields a regression coefficient of 1.48 ($t = 45.3$) on other-country imports. Dropping Computers and Electronics hardly affects this point estimate ($\beta = 1.53$, $t = 36.3$). The bivariate correlation between changes in U.S.-China imports by goods category and the corresponding changes in imports in the eight individual comparison countries used in constructing our instrument averages 0.54 in the 1991-2000 period and 0.56 in the 2000-2007 period.

²³It bears note that our CZ exposure variable is *by nature* a proxy since imports are not shipped to import-competing CZs for redistribution but rather are distributed broadly to wholesalers, retailers and consumers.

²⁴Estimating (5) 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.

per worker is predicted to reduce its manufacturing employment per working age population by three-quarters of a percentage point. That the estimated coefficient is of a similar in magnitude in both time periods and all three models underscores 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 ** (0.18)	-0.72 ** (0.06)	-0.75 ** (0.07)			
(Δ Future Period Imports from China to US)/Worker				0.43 ** (0.15)	-0.13 (0.13)	0.15 (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. $\sim p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Over the time period that we examine, U.S. manufacturing experienced a secular decline. A 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, 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 while column 5 shows the corresponding correlation for the 1980s and column 6 provides the results of the stacked first differences model. These correlations provide little evidence suggesting reverse causality. 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. While this exercise does not rule out the possibility that other factors contribute to the contemporaneous CZ-level relationship between rising China trade exposure and declining manufacturing employment, the Table 2 estimates demonstrate that this relationship was absent in the decades immediately prior to China's rise.

In Table 3, we augment the first difference model for the period 1990-2007 with a set of demographic and labor force measures which test robustness and potentially eliminate confounds. 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 to differences across manufacturing industries in their exposure to rising Chinese competition. The column 2 estimate implies 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. This specification finds a slightly smaller effect of import exposure on manufacturing employment than does the corresponding estimate in column 1, but the relationship remains economically large and statistically significant. Noting that the interquartile range in CZ-level import exposure growth in the time interval 2000 through 2007 was approximately one-thousand dollars per worker, the column 2 point estimate 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 2007.²⁵

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 ** (0.068)	-0.610 ** (0.094)	-0.538 ** (0.091)	-0.508 ** (0.081)	-0.562 ** (0.096)	-0.596 ** (0.099)
Percentage of employment in manufacturing ₁		-0.035 (0.022)	-0.052 ** (0.020)	-0.061 ** (0.017)	-0.056 ** (0.016)	-0.040 ** (0.013)
Percentage of college-educated population ₁				-0.008 (0.016)		0.013 (0.012)
Percentage of foreign-born population ₁				-0.007 (0.008)		0.030 ** (0.011)
Percentage of employment among women ₁				-0.054 * (0.025)		-0.006 (0.024)
Percentage of employment in routine occupations ₁					-0.230 ** (0.063)	-0.245 ** (0.064)
Average offshorability index of occupations ₁					0.244 (0.252)	-0.059 (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 ** (0.079)	0.664 ** (0.086)	0.652 ** (0.090)	0.635 ** (0.090)	0.638 ** (0.087)	0.631 ** (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 outsourcing 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 ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

²⁵ Appendix Table 1 shows that the 10-year growth in import exposure for CZs at the 75th and 25th percentile was 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 $1.06 \times -0.610 = -0.65$.

Column 3 augments the regression model with geographic dummies for the nine Census divisions, which absorb region-specific trends in the manufacturing employment share. These dummies modestly 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 variables are based on occupational task data, which are described in detail in Autor and Dorn (2011). Routine-intensive occupations are a set of jobs whose primary activities follow a set of precisely prescribed rules and procedures that make 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 motion 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 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 coefficient for occupational offshorability. The fully augmented model in column 6 indicates a sizable, robust 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. It is smaller where there is a larger initial foreign born population.²⁶

A concern for our 2SLS estimates is that in some sectors, import demand shocks may be correlated across countries. This would run counter to our instrumental variables strategy, which seeks to isolate supply shocks affecting U.S. producers, and would likely bias our results towards zero. To address

²⁶We have also estimated versions of the column 6 model that include, variously, state dummies and separate slope terms for the routine-intensive occupation share and offshorability index in both manufacturing and non-manufacturing employment. These variables have almost no effect on the coefficient of interest.

this concern, in untabulated 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.

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 3, is -0.171.²⁷ 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 attenuate the point estimate of interest towards zero. If we measure the change in import exposure per worker using lagged employment levels (as we do in constructing the instrument in equation (4)) instead of beginning of period employment (as we do in equation (3)), 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.

Having established the robustness of the basic setup, 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, and which includes Census division dummies and measures of population demographics and labor force composition.

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

One way to gauge the economic magnitude of these effects is to compare the estimated trade-induced reduction in manufacturing employment with the observed decline during 1990 to 2007. Such an exercises supposes that increased exposure to Chinese imports affects the *absolute* level

²⁷This table is discussed in greater detail below.

of manufacturing employment in the United States, and not just *relative* employment across U.S. commuting zones. Given the magnitudes of the U.S. trade deficit and China trade surplus (and the much larger increase in U.S. imports from China than in U.S. exports to China, as seen in Table 1), the possibility seems real that import competition from China has an absolute impact on U.S. manufacturing (at least as long as trade imbalances persist).

Our most conservative specification in Table 3 (column 6) implies that a \$1,000 per worker increase in import exposure over a decade 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 1990 and 2000 and by an additional \$1,839 per worker in the seven years between 2000 and 2007.²⁸ 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 1.10 percentage points in the second decade of our sample. In comparison, U.S. manufacturing employment per population fell by 2.07 percentage points between 1990 and 2000 and by 2.00 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 1990 and 2000, 55 percent of the decline between 2000 and 2007, and 44 percent of the decline for the full 1990 through 2007 period.

One sense in which this benchmark may overstate the contribution of rising Chinese imports to declining U.S. manufacturing employment is that our 2SLS estimates measure the causal effect of the Chinese *supply shock* on U.S. manufacturing whereas the import per worker measure that we employ refers to the *total change* in Chinese imports per worker, which combines both supply and demand forces. If the demand-driven component of Chinese imports has a less negative effect on manufacturing 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 that uses 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, with the remainder attributed to demand forces. This calculation implies that close to half (48%) of the observed variation in rising Chinese import exposure can be attributed to the supply-driven component. We more conservatively estimate that Chinese import competition explains 16 percent of the U.S. manufacturing employment decline between 1990 and 2000, 26 percent of the decline between 2000 and 2007, and 21 percent of the

²⁸In Appendix Table 2, the 2000-2007 change in import growth is multiplied by 10/7 to put it on decadal terms.

decline over the full period. For the mainland U.S. working-age population, these estimates imply a supply-shock driven net reduction in U.S. manufacturing employment of 548 thousand workers between 1990 and 2000 and a further reduction of 982 thousand workers between 2000 and 2007.²⁹

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. 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., consistent with the interpretation that growth in Mexican exports is largely driven by rising U.S. product demand rather than changing conditions in Mexico.³⁰ The 2SLS estimate of this coefficient, by contrast, is negative and significant. A likely explanation for this latter result is that our measure of predicted CZ-level exposure to Mexican imports is highly correlated with the

²⁹Using the Census/ACS data, we calculate that the U.S. mainland population was 157.6, 178.7 and 194.3 million adults ages 16 through 64 in 1990, 2000 and 2007 respectively. Our estimates therefore imply a supply-shock driven net reduction in U.S. manufacturing employment of approximately 1.53 million workers ($[0.5 \cdot (157.6 + 178.7) \times 1.14 + 0.5 \cdot (178.7 + 194.3) \times 1.84] \times (0.00596 \cdot 0.48) = 1.53$).

³⁰Unlike 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).

corresponding exposure measure for Chinese imports. Confirming this intuition, we find that the correlation between the predicted values of CZ-level exposure to Mexican imports and the predicted values for Chinese imports from the first stage models in columns 4 and 1, respectively, exceeds 0.70, implying that we cannot separately identify the Mexico/CAFTA versus China trade effect. Reassuringly, combining Mexico/CAFTA imports with Chinese imports has almost no effect on the point estimates, as was shown in column 3.³¹ The final 2SLS estimates in column 5, analyzing 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 sections 4.1 to 4.3 suggest that the exposure of CZs to growing imports from China is a quantitatively important determinant of the decline in the share of manufacturing employment in the working age population. We now expand our focus beyond manufacturing to study the impacts of China trade shocks on broader labor market outcomes.

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: directly, via a change in employment in the affected sector; and 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 and employment effects in local labor markets

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

³¹In related work that uses data for 1990 and 2000, McLaren and Hakobyan (2010) fail to find significant effects of NAFTA on local U.S. labor markets (though they do detect effects on industry wage growth)

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 specifications in panel A, which includes no controls 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. 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 (0.503)	* -0.360 (0.660)	-1.097 (0.488)	* -1.299 (0.826)	-0.615 (0.572)	-1.127 (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 (0.513)	0.147 (0.619)	-0.240 (0.519)	-0.408 (0.953)	-0.045 (0.474)	-0.549 (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 (0.746)	-0.026 (0.685)	-0.047 (0.823)	-0.138 (1.190)	0.367 (0.560)	-0.138 (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. $\sim p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

The lack of a significant effect of trade exposure on population flows is consistent with several hypotheses. 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 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, such that factor price equalization pins down the wage in all markets, making local factor prices 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). Costs to labor of moving between sectors (as in Artuc, Chaudhuri, and McLaren, 2010, and Dix-Carneiro, 2011) may contribute to costs of moving between regions. 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.

If working age adults do not depart from CZs facing adverse trade shocks, then the trade-induced decline in manufacturing employment must yield a corresponding rise in either non-manufacturing employment, unemployment, labor force exit or some combination of the three. In the first panel of Table 5, we study the impact of import shocks on the log change in the number of non-elderly adults in four exhaustive and mutually exclusive categories: employment in manufacturing, employment in non-manufacturing, unemployment and labor force non-participation. We find that a \$1,000 per worker increase in import exposure reduces the number of workers in manufacturing employment by 4.2 log points (~ 4.2 percent, $t = 4.04$). Perhaps surprisingly, this effect is not offset by a rise in non-manufacturing employment in the affected CZ; rather, there is a modest *decline* in local non-manufacturing employment on the order of 0.27 log points. This point estimate is not statistically significant, though we show below that there is a significant reduction in *non-college* employment in non-manufacturing. These net declines in manufacturing and non-manufacturing employment are echoed by sharp rises in the number of unemployed workers and labor force non-participants: a \$1,000 per worker import shock increases the number of unemployed and non-participating individuals by 4.9 and 2.1 percent, respectively. In concert with the results in Table 4, these results indicate that trade-induced declines in manufacturing employment accrue essentially one-for-one to rising unemployment and non-employment within affected CZs. These point estimates also underscore that the null results for population flows found in Table 4 are reliable. If trade-induced population flows *between* CZs were as large as trade-induced flows *within* CZs, these population flows would be detectable in our sample at available levels of precision.

Panel B of Table 5 presents a corresponding set of models for employment, unemployment and non-employment using as a dependent variable the *share* of the non-elderly adult population in

each category: declines in the population share in one category (e.g., manufacturing employment) must yield equivalent gains in other categories.³² Since population—the denominator of the share variable—is not systematically affected by the shock, normalizing by this measure is not problematic. The sum of the first two coefficients in panel B indicates 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, with the remainder due a (not significant) decline in non-manufacturing employment. The next two columns 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). Thus, the shock to manufacturing employment leads to a more than one-for-one rise in non-employment.

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 Log Population Counts and Population Shares by Employment Status

	Mfg Emp		Non-Mfg		Unemp		NILF		SSDI
	(1)		Emp		(3)		(4)		Receipt
	(1)		(2)		(3)		(4)		(5)
<u>A. 100 × Log Change in Population Counts</u>									
(Δ Imports from China to US)/Worker	-4.231 (1.047)	**	-0.274 (0.651)		4.921 (1.128)	**	2.058 (1.080)	~	1.466 (0.557)
<u>B. Change in Population Shares</u>									
<i>All Education Levels</i>									
(Δ Imports from China to US)/Worker	-0.596 (0.099)	**	-0.178 (0.137)		0.221 (0.058)	**	0.553 (0.150)	**	0.076 (0.028)
<i>College Education</i>									
(Δ Imports from China to US)/Worker	-0.592 (0.125)	**	0.168 (0.122)		0.119 (0.039)	**	0.304 (0.113)	**	.
<i>No College Education</i>									
(Δ Imports from China to US)/Worker	-0.581 (0.095)	**	-0.531 (0.203)	**	0.282 (0.085)	**	0.831 (0.211)	**	.

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. 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 are much more pronounced for non-college adults.³³ The next two rows of panel B show that a \$1,000 import shock reduces both college and non-college manufacturing employment per population by equivalent amounts, but have distinct effects

³²Note that our unemployment measure is the ratio of unemployed to the working age population, not the ratio of unemployed to total labor force participants. Consequently, $-\Delta EMP/POP = \Delta UNEMP/POP + \Delta NILF/POP$.

³³In our analysis, college education refers to any completed years of post-secondary schooling whereas non-college refers to high school or lower education.

on college versus non-college employment in non-manufacturing employment, unemployment and non-employment. Specifically, a \$1,000 import exposure shock reduces non-college employment in *non*-manufacturing by a highly significant 0.53 percentage points, which is comparable to its effect on non-college manufacturing employment.³⁴ By contrast, college employment in non-manufacturing increases modestly by 0.17 percentage points ($t = 1.37$). A potential explanation for this pattern is that the decline of manufacturing industries decreases the demand for non-traded services that are typically provided by low-skilled workers, such as transportation, construction, or retail trade.³⁵ On net, a \$1,000 import exposure shock reduces the employment to population rate of college adults by 0.42 percentage points and of non-college adults by 1.11 percentage points—which is nearly three times as large. For both groups, only about one-fourth of the net employment reduction is accounted for by rising unemployment, with the remainder accruing to labor force non-participation.

As detailed in Appendix Table 4, declining employment and increasing unemployment and non-participation are similar for males and females in percentage-point terms, though relative employment declines are larger among females because the initial share of manufacturing employment among women (8.3% in 1990) is considerably smaller than among men (17.3%). Employment-to-population reductions are equally concentrated among young, mid-career and older workers (ages 16-34, 35-49, and 50-64), though the employment losses are relatively more concentrated in manufacturing among the young and in non-manufacturing among the old. For the oldest group, fully 84% of the decline in employment is accounted for by a rise in non-participation, relative to 71% among the prime-age group and 68% among the younger group.

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 estimates in Panel B of Table 5 suggests that 9.9% (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. As of 2010, 4.6% 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 2011). It is likely that the increase in disability rolls is strongly concentrated among older workers and workers without a college education, though we

³⁴Of course, manufacturing employs fewer workers than non-manufacturing, so the proportionate reduction in non-manufacturing employment is smaller.

³⁵Disaggregating college workers into those with some college and those with a four-year degree or higher, the employment reduction in manufacturing is 40 percent larger for workers with some college than those with a four-year degree (−0.66 versus −0.48 percentage points) whereas the gain in non-manufacturing employment is 40 percent larger for workers with a four-year degree than those with some college (0.22 versus 0.14 percentage points).

cannot directly test this assumption since the SSDI data are not available to us separately by age or education group at the detailed geographic level.

5.2 Wage effects

In Table 6, we analyze effects of import exposure shocks on CZ wage levels. Our estimation approach follows the models above except that our dependent variable is the mean log weekly earnings in a CZ.³⁶ Because the outcome is only available for the employed, and bearing in mind 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)	
<u>A. All Education Levels</u>						
(Δ Imports from China to US)/Worker	-0.759 (0.253)	**	-0.892 (0.294)	**	-0.614 (0.237)	**
R ²	0.56		0.44		0.69	
<u>B. College Education</u>						
(Δ Imports from China to US)/Worker	-0.757 (0.308)	*	-0.991 (0.374)	**	-0.525 (0.279)	~
R ²	0.52		0.39		0.63	
<u>C. No College Education</u>						
(Δ Imports from China to US)/Worker	-0.814 (0.236)	**	-0.703 (0.250)	**	-1.116 (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 ≤ 0.10, * p ≤ 0.05, ** p ≤ 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. While they are somewhat larger overall for males than for females, with the largest declines found among college

³⁶We 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.

males and non-college females, we do not have sufficient precision to reject the null hypothesis that 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 presents estimates of the effect of import exposure on log employment counts in both sectors. Consistent with the estimates above, Table 7 confirms that import exposure reduces head-counts in manufacturing but has little employment effects outside of manufacturing, particularly for college workers.

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. Non-Manufacturing						
	All		Non-		All		Non-					
	Workers	College	College		Workers	College	College					
	(1)	(2)	(3)		(4)	(5)	(6)					
<u>A. Log Change in Number of Workers</u>												
(Δ Imports from China to US)/Worker	-4.231 (1.047)	**	-3.992 (1.181)	**	-4.493 (1.243)	**	-0.274 (0.651)	0.291 (0.590)	-1.037 (0.764)			
R ²	0.31		0.30		0.34		0.35	0.29	0.53			
<u>B. Change in Average Log Wage</u>												
(Δ Imports from China to US)/Worker	0.150 (0.482)		0.458 (0.340)		-0.101 (0.369)		-0.761 (0.260)	**	-0.743 (0.297)	*	-0.822 (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 ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

The effect of import exposure on mean wages found in panel B of 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.³⁷ One explanation for 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.

By contrast, 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, an effect that is similar for college and non-college workers. This result sug-

³⁷An 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.

gests that a negative shock to local manufacturing reduces the demand for local non-traded services while increasing the available supply of workers, 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 in employment and wages in local markets. These findings suggest that a variety of partial and incomplete labor market adjustments are operative. Because total 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 any wage effects are masked by shifts in employment composition. That wages fall in non-manufacturing, however, 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 the sector. Overall, the findings 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 broader(non-local) labor market.³⁸

6 Public transfer payments and household incomes

The decline in employment and wages in CZs facing 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 above 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 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 both the dollar and log change in individual transfers per capita for total transfers and for major subcategories.

³⁸We cannot rule out the possibility that there are also general equilibrium effects on national employment and wages. In our estimates, these would be absorbed by time dummies. The lack of a migration response means that these effects would primarily have to operate through traded goods prices rather than through labor mobility.

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		TAA Benefits		Unemp- loyment Benefits		SSA Re- tirement Benefits		SSA Disability Benefits		Medical Benefits		Federal Income Assist		Other Income Assist		Educ/ Training Assist	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
<u>A. Log Change of Transfer Receipts per Capita</u>																		
(Δ Imports from China to US)/Worker	1.01 (0.33)	**	14.41 (7.59)	~	3.46 (1.87)	~	0.72 (0.38)	~	1.96 (0.69)	**	0.54 (0.49)		3.04 (0.96)	**	1.08 (2.20)		2.78 (1.32)	*
R ²	0.57		0.28		0.48		0.36		0.32		0.27		0.54		0.37		0.33	
<u>B. Dollar Change of Transfer Receipts per Capita</u>																		
(Δ Imports from China to US)/Worker	57.73 (18.41)	**	0.23 (0.17)		3.42 (2.26)		10.00 (5.45)	~	8.40 (2.21)	**	18.27 (11.84)		7.20 (2.35)	**	4.13 (4.44)		3.71 (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 columns 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. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

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).³⁹ 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.⁴⁰ 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 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.

These transfer programs differ substantially in expenditure levels per capita (Appendix Table 2). 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, federal income assistance

³⁹Import exposure is denominated by non-elderly adult workers whereas transfer payments are denominated by total CZ *residents*. If we instead perform a 2SLS estimate of the effect of imports per worker on total transfers divided by total *workers*, we obtain a coefficient of 113.18 (s.e. 41.53). That this coefficient is roughly double that for transfers per capita point estimate reflects the fact that the ratio of U.S. employment to total population (including children and the elderly) is approximately 50 percent.

⁴⁰TAA 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 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.

(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. The substantial 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 \$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.⁴¹ 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, a point we return to below.

Import exposure shocks may also cause 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 import competition. The models in Table 9, which are estimated using data from the Census and American Community Survey (rather than the BEA 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).⁴²

⁴¹To the degree that SSA retirement benefits reflect deferred earnings rather than transfers per se, the trade-induced increase in retirement benefits payments should not have a tax-related deadweight loss component.

⁴²These estimates use the combined wage and salary income of working-age adults ages 16-64 in each household divided by the number of working-age adults. Households are weighted by their number of working-age adults.

The effect of import competition on household incomes is statistically significant and economically large. To confirm its plausibility, we benchmarked it against our earlier estimates of the effect of import exposure on employment and earnings among the employed. The estimates in the first two columns of Table 5 (panel B) indicate that a \$1,000 per worker increase in a CZ's import exposure reduces manufacturing and non-manufacturing employment per population 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 USD), 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 the 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 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. We thus calculate a further reduction in labor earnings of \$156 per adult accruing from reduced weekly earnings among the employed.⁴³ Combining the employment and earnings margins yields an estimated per adult reduction of \$487 per \$1,000 increase in trade exposure, which is similar to the per adult wage/salary impact estimate of \$549 obtained in Table 9.

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	Wage-Salary	Business Invest	SocSec +AFDC	Total	Wage-Salary
	(1)	(2)	(3)	(4)	(5)	(6)
<u>A. Relative Growth (%pts)</u>						
(Δ Imports from China to US)/Worker	-1.48 ** (0.36)	-2.14 ** (0.59)	-0.51 (0.74)	2.12 ** (0.58)	-1.73 ** (0.38)	-2.32 ** (0.51)
R ²	0.69	0.43	0.76	0.52	0.53	0.52
<u>B. Dollar Change</u>						
(Δ Imports from China to US)/Worker	-492.6 ** (160.4)	-549.3 ** (169.4)	40.1 (116.7)	17.3 ** (4.3)	-439.9 ** (112.7)	-476.5 ** (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 ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

⁴³The per-capita earnings impact from reduced wages in non-manufacturing is $-0.0076 \times \$36,142 \times 0.592 = -\163 , while the diminutive countervailing effect from higher manufacturing wages is $0.0015 \times \$44,233 \times 0.105 = \7 .

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

In this section, we consider alternative measures of trade exposure for U.S. commuting zones in order to gauge the robustness of our results.

First, we modify our definition of import exposure to include competition in other foreign markets. China’s growth not only displaces U.S. producers in the U.S. market but may also affect U.S. sales in the foreign markets that U.S. industries serve. We measure global U.S. industry exposure to import competition from China using initial U.S. exports to each market divided by the market’s imputed spending on industry output (calculated under the assumptions that preferences are Cobb-Douglas and that foreign industry expenditure shares equal those in the U.S.). Following equations (1) and (3), 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 (3) 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}). The large share of spending most countries devote to domestic goods means that the imputed share of expenditures directed towards U.S. products is small. 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 (3) with domestic plus international import exposure to Chinese trade. We adjust the instrument for import exposure in equation (4) 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.

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			
	Mfg		Non-Mfg	Mfg	Non-Mfg	Log Transfers		Avg Log HH Wage Inc	
	(1)		(2)	(3)	(4)	(5)		(6)	
<u>A. Baseline Results: Gross Chinese Imports per Worker (2SLS)</u>									
(Δ Imports from China to US)/Worker	-0.60 (0.10)	**	-0.18 (0.14)	0.15 (0.48)	-0.76 (0.26)	**	1.01 (0.33)	-2.14 (0.59)	**
<u>B. Domestic Plus International Exposure to Chinese Exports (2SLS)</u>									
(Δ Domestic + Intn'l Exposure to Chinese Imports)/Worker	-0.42 (0.05)	**	-0.10 (0.10)	0.11 (0.33)	-0.47 (0.18)	**	0.87 (0.22)	-1.75 (0.43)	**
<u>C. Exposure to Final Goods and Intermediate Inputs (2SLS)</u>									
(Δ Imports from China to US net of Imed Inputs)/Worker	-0.49 (0.12)	**	-0.01 (0.20)	0.71 (0.52)	-0.41 (0.37)		0.84 (0.36)	* -1.47 (0.88)	~
<u>D. Net Chinese Imports per Worker (2SLS)</u>									
(Δ Net Imports of US from China)/Worker	-0.45 (0.10)	**	-0.09 (0.15)	0.45 (0.42)	-0.47 (0.27)	~	0.73 (0.35)	* -1.64 (0.65)	*
<u>E. Change in China-US Productivity Differential (OLS Gravity Residual)</u>									
Δ Comparative Advantage China (Gravity Residual)	-0.29 (0.04)	**	-0.03 (0.08)	0.04 (0.28)	-0.26 (0.15)	~	0.53 (0.14)	** -0.93 (0.28)	**
<u>F. Factor Content of Net Chinese Imports per Worker (2SLS)</u>									
(Δ Factor Content of Net Imports from China)/Worker	-0.57 (0.10)	**	-0.12 (0.15)	0.59 (0.50)	-0.66 (0.26)	*	0.81 (0.36)	* -1.90 (0.60)	**

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 variables is 1.88 (1.75) in Panel A; 2.28 (2.17) in Panel B; 1.46 (1.48) in Panel C; 1.58 (1.66) in Panel D; 1.40 (1.79) in Panel E; and 1.50 (1.48) in Panel F. The first stage coefficient estimate is 0.61 (s.e. 0.07) for the models in Panel B; 0.72 (0.09) for the final goods import instrument and -1.05 (0.25) for the intermediate inputs import instrument in Panel C; 0.70 (0.10) for the import instrument and -0.32 (0.08) for the export instrument in Panel D; and 0.72 (s.e. 0.07) for the import instrument and -0.28 (0.06) for the export instrument in Panel F. 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. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

A second issue with measuring trade exposure is that imports from China include both final goods purchased by U.S. consumers and intermediate inputs purchased by U.S. firms. If trade with China increases the variety of inputs to which U.S. producers have access, it may raise their productivity (e.g., Goldberg, Khandelwal, Pavcnik, and Topalova, 2010), increasing their demand for labor and partially offsetting the impact of import competition in final goods. Panel C of Table 10 reports results in which we measure industry import exposure using total China imports per worker less China imports of intermediate inputs per worker, in which we calculate industry imported inputs by combining U.S. trade data with the 1992 U.S. input-output table (assuming that industry patterns of input usage are the same for imports as for U.S. domestic goods). We construct the instrument

for input-adjusted import exposure analogously. In column (1), the coefficient on import exposure is -0.49, 18% smaller than in panel A, and still very precisely estimated.

Another feature missing in our analysis is U.S. exports to China. Because U.S. imports from China are much larger than U.S. exports to China, excluding exports may not greatly affect our measure of trade exposure. Incorporating exports is complicated by China and the U.S. occupying different positions in global production chains. Whereas the model we outline in section 2 treats all products as final goods, in practice firms may produce inputs in one country, export the goods to a second country for further processing, and so on until the final product is delivered to consumers (Hummels, Ishii, and Yi, 2001). China is often the final link in the supply chain owing to its comparative advantage in labor-intensive assembly, which tends to be the last stage of production (Feenstra and Hanson, 2005), meaning that goods leaving China tend to be on their way to consumers. China’s place in global production suggests that although we do not explicitly account for supply chains, our approach still captures how imports from China (and from other countries whose value added is embodied in U.S. imports from China) affect the demand for U.S. goods.⁴⁴

The same is unlikely to hold for U.S. exports to China. U.S. firms tend to locate early in the production chain, meaning that U.S. products destined for China may be shipped through third countries (e.g., U.S. technology is used by Korea to manufacture chips for cell phones before these chips are sent to China for assembly and testing). Thus, there may be 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 construct *net* imports from China by subtracting U.S. exports from U.S. imports by industry, which following equation (3) yields:

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

We instrument for the net import measure using two variables: the potential import exposure index used in prior tables (equation 4) 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. Panel D of Table 10 presents estimates. A \$1,000 per worker increase in Chinese net import exposure reduces the manufacturing employment

⁴⁴While 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.

to population ratio by 0.45 percentage points. This point estimate is about 25 percent smaller and similarly precisely estimated to the model in panel A that uses gross rather than net import exposure.

An 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. To interpret the scale of the gravity measure, note that a one unit increase in the gravity measure corresponds to a \$1,000 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 scaling is comparable to the import exposure variable in our baseline specification with two slight differences: first, because the gravity residual corresponds to a logarithmic measure of productivity, it is appropriate to exponentiate this coefficient for comparison; second, since changes in Chinese relative productivity or trade costs will affect *net* rather than gross imports, the gravity estimates are most comparable to the net import exposure models in Panel D.

Panel E of Table 10 use the gravity-based approach to measure the exposure of CZs to Chinese trade. 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. 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).⁴⁵ We re-estimate our core regressions using the factor content of trade to measure import exposure in CZs. Because our data at the CZ level do not permit measurement of factor content by labor type, we treat labor as a composite factor. In panel F 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,

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

This measure of the labor content of U.S. net imports from China calculates CZ exposure to trade

⁴⁵The validity of the factor content approach was the subject of debate in the trade and wages literature of the 1990s (Krugman, 2000; Leamer, 2000; and Feenstra, 2010). See Burstein and Vogel (2011) for recent work.

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.⁴⁶ We instrument for the labor content of net imports from China in a manner analogous to our strategy for net imports in panel D.

The results in column 1 of panel F show that the net import of labor services of one U.S. worker displaces 0.81 workers in manufacturing, after adjusting for differences in the scale of the net-labor-services import measure (denominated in labor services per worker in a CZ) and the manufacturing-employment-per-population outcome (denominated in manufacturing workers per working-age population in a CZ).⁴⁷ These impact estimates are precisely estimated and 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.

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

8 Losses in efficiency from use of public benefits and involuntary labor-force non-participation

What do our results imply about 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 (Goldberg, Khandelwal, Pavcnik, and Topalova, 2010) should ensure that aggregate gains from trade are larger 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 competition is associated with lower manufacturing employment and

⁴⁶That 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 imports from (exports to) China to be relatively labor (capital) intensive.

⁴⁷The factor content of net imports is normalized by CZ employment, whereas manufacturing employment in the dependent variable is normalized by working-age 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 $-0.57 \times (1/0.70) = 0.81$ U.S. manufacturing workers.

lower wages in exposed local labor markets in no way contradicts this logic. It does, however, highlight trade’s distributional consequences.

One manner in which adjustment to import competition may partly offset 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 reduction in economic efficiency associated with U.S. benefit programs. The coefficient estimate 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. By multiplying this coefficient by the observed growth of exposure to Chinese imports and the fraction of this growth that we attribute to supply shocks, we obtain that rising import competition from China has been associated with an increase in annual transfers receipts of \$32 and \$51 per capita in 1990-2000 and 2000-2007, respectively.⁴⁸ Using Gruber’s (2010) estimate that the marginal excess burden of taxation (required to fund transfers) is equal approximately to 40 cents on the dollar, the increase in transfers resulting from import exposure implies an increase in annual deadweight loss of \$13 and \$21 in these two periods, or \$33 in total. Applying a confidence interval of plus and minus one standard error around the point estimate for induced transfers, we estimate the range of deadweight losses at \$22 to \$44 per capita

Another source of efficiency loss from trade adjustment is involuntary reductions in labor force participation, which will lead to deadweight losses if the market wage of involuntarily displaced workers exceeds their value of leisure. We benchmark the magnitude of this frictional cost by estimating workers’ forgone value of leisure during employment and comparing this to their market wage. The gap between these values is equal to workers’ surplus from employment or, in the case of involuntary unemployment, to the magnitude of the deadweight loss.

We assume that initially workers choose hours freely, so they are indifferent at the margin between supplying an additional hour of labor and consuming an additional hour of leisure. We write

$$w_0 u_c(y + w h_0, h_0) = -u_h(y + w_0 h_0, h_0), \quad (6)$$

where the left-hand side of this expression is equal to the marginal utility of the consumption afforded by an hour of labor at the optimal hours choice h_0 and wage w_0 , and the right-hand side is the marginal disutility of work, or equivalently, the marginal utility of leisure. Due to risk

⁴⁸Import exposure per worker rose by \$1,140 in 1990-2000 and by \$1,840 in the 7-year period 2000-2007. Column 1 in Table 8 finds that a \$1000 increase in exposure per worker induces \$58 additional in per-capita transfers, implying that increased trade flows led to an additional \$66 and \$106 in transfers per capita in 1990-2000 and 2000-2007 respectively. As in our benchmarks above for manufacturing employment, we scale this estimate downward by approximately half (52%) so that 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 \$32 and \$51 in the first 10 and last 7 years of our sample.

aversion, the marginal utility of consumption is globally declining in income, so a lower bound on the consumer's loss of welfare from a reduction in income (holding labor supply constant) is the initial marginal utility of consumption times the income loss u_c^0 . We therefore conservatively assume that $u_c(y + w_0 h_0, h_0) = u_c^0$ is constant at the initial wage.⁴⁹ Applying this simplification to (6), taking logs and differentiating yields the inverse compensated hours elasticity of labor supply:⁵⁰

$$\frac{\partial \ln w}{\partial \ln h} = \frac{\partial \ln (-u_h(y + w_0 h_0, h_0))}{\partial \ln h} = \frac{1}{\eta_h}.$$

To estimate worker surplus from employment, we integrate the labor supply function over the relevant range and subtract this value from labor earnings:

$$\Delta = w_0 h_0 - \frac{w_0 h_0}{1 + 1/\eta_h} = \frac{w_0 h_0}{\eta_h + 1}. \quad (7)$$

A higher labor supply elasticity gives workers lower surplus from employment since the wage demanded for an additional hour of labor is not much above the wage paid for the prior hour.

Next consider a trade-induced shock that leads to involuntary displacement—forcing some workers to reduce hours of work to zero—and, further, reduces the market wage that displaced workers would receive were they to hypothetically regain employment.⁵¹ In estimating the associated deadweight loss, we must recognize that trade-induced employment reductions are in part volitional, stemming from the effect of falling wages on labor supply. To estimate the deadweight loss from *involuntary* unemployment, we first net out the voluntary labor supply reductions on the extensive (participation) and intensive (hours) margins.

We estimate these voluntary responses by applying Hicksian labor force participation and hours elasticities of $\eta_e \approx 0.25$ and $\eta_h \approx 0.50$, respectively, drawn from Chetty (forthcoming). Our impact estimates in Tables 5 and 6 find that a \$1,000 import shock reduces wages by $\hat{\beta}_w = -0.76$ percent and reduces labor force participation by $\hat{\beta}_e = -0.77$ percentage points. The extensive margin elasticity of 0.25 implies that a 0.76 percent wage decline will generate a decline in labor force participation of 0.19 percent, which is roughly one quarter as large as what we observe in the data. We infer that approximately three-quarters of the trade-induced fall in employment is involuntary. Lower wages will also reduce desired hours among those who remain employed. To incorporate this response, we write the new market wage as $w'_0 : w'_0 < w_0$ with associated hours choice $h'_0 \approx h_0 (1 + \eta_h \ln(w'_0/w_0))$.

Substituting these adjusted wage and hours value into equation (7) yields the welfare loss from

⁴⁹Moreover, the literature suggests that consumption losses are much smaller than income losses for displaced workers, implying that income effects may also be relatively small (Gruber, 1997).

⁵⁰The associated inverse labor supply function is $w = (h/k_0)^{1/\eta}$, where $k_0 = h_0/w_0^\eta$.

⁵¹The decline in the market wage is a pecuniary cost that should arguably not be counted in the welfare calculation.

involuntary employment,

$$\Delta' = \frac{\alpha w_0 h_0 [1 + \eta_h (\alpha - 1)]}{\eta_h + 1}, \quad (8)$$

where $\alpha = w'_0/w_0$ and we approximate $\ln(w'_0/w_0) \approx \alpha \approx 1 + \hat{\beta}_w \times \Delta IPW_{ut}$. This equation says that the deadweight loss from involuntary unemployment is somewhat *less* than workers' surplus from employment since reductions in the equilibrium wage and associated reductions in hours of work reduce worker surplus even conditional on remaining employed.⁵²

Applying these estimates, we calculate that the exogenous component of rising China trade exposure increased involuntary unemployment and non-participation by 0.32 and 0.52 percentage points, respectively, in the first and second periods of our sample, with associated reductions in earnings per capita of \$65 and \$106. Using equation (8) to calculate the loss in worker surplus, we estimate deadweight losses from involuntary unemployment of \$43 and \$69 per capita. Allowing for a one standard error band for the estimated impact of trade exposure on the employment rate, we obtain a deadweight loss due to involuntary unemployment of \$87 to \$137 per capita during 1990 through 2007.⁵³

As affected workers retire or pass away, the trade-induced losses from either the transfers they receive or involuntary unemployment will dissipate whereas the gains from trade should persist. Nevertheless, in the medium run losses in economic efficiency from increased usage of public benefits and involuntary labor-force non-participation may offset a portion of the gains from trade from China.

9 Conclusion

The value of annual U.S. goods imports from China increased by a staggering 1,156% from 1991 to 2007, whereas U.S. exports to China grew by much less. 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 relative to earlier decades. Much previous

⁵²In the numerator of this calculation, a higher labor supply elasticity partly mitigates welfare loss from the adverse shock because a worker will *voluntarily* reduce hours by more for a given reduction in the wage.

⁵³Given a reduction of the employment rate by 0.77 percentage points per \$1,000 of import exposure, and our estimate that 48% of import growth is due to the China supply shock, we obtain a supply shock-induced decline of the employment rate by $1,140 \times -0.77 \times 0.48 = -0.42$ and $1,840 \times -0.77 \times 0.48 = -0.68$ percent for the two periods. Voluntary reduction of employment due to lower wages accounts for 25% of this effect, and the trade-induced involuntary reduction of the employment rate is thus -0.32 and -0.52 percentage points in the first and second period, respectively. Finally, using a weighted average of the income of college and non-college workers of \$32,033 in 2000 (where weights are given by the Table 5 point estimates for the decline in college and non-college employment to population, and the relative size of the college and non-college population in 2000) and a ratio of working age population to total population of 0.639, one can translate the involuntary employment reduction to an employment-induced decrease of per capita earnings of $-0.0032 \times 32,033 \times 0.639 = -\65 and $-0.0052 \times 32,033 \times 0.639 = -\106 . The corresponding DWL according to equation (8) is \$43 in the first and \$69 in the second period.

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, our 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 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 reform-induced changes within China: rising productivity growth, greater investment in labor-intensive export 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 not just through manufacturing employment, which unsurprisingly is adversely affected, but also along numerous other margins. Import shocks trigger 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. These changes contribute to rising transfer payments through multiple federal and state programs, revealing an important margin of adjustment to trade that the literature has largely overlooked. 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 transfer increases are for federal disability, retirement and in-kind medical payments. Unemployment insurance and income assistance play a significant but secondary role. By contrast, Trade Adjustment Assistance (TAA), which specifically provides benefits to workers who have been displaced by trade shocks, accounts for a negligible part of the trade-induced increase in transfers.

Theory suggests that trade with China yields aggregate gains for the U.S. economy. Our study highlights the distributional consequences of trade and the medium-run efficiency losses associated with adjustment to trade shocks. The consequences of China trade for U.S. employment, household income, and government benefit programs may help account for the apparent public ambivalence toward globalization and specific anxiety about increasing trade with China.

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. 2012. "New Trade Models, Same Old Gains?" *American Economic Review*, 102(1), 94-130.
- 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 Daron Acemoglu. 2010. "Skills, Tasks and Technologies: Implications for Employment and Earnings." in Orley Ashenfelter and David Card, eds., *Handbook of Labor Economics*, Volume 4, Amsterdam: Elsevier-North Holland, 2010, 1043-1171
- 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. 2010. *Supporting Work: A Proposal for Modernizing the U.S. Disability Insurance System*. Washington, DC: Center for American Progress and The Hamilton Project.
- 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.
- Beaudry, Paul, Mark Doms and Ethan Lewis. 2010. "Should the Personal Computer Be Considered a Technological Revolution? Evidence from U.S. Metropolitan Areas." *Journal of Political Economy*, 118(5), 988-1036.
- 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.
- Blanchard, Olivier Jean and Lawrence F. Katz. 1992. "Regional Evolutions." *Brookings Papers on Economic Activity*, 1992(1), 1-75.
- 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., 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.

- Chen YuYu, Ginger Zhe Jin, and Yang Yue. 2010. "Peer Migration in China." NBER Working Paper No. 15671.
- Chetty, Raj. Forthcoming. "Bounds on Elasticities with Optimization Frictions: A Synthesis of Micro and Macro Evidence on Labor Supply." *Econometrica*.
- 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.
- di Giovanni, Julian, Andrei Levchenko, and Jing Zhang. 2011. "The Global Welfare Impact of China: Trade Integration and Technological Change." Mimeo, University of Michigan.
- Dix-Carneiro, Rafael, 2011. "Trade Liberalization and Labor Market Dynamics." Mimeo, University of Maryland.
- 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.
- Eaton, Jonathan, Samuel Kortum, and Francis Kramarz. 2011. "An Anatomy of International Trade: Evidence from French Firms." *Econometrica*, 79(5), 1453-1498.
- 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.
- Feenstra, Robert C. 2004. *Advanced International Trade*. Princeton, NJ: Princeton University Press.
- 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. 1997. "The Consumption Smoothing Benefits of Unemployment Insurance." *American Economic Review*, 87(1), 192-205.
- Firpo, Sergio, Nicole M. Fortin and Thomas Lemieux. 2011. "Occupational Tasks and Changes in the Wage Structure." Mimeo, University of British Columbia.
- Goldberg, Pinelopi K., Amit K. Khandelwal, Nina Pavcnik, and Petia Topalova. 2010. "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India," *Quarterly Journal of Economics*, 125(4), 1727-1767.
- 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.

- Hanson, Gordon, and Chong Xiang. 2004. "The Home Market Effect and Bilateral Trade Patterns." *American Economic Review*, 94: 1108-1129.
- Harrison, Ann and Margaret McMillan. 2010. "Offshoring Jobs? Multinationals and U.S. Manufacturing Employment." *Review of Economics and Statistics*, forthcoming.
- Helpman, Elhanan, and Paul Krugman. 1985. *Market Structure and Foreign Trade*. Cambridge, MA: MIT Press.
- 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, Jakob 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.
- 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 Treffer. 2008. "Much 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.
- Melitz, Marc. 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Productivity." *Econometrica*, 71(6), 1695-1725.
- 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.
- Naughton, Barry. 2007. *The Chinese Economy: Transitions and Growth*. Cambridge, MA: MIT Press.
- 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].
- 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. 2005. "Trade Liberalization, Poverty, and Inequality: Evidence from Indian Districts." NBER Working Paper No. 11614.
- 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.

Appendix Tables

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

		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
Rank	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 $(\Delta \text{Imports from China to US})/\text{Worker}$ 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+	China+	Mexico/		All Other		
	(1)		other Low-Inc	Mexico/Cafta	Cafta		Exporters		
	(1)		(2)	(3)	(4)		(5)		
<u>A. OLS Estimates</u>									
(Δ Imports from specified exporter to U.S.)/Worker	-0.171 (0.028)	**	-0.182 (0.026)	**	-0.034 (0.031)		0.297 (0.050)	**	0.021 (0.005)
<u>B. 2SLS Estimates</u>									
<i>second stage estimates</i>									
(Δ Imports from specified exporter to U.S.)/Worker	-0.596 (0.099)	**	-0.587 (0.096)	**	-0.602 (0.110)	**	-1.870 (0.682)	**	-0.031 (0.018)
<i>first stage estimates</i>									
(Δ Imports from specified exporter to OTH)/Worker	0.631 (0.087)	**	0.621 (0.078)	**	0.632 (0.093)	**	1.146 (0.514)	*	0.420 (0.047)
T-statistic	7.3		7.9		6.8		2.2		8.9
<u>C. Descriptive Statistics</u>									
Mean and SD of (Δ Imports to U.S.)/Worker	1.88 (1.75)		2.13 (1.89)		2.76 (2.08)		0.88 (1.12)		9.04 (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 ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

Appendix Table 4. Imports from China and Employment Status of Working Age Population within CZs, 1990-2007: 2SLS Estimates.

Dep Vars: 10-Year Equivalent Changes in Population Shares by Employment Status (in %pts)											
I. Overall and by Sex						II. By Age Group					
Mfg Emp/ Pop		Non- Mfg Emp/ Pop		Unemp/ Pop	NILF/ Pop	Mfg Emp/ Pop		Non- Mfg Emp/ Pop		Unemp/ Pop	NILF/ Pop
(1)		(2)		(3)	(4)	(5)		(6)		(7)	(8)
<u>A. Entire Working Age Population</u>						<u>C. Age 16-34</u>					
(Δ Imports from China to US)/Worker	-0.596 (0.099)	**	-0.178 (0.137)		0.221 (0.058)	**	0.553 (0.150)	**	-0.686 (0.129)	**	-0.155 (0.145)
										0.271 (0.074)	**
										0.569 (0.128)	**
<u>B. Males</u>						<u>D. Age 35-49</u>					
(Δ Imports from China to US)/Worker	-0.625 (0.124)	**	-0.140 (0.151)		0.224 (0.062)	**	0.541 (0.159)	**	-0.637 (0.119)	**	-0.162 (0.119)
										0.236 (0.076)	**
										0.563 (0.157)	**
<u>C. Females</u>						<u>E. Age 50-64</u>					
(Δ Imports from China to US)/Worker	-0.555 (0.088)	**	-0.218 (0.133)		0.217 (0.060)	**	0.556 (0.149)	**	-0.353 (0.079)	**	-0.295 (0.195)
										0.105 (0.035)	**
										0.542 (0.199)	**

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 ≤ 0.01) in the full sample and in all reported subsamples. 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 ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

Data Appendix

Matching trade data to industries

Data on international trade for 1991 to 2007 are from the UN Comtrade 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 Comtrade data on imports for the United States (for which Comtrade 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.

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 equation (5) above for the effect of import exposure on manufacturing employment (suppressing covariates) as:

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

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

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

where subscript I_{IV} is the variation in the import exposure measure isolated by the IV 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

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

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

$$\hat{\beta}_{OLS} = \hat{\beta}_{IV} \times \frac{\sigma_{I_{IV}}^2}{\sigma_{I_{IV}}^2 + \sigma_{I_e}^2} + \hat{\beta}_e \times \frac{\sigma_{I_e}^2}{\sigma_{I_{IV}}^2 + \sigma_{I_e}^2}. \quad (10)$$

The OLS estimate is thus 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 on the two components equal 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 $\hat{\beta}_{IV} \times \sigma_{I_{IV}}^2 / (\sigma_{I_{IV}}^2 + \sigma_{I_e}^2)$ 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 $\sigma_{IV}^2 / (\sigma_{IV}^2 + \sigma_e^2) \simeq 0.48$. 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 the change in China's export-supply capability (\hat{A}_{Cj}), as shown in equation (1), using regression output from the gravity model of trade. Let China's exports to country k in industry j be X_{Cjk} and let U.S. exports to country k in industry j be X_{Ujk} . Using the standard gravity specification of the monopolistic competition model (e.g., Feenstra, 2004), we obtain the following equation for exports by China to country k in industry j relative to the U.S.:

$$\ln(X_{Cjk}) - \ln(X_{Ujk}) = \ln(z_{Cj}) - \ln(z_{Uj}) - (\sigma_j - 1)[\ln(\tau_{Cjk}) - \ln(\tau_{Ujk})], \quad (11)$$

where z_{hj} is the export capability of country h in industry j (determined by wages, labor productivity, and the number of product varieties produced in country $h=C,U$ for industry j), τ_{hjk} is the iceberg trade cost between country h and country k in industry j , and σ_j is the elasticity of substitution for industry j . The term, $\ln(z_{Cj}) - \ln(z_{Uj})$, therefore captures China's comparative advantage vis-a-vis the U.S. for industry j (which is constant across importing countries). The term in the brackets on the right of (11) is the difference in trade costs to country k between the China and the U.S. By taking the difference between China and U.S. exports to country k , we remove non-trade-cost related demand-side factors in country k from the regression (e.g., expenditure in country k), 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):

$$\ln(X_{Cjkt}) - \ln(X_{Ujkt}) = \alpha_j + \alpha_k + \epsilon_{jkt}, \quad (12)$$

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_k is an importer fixed effect (capturing time invariant differences in trade costs between China and the U.S. to country k). The residual from the regression in (12) is

$$\epsilon_{jkt} = \left[\ln \left(\frac{z_{Cjt}}{z_{Ujt}} \right) - \alpha_j \right] + \left[-(\sigma_j - 1) \ln \left(\frac{\tau_{Cjkt}}{\tau_{Ujkt}} \right) - \alpha_k \right]. \quad (13)$$

The first term on the right of (13) 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 (13) is China's differential trade cost relative to the U.S. in industry j and year t for country k . 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 (13) 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 (3), we use the following gravity-based measure of exposure to imports from China,

$$\Delta IPW_{git} = \sum_j \frac{L_{ijt-1}}{L_{Ujt-1}} \cdot \frac{\Delta \bar{\epsilon}_{jt} M_{UjCt-1}}{L_{it-1}}. \quad (14)$$

where $\Delta \bar{\epsilon}_{jt}$ is the mean change in the residual in (13) for industry j across destination markets k 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_{UjCt-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 (14) we use lagged values for employment shares, as in (4).

Small Open Economy Model

In this appendix, we develop a general equilibrium model of how increased import competition from China affects employment and wages in a U.S. commuting zone, which we treat as a small open economy. Productivity growth in China and global reductions in trade barriers facing China cause the country's exports to expand. As a commuting zone faces greater competition from China in the U.S. market and in other markets in which its firms sell goods, demand for CZ output contracts, causing CZ wages to fall. As long as the CZ is running a current-account deficit, there is a resulting shift in employment out of traded goods and into non-traded goods. Initially, we ignore the impact of changes in China on wages and income levels outside of a CZ, focusing on the *direct effects* of rising productivity/falling trade costs in China on a commuting zone, which operate through making the CZ's goods less competitive in its export markets. Below, we consider a two-economy model (e.g., for the U.S. and China), in which the same qualitative results obtain. Hsieh and Ossa (2012) model the effects of productivity growth in China in full global general equilibrium.

The total supply of labor in CZ i is L_i , where labor may be employed in traded goods or in non-traded goods. We assume that there is no migration between commuting zones (making the model short to medium run in nature). Allowing CZ labor supply to be an elastic function of the wage is a simple extension of the model. Demand for goods is given by a Cobb-Douglas utility function, with share γ of expenditure going to traded goods and share $1 - \gamma$ going to non-traded goods. There is a single non-traded good which is manufactured under the production function,

$$X_{Ni} = L_{Ni}^\eta, \quad (15)$$

where L_{Ni} is labor employed in non-traded goods and the coefficient $\eta \in (0, 1)$ indicates there is diminishing marginal returns to labor in production (due, e.g., to short-run constraints on expanding

production capacity). Profit maximization in the non-traded good implies that

$$W_i = \eta P_{Ni} L_{Ni}^{\eta-1}, \quad (16)$$

where W_i is the wage and P_{Ni} is the price of the non-traded good in commuting zone i . Because of diminishing returns in non-traded production, any shock that expands employment in the sector will tend to push down wages in the commuting zone. (Alternatively, we could consider (15) as an implicit function for the production of leisure and (16) as arising from utility maximization, requiring that wages equal the marginal utility of leisure.)

Market clearing for the non-traded good requires that,

$$P_{Ni} X_{Ni} = (1 - \gamma) (W_i L_i + B_i), \quad (17)$$

where B_i is the difference between expenditure and income in commuting zone i (i.e., $B_i > 0$ implies that CZ i is running a current-account deficit).⁵⁴ We treat the trade imbalance as given (due to US macroeconomic conditions) and investigate how its magnitude affects CZ labor-market adjustment. With balanced trade for a commuting zone, a positive shock to productivity in one of China's export sectors generates changes in the CZ wage and non-traded good price that re-equilibrate imports and exports. These adjustments keep total CZ employment in the traded sector from declining (although employment shifts out of the traded sector with positive Chinese productivity growth and into other traded sectors). With imbalanced trade a positive shock to Chinese export productivity reduces employment in CZ traded goods and increases employment in non-traded goods.⁵⁵

Traded goods are produced by firms in a monopolistically competitive sector (Helpman and Krugman, 1985).⁵⁶ There are two traded-good sectors, indexed by j , where consumers devote a share of spending $\gamma/2$ on each. It is straightforward to extend the model to multiple traded-good sectors (as in Hanson and Xiang, 2005); doing so does not change the qualitative results. Each of the M_{ij} firms in sector j is the unique producer of a differentiated product variety. The labor used to produce any individual variety in sector j is given by,

$$l_{ij} = \alpha_{ij} + \beta_{ij} x_{ij}, \quad (18)$$

where for sector j α_{ij} is the fixed labor required to produce positive output, β_{ij} is the labor required to produce an extra unit of output, and x_{ij} is the quantity of the variety produced. α_{ij} and β_{ij} (which are identical across firms within CZ i) reflect sectoral productivity in a commuting zone and therefore determine comparative advantage. For each traded sector j , demand for product varieties is derived from a CES sub-utility function, such that total demand for output of an individual

⁵⁴Implicitly, China's non-traded good is the numeraire.

⁵⁵The invariance of non-traded employment to trade shocks under balanced trade is due to the assumption of Cobb-Douglas preferences (similar results hold in a two-country model, meaning that the small-country assumption is not driving this outcome).

⁵⁶Our results generalize to other settings that have a "gravity" structure, as in Arkolakis, Costinot, and Rodriguez-Clare (2011).

variety, x_{ij} , is the sum over demand in each destination market k , x_{ijk} , given by,

$$x_{ij} = \sum_k x_{ijk} = \sum_k \frac{P_{ijk}^{-\sigma_j}}{\Phi_{jk}^{1-\sigma_j}} \frac{\gamma E_k}{2}, \quad (19)$$

where P_{ijk} is the delivered price in market k of a variety in sector j produced in commuting zone i , E_k is total expenditure in market k , and the term $\Phi_{jk}^{1-\sigma_j}$, which is a function of the price index, Φ_{jk} , for traded goods in sector j and market k , captures the intensity of competition in a particular market. The parameter $\sigma_j > 1$ is the elasticity of substitution between any pair of varieties in j . Under monopolistic competition, the price of each variety is a constant markup over marginal cost,

$$P_{ijk} = \frac{\sigma_j}{\sigma_j - 1} \beta_{ij} W_i \tau_{ijk} \quad (20)$$

where $\tau_{ijk} \geq 1$ is the iceberg transport cost of delivering one unit of a good in sector j from commuting zone i to market k . We assume that free entry in each sector drives profits to zero, implying that the level of output of each variety is $x_{ij} = \alpha_{ij} (\sigma_j - 1) / \beta_{ij}$ (adjustment in sectoral output and employment occurs at the extensive margin, through changes in the sector number of varieties/firms, M_{ij}). The final equilibrium condition is that labor supply equals labor demand:

$$L_i = L_{Ni} + L_{Ti}, \quad (21)$$

where $L_{Ti} = \sum_j M_{ij} l_{ij}$ is total employment in traded goods.

The sectoral price index plays an important role in the analysis for it is the channel through which competition from China affects a CZ. For each sector j , this index is given by,

$$\Phi_{jk} = \left[\sum_h M_{hj} P_{hjk}^{1-\sigma_j} \right]^{\frac{1}{1-\sigma_j}}, \quad (22)$$

where M_{hj} is the number of varieties produced by region h and P_{hjk} is the price of goods from region h sold in market k . Log differentiating (22), and defining $\hat{x} \equiv \Delta \ln x = \Delta x / x$, we obtain for each sector j ,

$$\hat{\Phi}_{jk} = -\frac{1}{\sigma_j - 1} \sum_h \phi_{hjk} \hat{A}_{hjk}, \quad (23)$$

where $\phi_{hjk} \equiv M_{hj} P_{hjk} x_{hjk} / \sum_l M_{lj} P_{ljk} x_{ljk}$ is the share of region h in purchases of sector j goods by market k and $\hat{A}_{hjk} \equiv \hat{M}_{hj} - (\sigma_j - 1) (\hat{W}_h + \hat{\beta}_{hj} + \hat{\tau}_{hjk})$ is the log change in the “export capability” of region h in market k , determined by changes in the number of varieties region h produces (\hat{M}_{hj}), its wages (\hat{W}_h), its labor productivity ($\hat{\beta}_{hj}$), and its trade costs ($\hat{\tau}_{hjk}$). The price index for sector j goods in market k declines if China has an increase in the number of varieties that it produces, a reduction in its marginal production costs, an increase in its factor productivity, or a reduction in its trade barriers (each of which causes \hat{A}_{Cjk} to rise, where C indexes China).

To solve the model, we plug (15) into (17), and (for each j) (18) and (20) into (19), which

produces a system of five equations in five unknowns, W_i , P_{Ni} , L_{Ni} , and M_{ij} for $j = 1, 2$.⁵⁷ After performing these substitutions and log differentiating the five equations, we end up with the following system:

$$\begin{aligned}\hat{W}_i &= \hat{P}_{Ni} - (1 - \eta) \hat{L}_{Ni}, \\ \eta \hat{L}_{Ni} &= \rho_i (\hat{W}_i + \hat{L}_i) + (1 - \rho_i) \hat{B}_i - \hat{P}_{Ni}, \\ \hat{L}_i &= \left(1 - \sum_j \delta_{ij}\right) \hat{L}_{Ni} + \sum_j \delta_{ij} \hat{M}_{ij}, \\ \sigma \hat{W}_i &= \sum_k \theta_{ijk} \left[\hat{E}_k + (\sigma_j - 1) \hat{\Phi}_{jk} \right] = \sum_k \theta_{ijk} \hat{E}_k - \sum_k \theta_{ijk} \sum_h \phi_{hjk} \hat{A}_{hjk}, \quad j = 1, 2\end{aligned}\quad (24)$$

where for commuting zone i $\rho_i \equiv W_i L_i / (W_i L_i + B_i)$ is the initial share of labor income in total expenditure, $\delta_{ij} \equiv M_{ij} l_{ij} / L_i$ is the initial share of traded sector j in total employment, and $\theta_{ijk} \equiv x_{ijk} / \sum_l x_{ijl}$ is the initial share of market k in the total shipments of sector j goods. Because the output of each variety is fixed, labor used in each variety, l_{ij} , is fixed; all adjustment in sectoral employment occurs through changes in the number of firms, M_{ij} , as seen in the third line of (24).

By assumption, for commuting zone i the only changes in the \hat{E}_k terms in (24) occur in China, where we treat $\hat{E}_C = \rho_C \hat{W}_C + (1 - \rho_C) \hat{B}_C$ as exogenous, and in CZ i itself, where $\hat{E}_i = \rho_i \hat{W}_i + (1 - \rho_i) \hat{B}_i$ and we treat \hat{W}_i as endogenous and \hat{B}_i as exogenous. As a trade shock causes wages in a commuting zone to change, the CZ's demand for its own goods will change, which will in turn generate further adjustments in wages. Relatedly, for commuting zone i the only changes in the \hat{A}_{hjk} terms in (24) are for China, where for each sector j we treat $\hat{A}_{Cj} = \hat{M}_{Cj} - (\sigma_j - 1) (\hat{W}_C + \hat{\beta}_{Cj} + \hat{\tau}_{Cj})$ as exogenous, and in CZ i itself, where for each sector j , $\hat{A}_{ij} = \hat{M}_{ij} - (\sigma_j - 1) \hat{W}_i$ and we treat \hat{M}_{ij} as endogenous, in addition to \hat{W}_{ij} . As a China trade shock causes a CZ's wage and number of firms to change, price indexes in the markets that the CZ serves will change, generating further adjustments in its wages and number of firms.⁵⁸

Imposing the zero migration assumption that $\hat{L}_i = 0$ and rearranging the first two expressions in (24), we obtain the following representation of the system of equations in (24):

$$\hat{P}_{Ni} = \hat{W}_i + (1 - \eta) \hat{L}_{Ni},$$

$$\hat{L}_{Ni} = (1 - \rho_i) (\hat{B}_i - \hat{W}_i),$$

⁵⁷For simplicity, we exclude the equation for adjustment in imported varieties. Because of the small-country assumption, changes in imports are determined by the outcomes of other equations in the system and do not affect other variables.

⁵⁸For notational simplicity, we assume that changes in China's trade costs are common across its destination markets—due, e.g., to its accession to the WTO—and that CZ i has no changes in its productivity or trade costs.

$$\hat{L}_{Ni} = -\tilde{\delta}_{i1}\hat{M}_{i1} - \tilde{\delta}_{i2}\hat{M}_{i2},$$

$$\hat{W}_i = a_{i1}\hat{\Gamma}_{i1} + b_{i1}\hat{B}_i - c_{i1}\hat{M}_{i1},$$

$$\hat{W}_i = a_{i2}\hat{\Gamma}_{i2} + b_{i2}\hat{B}_i - c_{i2}\hat{M}_{i2}, \quad (25)$$

where for sector $j = 1, 2$ we employ the following notational definitions: $\tilde{\delta}_{ij} \equiv \delta_{ij} / (1 - \sum_n \delta_{in})$ is the initial ratio of employment in traded sector j to employment in non-traded goods, the quantity $\hat{\Gamma}_{ij} \equiv \theta_{ijC} [\rho_C \hat{W}_C + (1 - \rho_C) \hat{B}_C] - \sum_k \theta_{ijk} \phi_{Cjk} \hat{A}_{Cj}$ is the China trade shock facing CZ i in industry j , and a_{ij} , b_{ij} , and c_{ij} are each positive constants that are functions of the model parameters or initial sectoral employment or expenditure shares ($a_{ij} \equiv [\sigma_j (1 - \sum_k \theta_{ijk} \phi_{ijk}) + \sum_k \theta_{ijk} \phi_{ijk} - \theta_{iji} \rho_i]^{-1}$, $b_{ij} \equiv a_{ij} \theta_{iji} (1 - \rho_i)$, and $c_{ij} \equiv a_{ij} \sum_k \theta_{ijk} \phi_{ijk}$). In the first two lines of (25), we see that wage shocks affect non-traded employment and non-traded prices only if trade is imbalanced ($\rho_i \neq 1$). This outcome depends on the first two equations in (24), which applies to the model even if we allow the country to be large enough to affect world prices, as is done below.

For CZ i , the China trade shock in sector j ($\hat{\Gamma}_{ij}$) is the difference between increased demand by China for the CZ's exports, given by $\theta_{ijC} [\rho_C \hat{W}_C + (1 - \rho_C) \hat{B}_C]$, and increased import competition from China in the markets in which the CZ sells goods, given by $\sum_k \theta_{ijk} \phi_{Cjk} \hat{A}_{Cj}$. Growth in China's demand for CZ i 's exports will be smaller the smaller is the share of CZ output that is destined for China (θ_{ijC}) and the more wage growth in China ($\hat{W}_C > 0$) is offset by growth in China's current-account surplus ($\hat{B}_C < 0$). Import competition from China will be more intense the larger is the increase in China's export capabilities (\hat{A}_{Cj}) and the larger is China as a source of supply for the markets that CZ i serves (captured by the term, $\sum_k \theta_{ijk} \phi_{Cjk}$).

Solving the system in (25), we obtain changes in the endogenous CZ variables (\hat{W}_{Ni} , \hat{L}_{Ti} , \hat{L}_{Ni} , \hat{P}_{Ni}) as functions of model parameters and the exogenous shocks ($\hat{\Gamma}_{i1}$, $\hat{\Gamma}_{i2}$, \hat{B}_i), where we show results for the change in total employment in traded goods (rather than for individual traded sectors), given by $\hat{L}_{Ti} = \sum_j \tilde{\delta}_{ij} \hat{M}_{ij}$, where $\tilde{\delta}_{ij} \equiv \delta_{ij} / \sum_l \delta_{il}$ is the share of sector j in total traded-good employment for CZ i . The solutions for the endogenous variables are:

$$\hat{W}_i = \frac{1}{g_i} \left[a_{i1} c_{i2} \tilde{\delta}_{i1} \hat{\Gamma}_{i1} + a_{i2} c_{i1} \tilde{\delta}_{i2} \hat{\Gamma}_{i2} + \left(b_{i1} c_{i2} \tilde{\delta}_{i1} + b_{i2} c_{i1} \tilde{\delta}_{i2} + (1 - \rho_i) c_{i1} c_{i2} \right) \hat{B}_i \right],$$

$$\hat{L}_{Ti} = \frac{1 - \rho_i}{g_i} \left[a_{i1} c_{i2} \tilde{\delta}_{i1} \hat{\Gamma}_{i1} + a_{i2} c_{i1} \tilde{\delta}_{i2} \hat{\Gamma}_{i2} - \left((1 - b_{i1}) c_{i2} \tilde{\delta}_{i1} + (1 - b_{i2}) c_{i1} \tilde{\delta}_{i2} \right) \hat{B}_i \right],$$

$$\hat{L}_{Ni} = \frac{1 - \rho_i}{g_i} \left[-a_{i1} c_{i2} \tilde{\delta}_{i1} \hat{\Gamma}_{i1} - a_{i2} c_{i1} \tilde{\delta}_{i2} \hat{\Gamma}_{i2} + \left((1 - b_{i1}) c_{i2} \tilde{\delta}_{i1} + (1 - b_{i2}) c_{i1} \tilde{\delta}_{i2} \right) \hat{B}_i \right],$$

$$\begin{aligned}\hat{P}_{Ni} = & \frac{1}{g_i}[(1 - f_i) \left(a_{i1}c_{i2}\tilde{\delta}_{i1}\hat{\Gamma}_{i1} + a_{i2}c_{i1}\tilde{\delta}_{i2}\hat{\Gamma}_{i2} \right) \\ & + \left((b_{i1} + (1 - b_{i1})f_i) c_{i2}\tilde{\delta}_{i1} + (b_{i2} + (1 - b_{i2})f_i) c_{i1}\tilde{\delta}_{i2} + (1 - \rho_i) c_{i1}c_{i2} \right) \hat{B}_i]\end{aligned}\quad (26)$$

where $g_i = c_{i2}\tilde{\delta}_{i1} + c_{i1}\tilde{\delta}_{i2} + (1 - \rho_i) c_{i1}c_{i2} > 0$, $f_i = (1 - \rho_i)(1 - \eta) > 0$, and $1 - b_{ij} > 0, j = 1, 2$. To summarize how trade shocks in China affect a CZ, we present the following comparative statics:

$$\begin{aligned}\frac{\partial \hat{W}_i}{\partial \hat{\Gamma}_{ij}} &= \frac{a_{ij}c_{il}\tilde{\delta}_{ij}}{g_i} \geq 0, \quad \{j, l\} = \{1, 2\}, \{2, 1\}, \\ \frac{\partial \hat{L}_{Ti}}{\partial \hat{\Gamma}_{ij}} &= \frac{(1 - \rho_i)a_{ij}c_{il}\tilde{\delta}_{ij}}{g_i} \geq 0, \quad \{j, l\} = \{1, 2\}, \{2, 1\}, \\ \frac{\partial \hat{L}_{Ni}}{\partial \hat{\Gamma}_{ij}} &= -\frac{(1 - \rho_i)a_{ij}c_{il}\tilde{\delta}_{ij}}{g_i} \leq 0, \quad \{j, l\} = \{1, 2\}, \{2, 1\}, \\ \frac{\partial \hat{P}_{Ni}}{\partial \hat{\Gamma}_{ij}} &= \frac{(1 - f_i)a_{ij}c_{il}\tilde{\delta}_{ij}}{g_i} \geq 0, \quad \{j, l\} = \{1, 2\}, \{2, 1\}.\end{aligned}\quad (27)$$

In traded sector j , productivity growth in China or a fall in China's trade barriers imply that $\hat{\Gamma}_{ij} < 0$. In (27), we see that the consequence of such a shock is a reduction in CZ nominal wages, a reduction in CZ employment in traded goods, an increase in CZ employment in non-traded goods, and a reduction in CZ prices of non-traded goods. The impact on wages is due to the decreased demand for CZ goods in its export markets (including the broader U.S. economy). The impacts on traded and non-traded employment depend on $\rho_i < 1$, meaning the CZ is running a current-account deficit. Regardless of the shift in employment between traded and non-traded goods, within traded goods there is a reallocation of employment out of sectors in which China's productivity is expanding.

Why does the impact of productivity growth in China on CZ traded and non-traded employment depend on the CZ's trade balance? With balanced trade, productivity growth in China merely reallocates CZ employment between traded sectors based on which sectors face a net increase in import competition from China (CZ employment contracts) and which experience a net increase in export demand by China (CZ employment expands). With imbalanced trade, increases in import competition are not offset by increases in export demand. The excess of imports over exports pushes employment out of exports (relative to balanced trade), with non-traded goods being the residual sector. The logic for a CZ also applies to the United States as a whole, meaning that a U.S. current-account deficit vis-a-vis China implies that greater import competition from China can cause U.S. employment in traded-good sectors to contract on net.

In (26), changes in wages, traded-good employment and non-traded good employment are each weighted averages of changes in trade shocks in each traded-good sector, where these weights are

functions of the share of each traded sector in total employment. These expressions motivate our measure of trade exposure in the empirical analysis.

Two Economy Model

A small open economy is a non-standard application of the monopolistic competition model. Typically, in such models all goods prices are endogenous, which is not the case in the application above where we have arbitrarily shut down price adjustment in all economies except CZ *i*. To verify that the results we obtain are not special to this setting, we solve a two-economy model, in which we compress CZs into a single aggregate U.S. region. We then examine the impact of productivity growth in China on U.S. wages, traded employment, and non-traded employment. To keep the analysis simple, we ignore trade barriers between the countries and assume the traded sector consists of a single industry (producing many varieties). No qualitative results depend on these restrictions.

Following equations (15)-(17), (20), and (21), we have the following equilibrium conditions for the U.S.:

$$\begin{aligned} W &= \eta P_N L_N^{\eta-1}, \\ P_N L_N^\eta &= (1 - \gamma)(WL + B), \\ P &= \frac{\sigma}{\sigma - 1} \beta W, \\ L &= L_N + Ml, \end{aligned} \tag{28}$$

where we take China's wage to be the numeraire (such that W is the U.S. wage relative to China's wage) and B is the difference between U.S. aggregate expenditure and U.S. aggregate income (equal to the difference between China's aggregate income and expenditure—i.e., $B + B^* = 0$) and is dominated in units of China's wage. The final equilibrium condition is that supply equals demand for each variety of traded goods:

$$x = \frac{P^{-\sigma} \gamma (WL + L^*)}{M \Phi^{1-\sigma} + M^* \Phi^{*1-\sigma}}. \tag{29}$$

We implicitly treat l , labor used to produce each variety, as exogenous given that its value is pinned down by the zero-profit condition (i.e., $l = \alpha \sigma$); zero profits also imply that x is fixed ($x = \alpha(\sigma - 1)/\beta$). For China, there are a corresponding set of equilibrium conditions, where we dominate China values using an (*). Because trade costs are zero, $x/x^* = (P/P^*)^{-\sigma}$, which together with the price-equals-marginal cost conditions in the U.S. and China imply that $W = (\beta^*/\beta)^{(\sigma-1)/\sigma}$, or that the U.S.-China relative wage is a function of relative labor productivities in the two countries.

Combining the conditions in (28) with the corresponding ones for China and incorporating the solutions for W , P , and P^* , we have a system with six equations and six unknowns (P_N , P_N^* , L_N , L_N^* ,

M , and M^*). We assume that the only shocks to the system are productivity growth in traded-good production in China ($\hat{\beta}^* < 0$) and an increase in the U.S. trade deficit/China trade surplus ($\hat{B} > 0$). Log differentiating, we have that $\hat{W} = \bar{\sigma}\hat{\beta}^*$, where $\bar{\sigma} \equiv \frac{\sigma-1}{\sigma}$, implying that the U.S. relative nominal wage declines in proportion to productivity growth in China.⁵⁹ The other equilibrium conditions are that:

$$\begin{aligned}
\hat{P}_N &= \bar{\sigma}\hat{\beta}^* + (1 - \eta) \hat{L}_N, \\
\hat{P}_N^* &= (1 - \eta) \hat{L}_N^*, \\
\hat{P}_N &= \rho\bar{\sigma}\hat{\beta}^* + (1 - \rho) \hat{B} - \eta\hat{L}_N, \\
\hat{P}_N^* &= -(1 - \rho^*) \hat{B} - \eta\hat{L}_N^*, \\
\hat{L}_N &= -\frac{\delta}{1 - \delta} \hat{M}, \\
\hat{L}_N^* &= -\frac{\delta^*}{1 - \delta^*} \hat{M}^*,
\end{aligned} \tag{30}$$

where $\rho = WL/(WL + B)$ is the initial share of labor income in total U.S. expenditure, $(1 - \rho^*) = B/(L^* - B)$ is the initial ratio of China's trade surplus to its aggregate expenditure, $\delta = Ml/L$ is the initial share of U.S. employment in traded goods, and $\delta^* = M^*l^*/L^*$ is the initial share of China's employment in traded goods. Solving the system in (30) we obtain,

$$\begin{aligned}
\hat{L}_N &= (1 - \rho) (\hat{B} - \bar{\sigma}\hat{\beta}^*) \geq 0, \\
\hat{L}_N^* &= -(1 - \rho^*) \hat{B} \leq 0, \\
\hat{M} &= -\frac{1 - \delta}{\delta} (1 - \rho) (\hat{B} - \bar{\sigma}\hat{\beta}^*) \leq 0, \\
\hat{M}^* &= \frac{1 - \delta^*}{\delta^*} (1 - \rho^*) \hat{B} \geq 0, \\
\hat{P}_N &= \hat{\beta}^* + (1 - \eta) (1 - \rho) (\hat{B} - \bar{\sigma}\hat{\beta}^*) \leq 0, \\
\hat{P}_N^* &= -(1 - \eta) (1 - \rho^*) \hat{B} \leq 0.
\end{aligned} \tag{31}$$

⁵⁹U.S. real wages may of course rise owing to lower prices for and increased numbers of Chinese varieties produced.

It is again the case that productivity growth in the traded sector in China lowers U.S. employment in traded goods ($\hat{M} < 0$) and raises U.S. employment in non-traded goods ($\hat{L}_N > 0$), where these results are conditional on the U.S. running an aggregate trade deficit. There is an ambiguous effect on U.S. non-traded prices. Increases in the magnitude of the U.S. trade deficit reinforce these changes.