

NBER WORKING PAPER SERIES

TRADE ADJUSTMENT:
WORKER LEVEL EVIDENCE

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Working Paper 19226
<http://www.nber.org/papers/w19226>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2013

We thank Stéphane Bonhomme, David Card, Pinelopi Goldberg, Lawrence Katz, Patrick Kline, Brian Kovak and numerous seminar and conference participants for valuable comments. Dorn acknowledges funding from the Spanish Ministry of Science and Innovation (ECO2010-16726 and JCI2011-09709). Autor and Hanson acknowledge funding from the National Science Foundation (grant SES-1227334). The findings and conclusions expressed herein are those of the authors and do not represent the views of the Social Security Administration or the National Bureau of Economic Research.

At least one co-author has disclosed a financial relationship of potential relevance for this research. Further information is available online at <http://www.nber.org/papers/w19226.ack>

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NBER Working Paper No. 19226

July 2013

JEL No. F16,J62

ABSTRACT

In the past two decades, China's manufacturing exports have grown spectacularly, U.S. imports from China have surged, but U.S. exports to China have increased only modestly. Using representative, longitudinal data on individual earnings by employer, we analyze the effect of exposure to import competition on earnings and employment of U.S. workers over 1992 through 2007. Individuals who in 1991 worked in manufacturing industries that experienced high subsequent import growth garner lower cumulative earnings and are at elevated risk of exiting the labor force and obtaining public disability benefits. They spend less time working for their initial employers, less time in their initial two-digit manufacturing industries, and more time working elsewhere in manufacturing and outside of manufacturing. Earnings losses are larger for individuals with low initial wages, low initial tenure, low attachment to the labor force, and those employed at large firms with low wage levels. Import competition also induces substantial job churning among high-wage workers, but they are better able than low-wage workers to move across employers with minimal earnings losses, and are less likely to leave their initial firm during a mass layoff. These findings, which are robust to a large set of worker, firm and industry controls, and various alternative measures of trade exposure, reveal that there are significant worker-level adjustment costs to import shocks, and that adjustment is highly uneven across workers according to their conditions of employment in the pre-shock period.

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1 Introduction

Among the most significant recent changes in the global economy is the rapid emergence of China from a technologically backward and largely closed economy to the world's third largest manufacturing producer in the space of just two decades. Between 1990 and 2000, the share of world manufacturing exports originating in China increased from 2% to 5%, and then accelerated to 12% in 2007 and to 16% in 2011 (Figure 1). China's export surge is the outcome of a major expansion in its manufacturing capacity, unleashed by economic reforms in the 1980s and 1990s (Naughton, 2007). Since 1990, China has accounted for over three quarters of the growth in manufacturing value added generated by low and middle income countries, as its share of manufacturing output within this group has risen from 15% to 44% (Hanson, 2012).

For U.S. manufacturing, China's expanding role in global trade represents a substantial competitive shock. Manufacturing still accounts for the majority of U.S. trade, and hence the rise of China presents stiff competition to the labor-intensive industries that remain in the United States.¹ Not only is China's export growth concentrated in manufacturing, but its growth in imports, in particular from the United States and other high income countries, has been comparatively sluggish, thus leading to large trade imbalances. During the last decade, China's average current account surplus was 5% of GDP, the mirror image of the U.S. current account deficit over the period. As Chinese imports to the United States surged, U.S. manufacturing employment underwent a historic contraction. Although the level of employment in U.S. manufacturing had been declining modestly since the start of the 1980s, this trend gained pace in the mid-1990s and accelerated sharply in the 2000s: the number of workers employed in U.S. manufacturing fell by 9.7 percentage points between 1991 and 2001 and by an additional 16.1 percentage points between 2001 and 2007.²

In the wake of China's spectacular growth, there has been a spirited if uneven policy debate about the consequences of rising trade competition for the United States. Whereas trade theory devotes attention to the fact that long-run gains from trade are expected to be positive, public debate about globalization frequently centers less on trade's net benefits than on the short-run costs of adjusting to import competition.³ Missing in the debate is hard evidence on whether and by how much U.S. manufacturing workers have been affected by trade with China. Though it is well documented that U.S. factories have closed and employment has declined in apparel, furniture, children's toys, and

¹According to the World Development Indicators, in 2010 China accounted for 17% of global value added in manufacturing, up from 5% in 1991.

²U.S. manufacturing employment was 18.3 million in 1991, 16.6 million in 2001, 13.9 million in 2007, and 11.4 million in 2011, according to County Business Patterns data.

³E.g., Wayne Ma, "China Denies Currency Manipulation," *Wall Street Journal*, October 17, 2012; Tom Barkley, "Trade Deal Clears Hurdle in Senate," *Wall Street Journal*, August 4, 2011.

other industries in which imports from China have surged (Bernard, Jensen, and Schott, 2006), we know little about how workers in these industries have adjusted to trade shocks.

In this paper, we examine the impact of exposure to rising trade competition from China on the employment and earnings trajectory of U.S. workers over the medium to long-run. We define trade exposure as the growth in U.S. imports from China over 1991 to 2007 that occurred in a worker's initial industry of affiliation. Our focus is on the extended consequences of trade shocks based on where a worker is employed in 1991, around the time the shock initiates. By holding the industry constant, we avoid selection problems arising from the post-shock resorting of workers across industries. The choice of the outcome period is dictated on the front end by the availability of bilateral trade data that can be matched to U.S. manufacturing industries and on the back end by the onset of the Great Recession, which severely battered U.S. manufacturing. These years span much of China's export boom, as the 1990s and especially the early 2000s (following China's WTO accession in 2001) are when the country's export growth accelerates (Figure 1).⁴

Using individual worker-level data from the U.S. Social Security Administration, we estimate the impact of exposure to Chinese import competition on cumulative earnings, employment, movement across sectors, and receipts of Social Security benefits over the period 1992 to 2007. The data permit us to decompose worker employment spells by firm and industry and to examine variation in trade impacts according to worker and firm characteristics. To account for possible correlation between industry imports and industry domestic demand or productivity shocks, we instrument for the change in U.S. imports from China using import growth in other high income countries within 397 harmonized product categories, each corresponding to a U.S. manufacturing sector.⁵ Key to our identification strategy is that China's growth over the period appears driven by improvements in its domestic productivity and the reallocation of resources to manufacturing arising from the dismantling of central planning, looser restrictions on rural-to-urban migration, and the liberalization of trade and investment (Naughton, 2007; Hsieh and Ossa, 2011; Brandt, Van Biesebroeck, and Zhang, 2012). Hsieh and Klenow (2009) report that since the early 1990s, the median Chinese manufacturing plant had average annual TFP growth at the astounding pace of 15%. To account for the possible correlation between workers' potential earnings and their initial industry affiliation, we

⁴Naughton (1996) marks 1984 as when China's export growth began. However, the government initially kept many restrictions on foreign trade and investment. In Figure 1, China's share of world manufacturing exports rose unevenly from 1% in 1984 to 2% in 1991. It was not until 1992, when Deng Xiaoping wrested power back from hardliners who had rebounded after the events at Tiananmen Square in 1989, that the country welcomed FDI by promoting Special Economic Zones (Naughton, 2007). The SEZs lured foreign firms to set up export plants in China. Between 1991 and 1994 alone, inward FDI in China grew from 1% to 6% of GDP.

⁵Our identification strategy is related to Bloom, Draca, and Van Reenen (2011) and Autor, Dorn, and Hanson (forthcoming).

draw on the longitudinal structure of the data to control flexibly for workers' employment histories, tenure at initial employer, years of work experience, and other characteristics.

Import competition is but one of the forces impinging on U.S. manufacturing in recent decades. Technological progress has been rapid in computer and skill intensive sectors (Doms, Dunne, and Troske, 1997; Autor, Katz, and Krueger, 1998), and to the degree this is correlated with industry trade exposure, it poses a potential confound for our identification strategy.⁶ To capture the extent to which industries are exposed to technical change, we control for capital intensity, measures of computer and high-tech equipment investments, as well as industry pre-trends in employment and wages. We further perform falsification tests to verify that future increases in trade exposure do not predict past changes in worker outcomes by industry. These robustness tests support the interpretation that our identification strategy isolates industry level shocks caused by rising import competition rather than other temporal and technological confounds. Our results are also robust to a broad set of alternative measures of trade exposure to China, including incorporating imports from other low income countries, U.S. exports to China, U.S. imports of intermediate inputs from China, and competition from China in other foreign markets that U.S. industries serve.⁷

Our work relates to the substantial labor literature on the long run consequences of job loss (Farber, 1999). A challenge in this line of research is to distinguish involuntary from voluntary worker separations from their employers. In pioneering work, Jacobsen, LaLonde, and Sullivan (1993) draw on administrative data to identify episodes in which plants let go a substantial fraction of their employees within a short span of time.⁸ To ensure that separations occurring during such mass layoffs are most likely involuntary, their analysis and subsequent work further restrict the sample to individuals who at the time of job loss were full-time workers and who had more than five years of tenure with their employer. Workers subject to mass layoffs suffer an immediate sharp decline in earnings and a smaller decline that persists over time. Wage loss is greater for workers with higher tenure but is otherwise similar across groups by age, gender, or skill.⁹

⁶Autor, Dorn and Hanson (2013) find that at the geographic level of U.S. local labor markets, trade and technology exposure are essentially uncorrelated.

⁷As an alternative to our main identification strategy, we additionally estimate the supply shock component of import growth from China using the gravity model of trade. This estimation rests on the weaker assumption that U.S. product demand shocks are uncorrelated with changes in China's comparative advantage. Changes in China's comparative advantage will of course affect U.S. product demand. Our identification assumption in the gravity approach merely requires that there is no incidental correlation between changes in U.S. product demand and Chinese comparative advantage not arising through this competitive channel.

⁸A second approach to study job loss uses the CPS Displaced Workers Survey (DWS), which asks workers who recently left their jobs if the separation was involuntarily. The DWS covers all types of job loss, but for each worker only records a single separation and only those within the last three years (Farber, 2005), which prevents one from investigating long-run consequences. See Addison, Fox, and Ruhm (1995) and Kletzer (2000) for work using the DWS to examine the correlation between job loss and import competition.

⁹See Sullivan and von Wachter (2009), von Wachter, Song, and Manchester (2009), and Couch and Placzek (2010)

While we follow the job-displacement literature in using administrative data to examine the long-run effects of shocks on worker outcomes, we break from tradition by focusing on the specific shock of China’s export growth.¹⁰ Identifying the source of the shock lets us see worker adjustment along four margins: the change in earnings at the initial employer (the intensive margin), the change in earnings associated with job loss (the extensive margin), the change in earnings associated with uptake of government benefits (the transfer margin), and the change in earnings associated with moving between employers and/or industries (the reallocation margin). We are thus able to determine where in the adjustment process workers experience income loss and which types of losses are more persistent. Because most prior studies analyzing the impact of firm and industry-level shocks on worker outcomes focus exclusively on displaced workers, that work either combines the four margins of adjustment that we analyze here or considers only a subset.¹¹ A further advantage of our approach is that we are able to include part-time workers and workers with low initial tenure, revealing how trade impacts vary according to an individuals’ labor market attachment.

Our work also relates to literature on the labor market impacts of trade. One strand, which emphasizes structural estimation of general equilibrium models, has progressed from approaches that assume workers are perfectly mobile across sectors, in which case trade shocks are manifested in changes in wages for broad skill groups, to recent work that allows for explicit labor market frictions, such that intersectoral labor mobility is costly and the labor market impact of trade shocks may vary across workers according to their sector of employment.¹² Allowing worker moves between industries to take time or to involve a loss in industry-specific human capital creates the possibility that increased import competition reduces the lifetime earnings of exposed workers.¹³ Our work is similar in spirit to this trade literature but imposes less structure on the data, thus allowing us to examine a wide variety of sources of heterogeneity in adjustment costs across workers, though we explicitly do not consider the *market level* impacts of trade shocks on wages.

for recent work that uses administrative data and see Kletzer (1989), Ruhm (1991), Neal (1995), Parent (2000), Chan and Stevens (2001), and Farber (2005) for representative work on job loss using survey data (including the DWS and the Health and Retirement Survey). Hummels, Jorgensen, Munch, and Xiang (2011) apply the Jacobsen-LaLonde-Sullivan (1993) approach to examine the displacement effects of trade shocks in Denmark.

¹⁰Menezes-Filho and Muendler (2011) also track worker adjustment to trade shocks over a long periods of time, in their case for formal-sector workers in Brazil following a reduction in import tariffs.

¹¹In a similar vein, Walker (2012) studies the impact of environmental regulations on worker adjustment by focusing on workers who are initially employed by industries newly regulated by the Clean Air Act.

¹²See Feenstra and Hanson (1999), Harrigan (2000), Robertson (2004), and Blum (2008) for approaches with perfect labor mobility, and Helpman, Itskhoki, and Redding (2010), Helpman, Itskhoki, Muendler, and Redding (2012), Coşar (2011), Dix-Carneiro (2011), and Coşar, Guner and Tybout (2011) for approaches that incorporate search frictions, industry specific human capital, or costly firm entry and exit. Whereas the former group of papers tends to focus on the United States, the latter group primarily uses data from Brazil. For work on related themes, see Davis and Harrigan (2007) and Helpman and Itskhoki (2010).

¹³See Neal (1995), Parent (2000), Polataev and Robinson (2008), and Gathmann and Schönberg (2010) on the importance of firm- and industry-specific human capital in worker adjustment to labor market shocks.

A second body of related trade literature estimates the short or medium run labor market effects of trade exposure by exploiting barriers that at least temporarily impede workers from changing employers, switching occupations, or moving to other locations.¹⁴ This work tends to find that there are significant negative transitory effects of trade shocks on wages and employment. However, by its nature, this approach may miss impacts that persist *after* an individual leaves his firm, abandons his industry, or relocates geographically. An additional complication is that wage effects estimated at the industry or region level may be contaminated by compositional changes resulting from worker exit, as low-wage workers may be those most likely to lose their jobs after an import shock.¹⁵ By utilizing the long-run panel structure of the SSA data, our work is able to capture the post-shock change in earnings that workers experience at the same firm, after moving to a different firm in the same industry, or after moving to a new industry altogether.¹⁶

To preview the results, we find that workers more exposed to trade with China have lower cumulative earnings, lower cumulative employment, and higher receipts of Social Security Disability Insurance (SSDI) over the sample window of 1992 through 2007. The difference between a manufacturing worker at the 75th percentile of industry trade exposure and one at the 25th percentile of exposure amounts to reduced earnings equal to 46% of initial yearly income and to one-half of an additional month where payments from SSDI are the main source of income. Trade exposure increases job churning across firms, industries, and sectors. More exposed workers spend less time working for their initial employer, less time working in their initial two-digit manufacturing industry, and more time working elsewhere in manufacturing and outside the manufacturing sector altogether.

A key theme that emerges from our results is that the magnitudes of job churn and adjustment in earnings and employment differ substantially across demographic groups. Workers with lower labor force attachment, shorter tenure, and lower earnings incur disproportionate losses in subsequent earnings and employment, while losses for workers with high initial earnings are generally quite modest. These results stand in sharp contrast to earlier literature studying mass layoffs, which broadly finds that earnings losses for affected workers are sizable and relatively uniform across demographic groups (Jacobson, LaLonde and Sullivan, 1993; Chan and Stevens, 2001; von Wachter,

¹⁴See Bernard, Jensen, and Schott (2006), Verhoogen (2008), Amiti and Davis (2012), and Hummels, Jorgensen, Munch, and Xiang (2011) on trade shocks at the firm level; Goldberg and Pavcnick (2003), Artuc, Chaudhuri, and McLaren (2010), McLaren and Hakobyan (2010), Ebenstein, Harrison, McMillan, and Phillips (2011), and Menezes-Filho and Muendler (2011) on trade shocks at the industry and occupation level; and Chiquiar (2008), Kovak (forthcoming), Topalova (2010), and Autor, Dorn, and Hanson (forthcoming) on trade shocks at the region level.

¹⁵Using data on U.S. commuting zones, Autor, Dorn, and Hanson (forthcoming) estimate large negative effects of import shocks on regional manufacturing employment but not on regional manufacturing wages, suggesting that low-wage workers may be non-randomly selected out of employment in trade-impacted industries.

¹⁶While the SSA data allows us to consistently observe the firm and industry dynamics of adjustment to trade shocks, they unfortunately do not allow us to reliably track workers' geographic mobility.

Manchester and Song, 2009; Couch and Placzek, 2010). A central analytic difference between the present paper and existing literature helps to illuminate the source of this disparity: distinct from studies analyzing mass layoffs, our industry-level trade shock approach does not condition on job separation. Hence, we capture additional margins of worker adjustment not seen in earlier work on mass layoffs, including reduced earnings absent job separation, anticipatory job change, or subsequent post-mass-layoff separations among workers initially retained.

These additional margins prove critical in understanding how different skill groups adjust to similar shocks. For a given size trade shock, high wage workers experience a *larger* reduction in their earnings and employment with their *initial* employer compared to low wage workers. However, high wage workers are more likely to separate early, and prior to mass layoffs from trade-exposed firms whereas low wage workers tend to separate later, and often during mass layoffs—suggesting that a disproportionate share of high skill exits is voluntary and, conversely, that a disproportionate share of low skill exits is involuntary. Consistent with this interpretation, separations among high skill workers lead to only modest net reductions in earnings—initial losses are countered by offsetting gains in subsequent jobs—while separations among low skill workers are only partially offset by earnings gains at other employers.¹⁷

We begin in Section Section 2 by documenting our empirical approach to estimating the effects of exposure to trade shocks, and Section 3 describes the data used in this study. Section 4 provides our primary OLS and 2SLS estimates of the impact of trade shocks on cumulative earnings, employment, and benefit receipts. Section 5 examines heterogeneity in the consequences of trade shocks by individual characteristics and conditions of initial employment, while Section 6 analyzes heterogeneity according to firm characteristics. Section 7 expands the inquiry to explore alternative measures of trade exposure. Section 8 concludes.

2 Empirical approach

The context for our analysis is one in which China experiences productivity growth and reductions in its trade costs, which lead its exports to expand. Trade theory predicts how such shocks affect wages in China, the United States, and the rest of the world (e.g., Hsieh and Ossa, 2011; di Giovanni, Levchenko, and Zhang, 2011). Our focus here is reduced form: we seek to capture the changes in earnings and employment that workers in exposed industries encounter when adjusting to the shock.

¹⁷These findings concord with Couch and Placzek (2010).

2.1 Industry Trade Shocks

To consider how productivity growth in China may affect U.S. industries, we apply the Eaton and Kortum (2002) model of trade in a multisectoral setting (e.g., Chor, 2010; Shikher, 2011).¹⁸ Using their framework, total output by U.S. industry j , Q_{uj} , can be written as the sum in demand for U.S. goods across destination markets:

$$Q_{uj} = \sum_n \frac{T_{uj} (w_{uj} \tau_{nuj})^{-\theta}}{\Phi_{nj}} X_{nj}, \quad (1)$$

which depends on the technological capability of U.S. industry j , T_{uj} , unit production costs in U.S. industry j , w_{uj} , bilateral trade costs between the United States and country n in industry j , τ_{nuj} , expenditure in country n on industry j , X_{nj} , and the “toughness” of competition in country n ’s market for outputs of industry j , $\left(\Phi_{nj} = \sum_h T_{hj} (w_{hj} \tau_{nhj})^{-\theta}\right)$, which in turn is a function of productivity, production costs, and trade costs in the other countries (indexed by h) that export to country n , including China.¹⁹ As China experiences productivity growth in industry j or a reduction in its production or trade costs, U.S. firms face stiffer competition in the markets that they and China both serve. Totally differentiating (1), we obtain the direct effect of China productivity and cost shocks on the demand for outputs of U.S. industry j ,

$$\hat{Q}_{uj} = - \sum_n \left[\frac{X_{nuj}}{Q_{uj}} \right] \left[\frac{X_{ncj} (\hat{A}_{cj} - \theta \hat{\tau}_{ncj})}{X_{nj}} \right], \quad (2)$$

where $\hat{x} \equiv d \ln x$, $\hat{A}_{cj} \equiv \hat{T}_{cj} - \theta \hat{w}_{cj}$, and X_{nuj} is initial sales by U.S. industry j in country n .²⁰ In (2), the first term in brackets is the share of country n in U.S. sales for industry j and the second term in brackets is the change in the import penetration ratio for industry j in country n that is mandated by changes in China’s productivity, production costs, and trade costs. Supply-driven changes in China’s exports will tend to reduce demand for U.S. industrial production. In the empirical analysis, we initially focus on import penetration in the U.S. market, as the United States is the dominant destination market for most U.S. industries (Bernard, Jensen, Redding, and Schott, 2009). We later incorporate changes in import penetration in other destination markets as well.

Turning to the data, our baseline measure of trade exposure is the change in the import pene-

¹⁸Other trade models that have a “gravity” structure, as in Arkolakis, Costinot, and Rodriguez-Clare (2012), produce similar specifications. What differs across these models is the interpretation given to \hat{A}_{cj} in equation (2) below. In the Eaton-Kortum model, this value is the combined effects of changes in industry productivity and unit costs, whereas in Krugman (1980), \hat{A}_{cj} would include changes in the number of industry product varieties a country produces.

¹⁹The parameter θ captures the dispersion in productivity across firms in the industry.

²⁰In equation (2), we do not consider the general equilibrium effect of China on global outcomes. Our empirical approach allows for such effects by using observed changes in imports to measure trade exposure.

tration ratio for a U.S. industry over the period 1991 to 2007, defined as,

$$\Delta IP_{j,\tau} = \frac{\Delta M_{j,\tau}^{UC}}{Y_{j,91} + M_{j,91} - E_{j,91}}, \quad (3)$$

where for U.S. industry j , $\Delta M_{j,\tau}^{UC}$ is the change in imports from China over the period 1991 to 2007 and $Y_{j0} + M_{j0} - E_{j0}$ is initial absorption (measured as industry shipments, Y_{j0} , plus industry imports, M_{j0} , minus industry exports, E_{j0}). We choose 1991 as the initial year as it is the earliest period for which we have disaggregated bilateral trade data for a large number of country pairs that we can match to U.S. manufacturing industries.²¹ The quantity in (3) will mirror that in (2) if the growth in U.S. imports from China is primarily the result of domestic supply shocks in China or changes in its trade costs. Indeed, over the period we consider, China underwent enormous changes in industrial productivity associated with TFP growth, human and physical capital accumulation, migration to urban areas, and improvements in the country's infrastructure that followed the country's transition from a centrally planned economy to a more market-oriented one, all of which contributed to its export surge (Naughton, 2007; Hsieh and Klenow, 2009; Bloom, Draca and Van Reenen, 2011; Hsieh and Ossa, 2011; Brandt, Van Biesebroeck, and Zhang, 2012).

Nevertheless, one concern about (3) as a measure of trade exposure is that observed changes in the import penetration ratio may in part reflect domestic shocks to U.S. industries. Even if the factors driving China's export growth are internal supply shocks, U.S. industry import demand shocks may still contaminate observed bilateral trade flows. To capture the China supply-driven component in U.S. imports from China, we instrument for trade exposure in (3) with the variable,

$$\Delta IPO_{j\tau} = \frac{\Delta M_{j,\tau}^{OC}}{Y_{j,88} + M_{j,88} - X_{j,88}} \quad (4)$$

where $\Delta M_{j,\tau}^{OC}$ is the change in imports from China from 1991 to 2007 in non-U.S. high income countries, based on the industry in which the worker was employed in 1988, three years prior to the base year.²² We use industry of employment in 1988, rather than 1991, to account for worker sorting across industries in anticipation of future trade with China (or other low-income nations).

The motivation for the instrument in (4) is that high income economies are similarly exposed to growth in Chinese imports that is driven by supply shocks originating in China. The identifying assumption is that industry import demand shocks are weakly correlated across high-income economies. There are several possible threats to our identification strategy. A first threat arises if

²¹Our approach requires data not just on China's U.S. trade but also its trade with other countries.

²²These countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland, which are the high income countries for which we can obtain disaggregated bilateral HS trade data back to 1991.

product demand shocks are correlated across high-income countries. In this case, our IV estimates may be contaminated by correlation between import growth and unobserved components of product demand, which would tend to bias the impact of trade exposure on earnings and employment toward zero. To address this concern, as described in more detail in section 6, we alternatively measure the change in trade exposure using a gravity-based strategy, which captures the change in China’s comparative advantage and market access vis-a-vis the United States. The gravity approach neutralizes demand conditions in importing countries by using the change in China’s exports relative to U.S. exports within destination markets, helping isolate supply and trade-cost-driven changes in China’s export performance. Our gravity and IV estimates end up being very similar, suggesting that correlated import demand shocks across countries are not driving our results.²³

Another threat to identification is that growth in imports from China may be due to technology shocks affecting all high-income countries that have shifted employment away from apparel, footwear, furniture, and other labor-intensive industries. In the estimation, we will attempt to control for confounding technology shocks using an extensive set of initial-year industry characteristics. Notably, recent evidence does not suggest that automation and related changes in technology are the driving force behind rising import penetration from China and other low-income economies. Bloom, Draca, and Van Reenen (2011) find that it is import competition from China that drives innovation in high-income countries, rather than the converse.²⁴ Further, China’s explosive growth suggests that its expanding global heft in manufacturing is the primary explanation for its export boom (Hanson, 2012). Between 1992 and 2007, China accounted for an astonishing three quarters of worldwide growth in manufacturing value added that occurred in low and middle-income nations. This heft is reflected in China’s rapidly expanding market share in high income countries, even when just looking among low-wage suppliers. Between 1991 and 2007, China’s share of manufacturing imports from low-income countries increased from 77.4% to 89.8% in the United States and from 75.4% to 89.5% in Europe and Japan.²⁵ China’s share of the U.S. market has grown sharply even relative

²³The gravity approach also addresses the concern that negative U.S. productivity shocks are behind growing imports from China. The change in China-U.S. relative exports incorporates the change in China’s industry productivity growth relative to that in the United States, such that productivity growth in either country may affect labor-market outcomes. Still, it appears that the change in China’s productive potential is the overwhelmingly dominant factor. Brandt, van Biesebroeck and Zhang (2012) estimate that over the period 1998 to 2007, China had average annual TFP growth in manufacturing of 8.0%, whereas in the United States, based on the NBER productivity database, the corresponding figure is 1.2% (weighting by industry employment in 1998 and excluding the semiconductor industry; including semiconductors, the value is 4.2%).

²⁴Comparing the effects of trade and technology on manufacturing employment across local U.S. labor markets during 1980 through 2007, Autor, Dorn and Hanson (2013) find that, concurrent with the rapid growth of U.S. imports from China, the effect of trade competition on the manufacturing sector has accelerated while, conversely, the effect of technological change on employment composition inside of manufacturing has slowed, with the largest impacts detected in the 1980s and the smallest impacts found in the 2000s.

²⁵The immense scale of China’s expansion suggests that absent its opening to global trade and investment other

to Mexico and Central America (from 40.6% in 1991 to 64.3% in 2007), despite these nations having signed free trade agreements with United States during the period.

Appendix Figure 1 plots the value in (3) against the value in (4) for the workers in our main sample, as defined below, which is equivalent to the first-stage regression in the estimation without detailed controls. The coefficient is 0.855 and the t-statistic and R-squared are 9.20 and 0.34, indicating the strong predictive power of import growth in other high income countries for U.S. import growth from China. Our later estimates using the gravity model to measure trade exposure (as in Autor, Dorn, and Hanson, forthcoming) permits weaker identifying assumptions.

2.2 Measuring Industry Trade Exposure

Data for U.S. imports are from UN Comtrade, concorded from HS product codes to four-digit SIC industries (see the Data Appendix). Data for U.S. four-digit industry shipments are from the NBER Productivity Database (Bartelsman, Becker, and Gray, 2000).

There is immense variation in import growth across industries. Figure 2 plots on the horizontal axis the change in industry import penetration from China from 1991 to 2007 and on the vertical axis the share of production workers in industry employment in 1991—meant to capture industry dependence on less-skilled labor. Each four-digit industry is a point on the graph. We use common symbols for industries that fall within each of ten broad sectors, where each sector consists of industries that have relatively similar production-worker employment shares.

Focusing first on changes in import penetration at the sector level, which are reported in the legend to Figure 4, the sectors with the largest increase in exposure from 1991 to 2007 are those intensive in the use of production workers. These include toys, sports equipment, and other products, with a 32.6 percentage point increase in import penetration; apparel, leather (footwear), and textiles, with a 16.7 percentage point increase; and furniture and wood products, with a 15.2 percentage point increase. Also exposed is machinery, electrical machinery, and electronics where import penetration grew by 15.2 percentage points. In the United States, this sector contains both more-skill and less-skill intensive industries, evident in the vertical range of the black plus signs in Figure 2. In China, the dominant industries within this sector include finished computers and telecommunications equipment (e.g., cell phone handsets), within which the country specializes in the processing of electronic components and final assembly. The least exposed sectors in Figure 2—food products, beverages, and tobacco, chemical and petroleum products, and transportation equipment—each have

low-income countries would have been hard pressed to sustain the increase in low-wage-country import penetration seen in the United States and other high-income countries in the last two decades.

changes in import penetration of less than two percentage points. They have in common intensive use of natural resources (land, oil reserves) or physical capital. Overall, the broad patterns of sectoral import growth are consistent with China's strong comparative advantage in labor-intensive activities (Amiti and Freund, 2010; Huang, Ju, and Yue, 2011).

However, factor intensity cannot be the whole story. Visible in Figure 3 is wide variation in the change in industry import penetration *within* sectors. The location of the green diamonds high on the vertical axis confirm the apparel and textile industries' heavy dependence on production workers. Yet, within the sector, the most exposed industries see changes in import penetration of over 90 percentage points, whereas the least exposed see changes of less than 10 percentage points. Factors affecting within sector export performance include the ease of offshoring (Feenstra and Hanson, 2005), proximity to upstream suppliers or downstream buyers (Koopman, Wang, and Wei, 2012), and the phase-out rule favoring state-owned firms in exporting (Khandelwal, Schott, and Wei, forthcoming). In the empirical analysis, we will include controls for the ten broad sectors, meaning that we identify the impact of trade exposure on long-run outcomes based on variation in import growth among industries with similar skill intensities.

One simplification of the model behind equation (2) is the absence of intermediate inputs. In actuality, China's export production relies heavily on imported intermediates. During the sample period, approximately half of China's manufacturing exports were produced by export processing plants, which import parts and components from abroad and assemble these inputs into final export goods (Feenstra and Hanson, 2005). The importance of processing plants in China's exports may create the impression that the country's position in global production is limited to the low-value added task of product assembly. Because assembly occurs at the end of the production chain, the gross value of China's exports may overstate the actual value added in China. However, recent evidence suggests that the domestic content of China's exports is substantial and rising. Koopman, Wang, and Wei (2012) find that the share of domestic value added in China's total exports rose from 50% in 1997 to over 60% in 2007. Even within the highly specialized export processing sector, domestic value added rose from 32% of gross exports in 2000 to 46% in 2006 (Kee and Tang, 2012). Our instrumental variable strategy does not require that China is the sole producer of the goods it ships abroad but rather that the growth of its gross manufacturing exports is driven largely by factors internal to China (as opposed to shocks originating in the United States).

To account for how complexities in global production may affect the transmission of trade shocks in China to U.S. industries, we use six alternative measures of changes in import competition, alongside our principal measure in equation (3). These measures, which are discussed in more detail

in section 6.2, include (i) the change in import penetration from China calculated using the gravity model of trade, (ii) changes in import penetration due to trade with all low-wage countries and not just China, (iii) changes in import competition from China in all domestic and foreign markets that U.S. industries serve (and not just the U.S. market), (iv) changes in net imports (i.e., imports – exports) from China, (v) changes in the net labor content of U.S. trade with China, and (vi) changes in import penetration due to China net of changes in imported intermediate inputs.

To summarize our approach, we examine changes in outcomes for workers over the 1992 to 2007 period that are associated with exposure to the growth in imports from China. We measure a worker’s exposure according to his industry of employment in the pre-shock period. By taking workers and their initial industry of employment as the unit of analysis, we isolate the long-run changes in outcomes that are associated with greater exposure to trade at the time China’s export growth accelerates. Under what conditions would we fail to find evidence of worker-level adjustment? If labor markets are frictionless, such that workers can easily change industries and obtain similar compensation levels in alternative lines of work (i.e., they do not face inter-firm or inter-industry wage differences), we will see no impacts from exposure to China trade—though in this case, we should be able to detect inter-firm and inter-industry mobility induced by trade exposure. If growing imports from China cause wages to change for entire skill groups, our approach would also fail to identify adjustments in earnings or employment, since in this case the wage effects would not be firm or industry-specific. We *will* find trade impacts on worker outcomes if trade shocks induce exposed firms to cut wages and employment *and* either (i) it is costly for workers to change their employers or to change their industries (due, say, to the presence of firm or industry-specific human capital; e.g., Neal, 1995), or (ii) costly job search or other barriers complicate obtaining another job once a worker has lost his initial employment (Rogerson and Shimer, 2011; Helpman, Itskhoki, and Redding, 2010); or (iii) workers in affected industries tend to be those who are more likely to exit the labor force in response to an adverse wage shock (Blau, 1994; Peracchi and Welch, 1994).

3 Data sources and measurement

Our main source of data on U.S. workers is the Annual Employee-Employer File (EE) extract from the Master Earnings File (MEF) of the U.S. Social Security Administration. The EE contains longitudinal earnings histories for a randomly selected one percent of workers in the United States. Most of our analysis studies the impact of import competition on workers’ career outcomes during the years 1992 and 2007, while using data since 1972 as control variables and for robustness checks.

For each worker and year, we observe total annual earnings, and an employer identification number (EIN) and detailed industry code (SIC) for the worker's main employer.²⁶ We augment the EE data by adding various additional Social Security Administration data files that provide basic demographic characteristics of workers, their income obtained from Social Security benefits and from self-employment, and information on firm's total employment and payroll. The Data Appendix provides more details.

We focus on workers who were born between 1943 and 1970 and study their outcomes over the period 1992 to 2007, during which these individuals were between 22 and 64 years old. We use two samples in the estimation. Our primary sample of 508,129 workers consists of workers with high labor-force attachment prior to the outcome period, which we define as earnings in each year from 1988 to 1991 that equal or exceed the equivalent of 1,600 annual hours of work at the real 1989 Federal minimum wage. The full sample, containing 880,465 workers, adds workers with low labor-force attachment and comprises all working-age individuals who had positive earnings (and a valid industry code) for at least one year each during 1987 through 1989 and 1990 through 1992.²⁷

We study five main worker outcomes over the sample period: total labor earnings, the number of years with positive labor earnings, earnings per year for years with non-zero earnings, total self-employment income, and total Social Security Disability Insurance (SSDI) benefits received.²⁸ Appendix Table 2 describes variation in these outcomes across workers. For the sample with high labor-force attachment (in column 1), the average worker had positive labor earnings in 14.2 of the 16 years, cumulatively earned 19.2 times their initial average annual wage (measured as the average of their annual wage between 1988 and 1991), earned an average of 1.3 their initial annual earnings in years in which earnings were non-zero, and spent 0.3 years (4 months) receiving SSDI income with no labor income. Among individuals initially employed in manufacturing (column 2), the average increase in import penetration from China was 7.7 percentage points, with an increase of 24.7 percentage points for workers at the 90th percentile of trade exposure and less than 0.1 percentage points for workers at the 10th percentile.

²⁶For workers who have multiple jobs in a given year, we aggregate earnings across all jobs and retain the EIN and SIC of the employer that accounted for the largest share of the worker's earnings.

²⁷Observations from the first period are necessary to construct (4) and for the second period to construct (3).

²⁸Because the sample is limited to individuals of working age, the vast majority of non-elderly workers who report Social Security benefits receive them in the form of SSDI, rather than Social Security Retirement Income (whose primary recipients are aged 65 or older) or SSI, whose primary recipients do not have sufficient prior work history to qualify for SSDI.

4 Initial Results

The data permit us to examine cumulative worker outcomes over the sample period as well as transitions between employers, spells of non-employment, and spells with positive income from Social Security benefits. In this section, we begin the analysis by examining the impact of trade exposure on total earnings and employment and then consider worker adjustment to trade shocks through transitions between jobs and periods of receiving benefits.

We begin by fitting models of the following form:

$$\tilde{E}_{ij\tau} = \beta_0 + \beta_1 \Delta IP_{j\tau} + \beta_2 IP_{j,91} + X'_{ij,0} \beta_3 + Z'_{j,0} \beta_4 + e_{ij\tau}, \quad (5)$$

where $\tilde{E}_{ij\tau} = \sum_{t=92}^{t=07} E_{ijt} / \bar{E}_{it_0}$ is cumulative earnings over 1992 to 2007, normalized by average annual earnings over 1988-1991, for worker i employed in industry j in 1991. $\Delta IP_{j\tau}$ is the change in import penetration from China over 1991 to 2007 in industry j as defined in equation (3); $IP_{j,91}$ is import penetration from China in industry j in 1991. The vector X_{ij0} contains controls for the worker's gender, birth year, race, and foreign-born status; and average log annual earnings over 1988 to 1991 and its interaction with (as well as the main effects for) worker age, indicators for job tenure as of 1991 in the worker's primary firm (0-1, 2-5, 6-10 years), indicators for the size of the primary firm (1-99, 100-999, 1000+ employees), and indicators for count of years between 1978 and 1988 in which the worker had positive earnings (4-5, 6-8, 9-11 years). The vector $Z_{j,0}$ controls for economic conditions in industry j in 1991, discussed in more detail below. While trade exposure and industry characteristics vary at the level of workers' 4-digit industries in 1991, standard errors are clustered at the level of 3-digit industries, thus allowing for correlation in error terms among workers who are initially employed in the same or in closely related industries.

Cumulative earnings embody the sum of labor-market shocks over the sample period. Normalizing cumulative earnings by workers' initial (pre-shock) earnings \bar{E}_{it_0} provides a natural metric for assessing the effect of shocks on the evolution of earnings. Relative to the conventional approach of including person fixed-effects to remove worker-specific earnings means and taking the logarithm of earnings to provide a proportional scale, this normalization has two virtues: the earnings baseline measure is constructed with only *pre*-shock earnings and so is not contaminated by post-shock outcomes; and denominating post-shock earnings by the pre-shock baseline provides proportionate scaling while circumventing the problem that the logarithm of earnings is undefined for years with zero earnings.

In equation (5), we model the cumulative shock due to trade exposure as a function of import

penetration in 1991 plus the growth in import penetration from 1991 to 2007, which is equivalent to the initial condition plus the average annual change. Implicitly, our analysis compares workers with similar demographic characteristics, initial earnings, initial experience on the job, initial employer size, and average industry characteristics, some of whom work in industries that see subsequent increases in import competition from China and some of whom do not. Because we compare workers with similar pre-shock observable characteristics, we do not capture changes in wages that are common to workers in a given skill or experience group. Our interest is in seeing whether otherwise similar workers have distinct long-run outcomes based on differential initial exposure to import competition from China, as would be consistent with costly worker adjustment to trade shocks.

An obvious challenge for the analysis is that industries that are subject to greater import competition may be exposed to other economic shocks that might be confounded with China trade. To address this concern, we include extensive industry controls and also employ falsification tests. Our main models control for the ten manufacturing sectors described in section 2, as well as for a large set of industry characteristics as measured in 1991 (or 1990): the share of production workers in employment, the ratio of capital to value added, the industry average log wage (from Bartelsman, Becker, and Gray, 2000), the share of computers and high-tech equipment in total investment, the share of imported intermediate inputs in material purchases (from Feenstra and Hanson, 1999), and import penetration by countries other than China. The intensity with which an industry uses production labor or capital may indicate the exposure of the industry to technical change. In recent decades, technological progress within manufacturing has been most rapid in computer and skill intensive sectors (Doms, Dunne, and Troske, 1997; Autor, Katz, and Krueger, 1998). Initial non-China import penetration and use of imported intermediates captures overall industry exposure to trade in final goods and to offshoring.

Over the time period that we examine, U.S. manufacturing experienced a secular decline, with the most pronounced contractions occurring in labor-intensive industries. Could increased imports from China 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 perform two robustness tests. We augment equation (5) to include the change in each industry's share of manufacturing employment and the change in its log average wage during the prior 16 years. These variables capture pre-existing trends in industry growth that predate the rise of exposure to China trade. We also conduct falsification tests by regressing *past* earnings and employment outcomes for workers on *future* changes in their industry's trade exposure to China.

4.1 Baseline Regressions

Table 1 presents estimates of the relationship between Chinese import exposure and cumulative earnings from 1992 to 2007, normalized by average annual earnings over 1988 to 1991, such that total labor earnings are denominated as a multiple of initial annual income. We begin by using the restricted sample of individuals with high labor-force attachment, who report labor earnings corresponding to at least a full-time minimum wage job in each of the four consecutive years 1988 to 1991. The first two columns of Table 1 regress cumulative earnings on the change in Chinese import penetration and a full set of birth year dummies that accounts for life cycle variation in earnings. The regression in column 1 is estimated by OLS, whereas the regression in column 2 is estimated by two-stage least squares, using the variable described in (4) as an instrument for the change in import penetration given in (3). In both cases, there is a negative and statistically significant relationship between the change in import penetration and cumulative earnings over 1992 and 2007. Greater exposure to imports from China based on a worker’s initial industry of employment is associated with lower total earnings over the subsequent 16-year period.

To interpret the coefficient estimates, we compare a manufacturing worker at the 75th percentile of the change in trade exposure (7.30 percentage points) with a manufacturing worker at the 25th percentile (0.62 percentage points, see Appendix Table 2).²⁹ The implied differential reduction in earnings over the 16-year outcome period for the worker at the 75th percentile is 20% ($-2.94 \times (7.30 - 0.62)$) of initial annual earnings in column 1, and 38% ($-5.73 \times (7.30 - 0.62)$) of initial annual earnings in column 2. The 2SLS estimate is roughly twice the magnitude of the OLS estimate, which is consistent with there being a positive correlation between U.S. industry import demand shocks and U.S. industry labor demand, which would bias the OLS estimate towards zero.³⁰

In column 3, we add dummies for female, non-white and foreign-born. These controls have little impact on the magnitude of the coefficient on import exposure.³¹ Column 4 additionally controls for individuals’ work history by adding dummies for tenure at 1991 firm (0-1, 2-5, 6-10 years), experience (4-5, 6-8, 9-11 years), and size of 1991 firm (1-99, 100-999, 1000-9999 employees). Column 5 adds controls for workers’ earnings histories, including the worker’s annual log wage averaged over 1988-

²⁹Non-manufacturing workers are not informative as a comparison group since by definition they have zero trade exposure.

³⁰A second difference between these specifications is that the OLS model uses 1991 industry affiliation in its exposure measure while the the 2SLS model uses 1988 industry affiliation for the exposure instrument, and 1991 industry affiliation for the endogenous regressor. Since the first stage predictive relationship will be tighter for workers who remain in the same industry in both 1988 and 1991, and if, plausibly, workers with stronger industry attachment are differentially affected by industry-specific shocks, this industry attachment link may also contribute to the greater magnitude of the 2SLS point estimates.

³¹As expected, cumulative earnings over the period are lower for women, non-whites, and the foreign born.

1991, an interaction of initial wage with age, the change in log wage between 1988 and 1991, as well as the level and trend of the 1991 firm’s log mean wage for the period 1988-1991. Unreported coefficient estimates indicate that workers with higher initial earnings, higher tenure, or larger initial employers have higher cumulative earnings. These many additional controls modestly increase the magnitude and precision of the coefficient of primary interest.

To account for cross-industry heterogeneity in exposure to other shocks, the remaining four columns of the table successively add an extensive set of industry-level controls, including: initial trade penetration by Chinese and non-Chinese imports in the worker’s industry (column 6); dummies for 10 manufacturing sub-industries (column 7); the 1991 employment share of production workers, log average wage, and capital/value added, and 1990 level of computer investment, share of investment allocated to high-tech equipment, and fraction of intermediate goods among imports in the worker’s industry (column 8); and controls for changes in industry employment share and log average wage level during the preceding 16 years, 1976-1991 (column 9). The inclusion of 10 dummy variables for manufacturing sub-sectors is particularly noteworthy because it implies that the subsequent regression models compare outcomes for manufacturing workers who are initially employed in different industries of the same sub-sector, rather than comparing workers across very different fields of economic activity. Looking across columns, these additional controls have little substantive impact on the estimated impact of import penetration. The coefficient of -6.86 on the import penetration in the final column is about 20 percent larger than in the initial 2SLS specification (column 2). This suggests that conditional on demographic measures, workers with somewhat higher potential earnings are initially employed in industries that subsequently experience sharper rises in trade exposure. Accounting for these sources of heterogeneity thus leads to a somewhat larger estimate of the earnings losses that workers experience due to trade exposure. To gauge the economic magnitude of this point estimate, we again compare the implied impact on earnings of a manufacturing worker at the 75th versus 25th percentile of the change in trade exposure. Multiplying by the point estimate in column (9), we find a reduction of cumulative earnings by approximately one half of an initial annual wage for the more exposed worker ($-6.86 \times (7.30 - 0.62) = 45.8$)

In Table 2, we consider two additional outcome measures and perform falsification tests. The first column of the upper panel replicates the final (and most exhaustive) specification for cumulative earnings from column 9 in Table 1, which will serve as our baseline specification. The second column considers a second outcome measure: the number of years between 1992 and 2007 in which the worker has non-zero labor earnings. This is a coarse measure of the extensive margin of employment: an individual who works a single day in a year will have non-zero earnings, so even prolonged periods of

non-employment will go undetected unless they span a full calendar year. The point estimate of -0.53 in column (2) is negative, suggesting that increases in industry trade exposure reduce subsequent years of employment. But this coefficient is not statistically significant and it implies only a modest effect of trade exposure on years with positive earnings.³²

The third column of Table 2 considers the impact of trade exposure on earnings per year of employment (expressed in multiples of the initial annual wage) for years in which labor earnings are non-zero. The point estimate of -0.39 ($t=2.8$), suggests that trade exposure modestly depresses future earnings, consistent with column 1. This estimate implies that earnings are differentially reduced by 2.6% *per year* (-0.39×6.7) for a worker initially employed in an industry at the 75th of exposure relative to a worker at the 25th percentile of exposure.³³ The reduction in cumulative earnings evident in column 1 appears to be largely the result of changes in within-year earnings, rather extended periods of non-employment. These within year earnings changes are, in turn, a combination of reduced earnings per hour and reduced hours worked—the relative contributions of which we cannot disentangle with our data—meaning that our results do not negate an impact of import competition on *within-year* employment changes.

Figure 3 offers a dynamic view of the Table 2 findings by plotting the estimated effect of import exposure on worker outcomes on an annual basis for the years 1988 through 2007. The estimating equations underlying the three panels of Figure 3 are identical to those used in Table 2 except that in place of workers’ cumulative outcomes over the period 1992 through 2007, we estimate the models separately for each outcome year, with the dependent variable equal to workers’ outcomes in the corresponding year. Trade exposure remains the total change over the 1991 to 2007 period, such that the figures depict how the total impact of trade exposure cumulates over time. The top panel, depicting the estimated impact of trade exposure on worker earnings per year (as a fraction of pre-period earnings), reveals a significant adverse effect in essentially every year between 1992 and 2007. Consistent with the Table 2 estimates, however, very little of the decline in earnings stems from a rise in zero earnings years, as seen in the middle panel; indeed, only one of the 16 point estimates for years 1992 through 2007 in the middle panel is significantly different from zero. The bottom panel shows instead that the adverse impact of industry trade exposure on workers’ subsequent earnings

³²The drop in employment years for a manufacturing worker at the 75th percentile of exposure relative to a worker at the 25th percentile is 3.6% of a year (-0.54×6.7), or about two weeks, during the 16-year outcome period.

³³In comparing columns 2 and 3 to the estimate in column 1, note that 16 times the reduction in earnings per year (column 3) plus the reduction in years with earnings (column 2) is $16 \times -0.39 - 0.54 = -6.78$, which is quite close to the estimated effect for cumulative earnings (column 1). Note, however, that these numbers will generally not match the column (1) estimate exactly since there are important differences between manufacturing workers’ average years of employment (14.2 years) over these 16 years and their cumulative earnings (19.2 times initial wages), reflecting the fact that workers’ real earnings typically rise until late career. Consequently, an employment reduction by one year will typically reduce earnings by more than the equivalent of one initial annual wage.

arises primarily from a fall in within-year earnings. This within-year fall is due to some combination of changes in hours worked and hourly earnings, as noted above. Figure 3 also reveals a striking time pattern: the estimated adverse effect of trade exposure on worker outcomes roughly doubles in magnitude after 2000. This growth, which coincides with China’s accession to the WTO in 2001 and the accompanying surge in Chinese imports (Figure 1), lends additional credibility to the main findings in Tables 1 and 2. Not only do workers initially employed in more trade-exposed industries experience significantly lower earnings overall during the 1991 through 2007 period, the magnitude of these negative relationships jumps discontinuously as Chinese imports surge.

To further probe the consistency of time patterns in Chinese imports and workers’ outcomes, we explore in panel B of Table 2 whether the growth in import competition from China in the 1990s and 2000s “predicts” earnings and employment outcomes for an *earlier* cohort of workers that was not directly exposed to Chinese competition. We draw on an extended version of the Social Security data to construct cumulative earnings from 1976 to 1991 for workers who were between 22 and 64 years of age during this earlier period, and use these data to examine whether their employment outcomes during 1976 through 1991 are correlated with *later*, post-1991 changes in Chinese import penetration that subsequently occurred in their industries.³⁴ The estimates in panel B of Table 2 provide scant evidence of this confound. Column 1 estimates a negative relationship between cumulative earnings and future industry-level China trade exposure occurring during the 1990s and 2000s, but the point estimate is insignificant and less than one-tenth the magnitude of the analogous contemporaneous estimate in panel A. Column 2 finds a weakly *positive* relationship between years of non-zero labor income and subsequent industry trade exposure, opposite to panel A. Finally, column 3 finds a small, negative and insignificant relationship between annual wages in years with non-zero earnings and subsequent trade exposure. In net, future trade exposure is a poor predictor for past earnings and employment outcomes for workers. These estimates suggest that our main findings are not plausibly attributable to preexisting industry-level trends that could drive both the long-run decline of manufacturing and the rise of import competition from China.

The time pattern of results in Figure 3 also highlights an important nuance in the interpretation of our impact estimates: the rise in China trade exposure is not a discrete event akin to a mass layoff, but rather an ongoing process that builds momentum in the early 1990s as China fully embraces export-led development, and accelerates as China joins the WTO in 2001. It is noteworthy that after 1991, the increase in trade exposure exhibits strong serial correlation at the industry level. There are

³⁴The sample for the analysis of the 1976-1991 period uses the same sampling criteria as our main sample, and is hence restricted to workers who earned at least the equivalent of \$8,193 at 2007 values in each of the four years preceding the outcome period.

no sizable industries that experienced large trade competition only in the 1990s but not in the 2000s, or vice versa. Specifically, industries that are in the top tercile of trade exposure in one decade and in the bottom tercile in the other account for just 1% of all manufacturing workers in our sample. Therefore, it is not feasible to distinguish outcomes for workers whose industries became exposed to China particularly early or particularly late. Instead, we parameterize the cumulative rise in China’s import penetration as a single long change over the period 1991 through 2007 throughout the paper (see equation (5)). However, the evolution of the impact coefficients in Figure 3 provides insight into the timing of outcomes as the trade shock unfolds and accelerates after 2001, and as workers adjust to the shock. This latter process, in turn, encompasses multiple channels of adjustment. Mechanically, we expect the relationship between workers’ 1991 industry affiliations and subsequent shocks to their industries to decline over the course of the sample because workers’ initial sectoral affiliations become less relevant as time unfolds. Simultaneously, as our subsequent analysis suggests, low skill workers in particular may adjust more slowly to an unfolding shock, in some cases remaining with their initial employer until a mass layoff occurs. If workers and firms are able to initially weather a competitive shock but are unable to do so indefinitely, the worker-level adverse impact of an initial trade shock may in fact build with time. These considerations underscore that the time pattern of impact coefficients in Figure 3 does not constitute an “event study” as in traditional mass-layoff analyses—that is, a discrete shock followed by a time path of adjustments—but rather depicts the interaction between two economic forces, rising import penetration and ongoing worker adaptation.

4.2 Worker Churning across Firms, Industries and Sectors

We now explore empirically how workers and, indirectly, their employers, adapt to an increase in import competition. Firms may adjust labor quantities by temporarily or permanently reducing employment. Workers who perceive a competitive threat to their firm or industry may voluntarily seek new employment. Workers who separate from their jobs voluntarily or involuntarily must decide whether to search for a position in a similar line of work, which may reward the skills they have accumulated on the job, or to search more broadly in fields of work where their earnings potential may be lower. The SSA data permit us to evaluate the margins along which workers adjust to changes in import penetration by decomposing the total worker-level effect of trade exposure seen in Table 2 into a set of additive, mutually exclusive channels of adjustment, including the direct impact of rising import competition on workers’ tenure and earnings at their initial employers, as well as subsequent, potentially offsetting, worker moves among employers, across sub-sectors of manufacturing, and between the manufacturing and non-manufacturing sectors.

Panels A through C of Table 3 perform this decomposition by estimating a variant of equation (5) for cumulative earnings, years of work, and earnings per year of employment. For this exercise, we partition the outcome variable into values observed at the worker’s initial employer (column 2), at other employers within the worker’s initial two-digit industry (column 3), at employers within manufacturing but outside the worker’s initial industry (column 4), outside of manufacturing entirely (column 5), and at new employers whose industry is unrecorded in the data (column 6).³⁵ For panels A and B (containing results for cumulative earnings and cumulative years of employment), summing the coefficients in columns 2 through 6 produces the value in column 1.

In column 2A, the negative and significant coefficient on import penetration indicates that workers more exposed to China trade have sharply reduced earnings at their initial employer. Further, the negative coefficient in column 3A implies that workers more exposed to imports also obtain lower subsequent income from other firms in the same two-digit industry as their initial employer.

These results suggest that manufacturing workers with greater exposure to import competition are more likely to separate from their initial employers and less likely to join other firms in closely related industries that may suffer from similar trade exposure. Indeed, the second and third column of panel B, which consider employment rather than earnings, indicate that reduced earnings at the initial firm and at other firms in similar industries stem partly from shorter employment spells. Between 1992 and 2007, the average manufacturing worker in the main (i.e., high labor force attachment) sample spent 7.7 years working in his 1991 two-digit industry, with approximately one-fifth of this time at firms other than the 1991 employer (Appendix Table 1). Comparing workers at the 75th versus the 25th percentile of trade exposure, the more-exposed worker spent 0.4 fewer years ($-6.2 \times 6.7/100$) working for his initial firm and 0.6 fewer years ($(-6.2 - 2.0) \times 6.7/100$) working in his initial two-digit industry. The substantial trade-induced reduction of a worker’s years of employment in the initial firm and industry contrasts sharply with the small overall decline in employment as measured in column 1 ($-0.03 = -.53 \times 6.7/100$). We can therefore infer that trade-impacted workers are able to largely offset their employment losses in the initial firm and industry by moving across industries.

Where do these offsets accrue? In column 4B, we use as a dependent variable the years of employment in the same sector as the 1991 employer but in a different firm and two-digit industry. For manufacturing workers, this variable measures total employment at firms in two-digit manufacturing industries other than their initial industry and employer. The coefficient on import penetration is positive and precisely estimated, indicating that more trade-exposed workers are relatively more

³⁵Industry information is missing for all firms that were incorporated in or after the year 2000. Prior to 2000, the data contains very few firms with missing industry codes.

likely to work in different industries within manufacturing. These offsetting employment gains within manufacturing are only about half as large as the losses incurred with the original employer and sector ($4.65/(6.20 + 2.04) = 0.56$). Thus, an increase in trade exposure in the worker's initial firm reduces the worker's total manufacturing employment, even net of mobility within the sector.³⁶ Columns 5B and 6B complete the employment picture by considering employment years outside of the worker's initial sector and at firms whose industry could not be identified. Workers who are initially in trade exposed industries experience offsetting employment gains in both categories, though results for employment outside of manufacturing are imprecisely estimated. Taken together, these results underscore that more trade exposed workers are subject to increased churning across employers and industries.

The upper two panels of Figure 4 depict the dynamics of trade exposure and job change, following the format of Figure 3. Increased import penetration in a worker's initial industry strongly decreases the likelihood that the worker remains with the original employer (top panel). Logically, this effect cumulates over the course of the sample window, and it is statistically significant in all years after 1995. Conversely, increased industry trade exposure at the initial job raises the likelihood that the worker is subsequently employed by a different firm (middle panel). That the positive effect of trade exposure on the probability of reemployment at another employer is smaller than its negative effect on ongoing employment at the original firm indicates that some share of trade-induced separations lead to spells of non-employment, as previously documented by the middle panel of Figure 3.³⁷

While workers appear able to make up for most of the *employment* loss in the initial firm and two digit industry through employment further afield, they appear less successful in offsetting lost *earnings*. Columns 4A to 6A of Table 3 indicate that earnings gains in other manufacturing industries are only half as large as the losses incurred with the original employer and industry ($5.91/(9.11 + 3.00) = 0.49$), while earnings gains outside of manufacturing are on net close to zero. Panel C documents that the discrepancy between the large reduction in cumulative earnings and the more modest reduction in employment years is explained by lower earnings per year of employment.

³⁶Column 6B shows moderate employment gains at firms with missing industry code, a large majority of which were incorporated in the years 2000 to 2007, when a new data collection process no longer facilitated information on industry. Even if one assumes that all new firms that employ former manufacturing employees operate in the manufacturing sector, there is still a sizable negative effect of trade exposure on manufacturing employment or earnings, which may be seen by summing the coefficients across columns 1, 2, 3 and 5 of Panel A or B.

³⁷Note that the outcome variables in the top and middle panels of Figure 4 are essentially cumulative probabilities (ignoring the slight probability that a worker separates from and subsequently rejoins the original firm). Thus, the almost perfect monotonicity of the time pattern of results in the figure is to be expected. More interesting is that, distinct from Figure 3, there is no 'jump' in either job change measure following the China trade surge in 2001. This indicates that the risk set of potential *initial* job separations and *initial* firm changes away from the original employer were largely depleted by 2001 (though the post-2001 trade surge clearly matters for cumulative outcomes).

Trade-exposed workers not only obtain lower earnings per year at their initial firm but also at other firms that employ them subsequently within or outside manufacturing. This pattern of results is consistent with the interpretation that workers possess job or industry-specific skills that they can no longer gainfully employ once they leave the initial firm or industry.³⁸ By taking the ratio of the coefficients in panel B to panel A in column 2, we can calculate that approximately two-thirds (68%) of reduced earnings at the initial employer stem from fewer years worked at the firm and about one-third is due to lower earnings per year worked. For manufacturing earnings as a whole, approximately 60 percent of the total earnings effect is due to reduced years of employment, with the remainder due to reduced earnings per year.

4.3 Worker Receipt of Social Security Benefits

Alongside changes in employment and earnings, a complementary channel by which workers may adjust to employment shocks is through job search, retraining and transfer programs, such as the federal Trade Adjustment Assistance (TAA) program, state unemployment insurance programs, and numerous need-based transfer programs. One such adjustment program that is observable in our data is the federal Social Security Disability Insurance (SSDI) program, which as noted above, provides income transfers and Medicare coverage to workers who have developed a physical or mental disability that prevents them from being gainfully employed.³⁹ Since workers cannot obtain SSDI if they are employed, it is plausible that the trade-induced declines in employment and earnings seen in Table 2 may have a counterpart in increased SSDI participation and benefits receipt. We explore this possibility in Table 4 by analyzing the impact of trade exposure on SSDI enrollment along four margins: the probability of receiving SSDI at any point, the number of years with positive SSDI income, the number of years receiving SSDI as a primary income source, and cumulative income from SSDI. Analogous to Table 3, the first panel of Table 4 decomposes the effect of trade exposure on years of employment into four mutually exclusive categories according to the *primary* source of income during the year that is observed in our data: labor income (column 1); self-employment

³⁸These results in panel C must be interpreted with some caution, however, since the earnings-per-year effects combine variation stemming from changes in weeks worked, hours worked per week, and earnings per hour of work.

³⁹To become insured by the SSDI program, an individual must have worked in at least five of the ten most recent years in covered employment. Medicare eligibility commences two years after the onset of disability. SSDI receipt is in almost all respects equivalent to early retirement through the Social Security retirement program; in fact, workers transition seamlessly (with no change in cash or medical benefits) from SSDI to Social Security retirement when they reach the full retirement age. See Autor and Duggan (2006) for additional details on the SSDI program's eligibility criteria, application and screening process, benefits provision, and interactions with the labor market. Prior literature has established that enrollment in the SSDI program is generally countercyclical, and that local economic shocks can induce sharp rises in SSDI applications and subsequent awards (Black, Daniel and Sanders, 2002; Autor and Duggan, 2003; Autor, Dorn and Hanson, forthcoming).

income (column 2); SSDI income (column 3); and no recorded income (column 4).

Echoing the results in Table 2, column 2A shows a negative but insignificant relationship between trade exposure and years with labor earnings as the main source of income: among the workers in our main sample (i.e., possessing strong labor force attachment prior to the outcome period), spending a full calendar year out of work is uncommon. In column 2A of Table 4, trade exposure is also negatively but not significantly correlated with total years in which self-employment is the primary income source, indicating that transitions into self-employment are not a quantitatively important mechanism for worker adjustment to trade shocks. However, column 3A finds that trade exposure predicts a significant increase in years receiving SSDI as the primary income source. Applying our 75th and 25th percentile comparison among manufacturing workers, the more trade-exposed worker spends an additional half month receiving SSDI benefits as the primary income source during the sixteen year outcome window. To place this magnitude in context, the average manufacturing worker spends approximately five months (0.43 years) over the sample period with SSDI benefits as his or her main income source.⁴⁰

In untabulated results, we repeat the analysis above while replacing receipt of SSDI with receipt of any type of Social Security benefit, which includes Social Security Retirement Income and Supplemental Security Income in addition to SSDI. The results are nearly identical to those in panel A of Table 4, indicating that almost all of the responsiveness of Social Security benefits to import penetration is coming through SSDI. This feature of the results is logical given that our main sample consists of working-age individuals with high-attachment to the labor force who are unlikely to qualify for other types of Social Security payments.⁴¹

Panel B of Table 4 studies more closely the impact of trade exposure on income (rather than employment) by considering self-employment and SSDI income alongside wage income. For purposes of comparison, column 1B repeats the earlier estimate of the effect of trade exposure on total wage earnings. Column 2B finds a negligible impact of trade exposure on self-employment income. Commensurate with the increased duration of SSDI benefit receipts documented in column 3A, column 3B shows a positive and statistically significant effect of trade exposure on receipt of SSDI income (measured in percentage points of the initial average wage). The point estimate of 0.35 implies that a manufacturing worker at the third quartile of exposure receives an additional 2.3%

⁴⁰Workers may exit the labor force and obtain SSDI in the same calendar year without having both sources of income concurrently. In addition, SSDI recipients are permitted to work up to a Substantial Gainful Activity threshold (currently \$1,010 per month for non-blind adults) without jeopardizing their SSDI benefits.

⁴¹Supplemental Security Income is a need-based entitlement for disabled adults. A prior work history is not required to qualify for SSI, but individuals must have very low income and assets. For individuals with significant work history who qualify for SSDI benefits, these benefits will generally place them over the income limits for SSI eligibility.

of initial annual earnings in SSDI benefits relative to a manufacturing worker at the first quartile of exposure. Thus, SSDI benefits only replace a small fraction—about 5 percent—of the income lost to trade exposure.⁴²

Panel C decomposes the increased duration of SSDI benefit receipts into intensive and extensive margin components. While trade exposure significantly increases the likelihood that a worker receives SSDI benefits at some point in the next sixteen years, the impact is modest. Comparing the 75th and 25th percentile manufacturing worker, the increment to the probability of *any* SSDI receipt over sixteen years is only six tenths of a percentage point, with no significant effect on years of receipt conditional on receiving SSDI. This pattern is also evident in the bottom panel of Figure 4, which shows that the effect of trade exposure on the incidence of SSDI receipt cumulates quite slowly over the course of the 16 year outcome window. Thus, disability plays an important role on the extreme extensive margin—among workers who exit the labor force altogether—but the majority of trade-exposed workers remain attached to the labor market, albeit at reduced earnings levels. As our subsequent analysis shows, SSDI provides a more important margin of adjustment for lower wage and less attached workers.

5 Heterogeneity in Worker Adjustment to Trade Exposure

We have so far followed the extensive literature on mass layoffs by limiting our sample to workers with high labor force attachment, defined as those whose labor earnings in each year 1988 to 1991 equaled or exceeded full-time, full-year minimum wage employment. An exclusive focus on highly attached workers may potentially miss an important dimension of heterogeneity in workers' adjustment to adverse shocks. If less attached workers are at greater risk of job displacement or face weaker outside employment options, their employment prospects and earnings may be differentially harmed by adverse trade shocks. Alternatively, if these workers are particularly likely to exit the labor market regardless of circumstances, adverse trade shocks may not greatly alter their career trajectories. We next compare our initial results to estimates for the full sample that includes workers with low labor force attachment, and then extend the analysis to explore heterogeneity in trade adjustment according to workers' firm tenure, age, and earnings levels.

⁴²Our data indicate that SSDI payments average 47 percent of initial average labor earnings for years in which workers in our sample receive SSDI. Thus, if trade exposure affected earnings only through fewer years of employment but not through lower earnings per year of employment, workers who qualified for SSDI could replace a larger fraction of lost earnings through receipt of disability benefits.

5.1 High versus Low Labor-Force Attachment Workers

Table 5 expands our sample to include workers who had *any* labor income in at least one year during 1987-1989 and one year during 1990-1992, which brings our sample size from 508,129 to 880,465. While our data do not contain information on hours worked, it is likely that the expanded sample contains many more part-time and intermittent workers. For consistency with the broadened sample definition, trade exposure is now measured as the average exposure of the industries that employed a worker during the years 1990 to 1992 while the instrument is based on industry affiliation in 1987 to 1989. All firm- and industry-specific control variables are also averaged over 1990 through 1992, and outcomes are measured over the subsequent period of 1993 to 2007.

We begin in panel A of Table 5 by replicating the main specification of Table 4 for the original high labor-force attachment sample while using the suitably modified variable definitions. These changes in variable definitions have no substantive effect on the main estimates. Combining high and low labor-force attachment workers in panel B magnifies trade's negative impact on years worked and positive impact on SSDI reliance. In column 1B of Table 5, the negative coefficient on total years with main income from labor earnings is sixty percent larger in absolute value than the high attachment coefficient in panel A (and is now marginally statistically significant), implying that among low attachment workers, adjustment at the extensive margin of employment is relatively common. In column 2, the reduction in years with main income from self-employment is larger in absolute value terms in the full sample (panel B) than in the high attachment sample (panel A), an outcome that may seem surprising if one imagines that workers with low attachment to wage and salary employment are more likely to participate in self-employment. However, these workers also tend to have relatively low incomes, and for them the loss of wage and salary earnings from a negative trade shock may inhibit business investment.

Columns 3 and 5 capture the differential responsiveness of SSDI take up in the two samples. Extending the sample to include low attachment workers increases the coefficient on cumulative years with SSDI as the main income source by a factor of 2.6 (column 3) and the coefficient on ever receiving SSDI income by a factor of 2.2 (column 5). Because low attachment workers are more likely to exit the labor force after a trade shock, as seen in column 1, they are also more likely to take up SSDI, which is unavailable while workers are gainfully employed. Thus, greater usage of SSDI benefits and larger extensive margin employment adjustments go hand-in-hand.

5.2 Initial Job Tenure and Age

Low tenure workers comprise a second segment of the labor market that is omitted by mass layoff studies. One might hypothesize that seniority-based employment rules insulate older workers from external shocks while exposing younger workers to greater risk of career disruption (Oreopoulos, von Wachter and Heisz, 2012). Alternatively, workers with higher tenure may experience greater losses from trade exposure since their ability to adapt to new employers, industries and skill sets may be more limited (Jacobsen, LaLonde, and Sullivan, 1993). In the first two panels of Table 6, we compare the impact of trade exposure on employment and earnings for workers with low job tenure at their initial firms (defined as less than five years as of 1991) to those with high initial tenure (five-plus years in 1991).⁴³ We apply a condensed version of the specification in Table 3, which disaggregates worker outcomes into three mutually exclusive categories according to employment venue: the initial employer (column 2), subsequent employers in manufacturing (column 3), and employers outside manufacturing or with a missing industry code (column 4).⁴⁴ For reference, Appendix Table 2 displays the average trade exposure of manufacturing workers in both high and low tenure subsamples, as well as the exposure for workers of other subsamples that we explore subsequently. While average trade exposure for low-tenure workers is about one-fourth larger than for high-tenure workers, there is little difference in the timing of exposure within the 1991 to 2007 period. In each subsample that we consider, about one quarter of the increase in trade competition occurs 1991 to 1999, and three quarters in 1999 to 2007, when import growth from China accelerates strongly. The different coefficient estimates for trade impacts on earnings and employment across subsamples of workers cannot therefore be explained by a differential timing of import shocks.

Akin to the Table 5 estimates for low-attachment workers, panels A1 and A2 of Table 6 reveal that the negative impacts of trade exposure on cumulative earnings and on earnings per year worked are substantially larger for the low tenure group. In panel A1, the effect of trade exposure on cumulative earnings for low-tenure workers is 8.7 times as large as the estimated effect for high-tenure workers (panel A2). The difference between low and high tenure workers begins with their experience at the initial employer. Low-tenure workers experience more than twice the reduction in employment years as high-tenure workers, and more than three times the loss in earnings at the initial firm (panels A1 and A2, column 2). Subsequently, low tenure workers make up almost none of these earnings losses through additional earnings from other employers (panel A1, columns 3 and 4). The comparatively modest but still negative and significant cumulative earnings losses for high tenure workers at the

⁴³The low and high-tenure groups are drawn from our primary sample with high-attachment workers.

⁴⁴For workers initially employed in manufacturing, 'same sector' and 'other sector' denote manufacturing and non-manufacturing, respectively.

initial firm are offset—by a factor of nearly two-thirds—through gains at employers outside the initial sector (panel A2, column 4).

One reason low tenure workers may be more affected by trade is simply that they are young, with employers preferring to sever ties first with those having less labor-market experience. Panels B1 and B2 of Table 6 separate workers by age, with the younger cohort being 22 to 35 years old in 1992 and the older cohort being 36 to 49 years old in that year. Coefficient estimates are modestly larger for the younger workers, but the difference between the two groups is slight and statistically insignificant. Thus, the larger impacts of trade on low tenure workers in panels A1 and A2 appears to be driven more by their brief attachment to their initial employer than by their youth.

5.3 Estimates by Initial Earnings Level

The clear pattern emerging from Tables 5 and 6 is that workers who have a weaker foothold in the labor market suffer the largest proportionate earnings losses from trade shocks. This suggests more broadly that the adverse effects of trade shocks may be greatest for workers with low earnings capacity, a possibility that we explore in Table 7 by separately estimating the impact of trade on workers subdivided into terciles of average annual pre-exposure earnings (1988 through 1991) *relative* to others in their age cohort. By making within-cohort comparisons, this sample split captures differences in earnings capacity that are likely to stem from factors such as education and ability—not directly observable in our data—rather than experience and seniority.

Table 7 confirms that the adverse impacts of trade exposure on worker outcomes are inversely monotone in earnings. Column 1 of the top panel finds a large and highly significant negative estimate of the impact of trade exposure on cumulative earnings of bottom-tercile workers. Scaling by the 75/25 metric, the point estimate implies that a low-wage worker in manufacturing at the 75th percentile of exposure loses 1.2 (-18.3×6.7) additional years of initial annual earnings over the subsequent sixteen years relative to a worker at the 25th percentile of exposure. This effect is nearly three times as large as the impact for the full sample (Table 1, column 9).⁴⁵ In comparison, the estimated impact for middle-tercile workers (panel B) is only half as large as the impact for bottom tercile workers, while the estimated impact for top-tercile workers is essentially zero.

Why are the adverse impacts much larger for low than high-wage workers? One possibility is

⁴⁵In unreported results, we estimate regressions parallel to those in Table 7 for men and women separately. When dividing the sample by the initial wage, the impacts of trade shocks on male and female earnings and employment within each wage group are very similar. However, it merits note that women constitute a relatively higher fraction of low-wage workers. In the high attachment sample, 46% of all women are in the bottom wage tercile while only 21% of women are in the top tercile. Consequently, when dividing the sample by sex, but *not* by the initial wage, the impact of trade shocks on women is larger than for men.

that import competition differentially reduces firms' demand for lower skill workers while leaving the careers of high-wage workers relatively unscathed. The subsequent rows of Table 7 do not support this conjecture. High, middle and low-wage workers all experience similar (and large) declines in their earnings obtained from the initial employer (column 2). What differs between these earnings groups is their subsequent labor market adjustments. High-wage workers appear to recover from initial shocks by moving out of the shocked sector. Middle and low-wage workers are much less able to offset those losses through sectoral mobility. We estimate that high-wage workers on average make up about one-fourth of their loss with the initial employer through additional earnings from other firms in the same sector (column 3), and they recoup most of the remaining three-fourths at employers outside of the sector (column 4). Middle-wage workers, by contrast, replace around one-third of earnings lost with the initial employer through earnings elsewhere in the same sector, and they suffer further losses outside of the original sector. At the further extreme, low-wage workers experience no offsetting increase in earnings within the same sector, and they accrue even larger earnings declines outside of the original sector.

The second row of Table 7 offers further insight into the adjustment process by focusing on years of employment rather than cumulative earnings. Workers at all wage levels experience substantial reductions in years of employment at the initial employer, with the magnitude of this reduction nearly twice as great for high-wage relative to middle or low-wage workers. Nevertheless, all three groups appear to largely offset lost earnings *years* (though not lost earnings) at the initial firm through additional employment. But their subsequent employment venues differ substantially. Low-wage workers primarily offset lost employment years at the initial firm with employment elsewhere in the manufacturing sector; middle-wage workers offset losses with extra employment both inside and outside manufacturing; and high-wage workers appear primarily to obtain new employment outside manufacturing—highlighting that these workers are particularly mobile across firms and industries.

The third row of each panel in Table 7 completes the picture. The fact that low and middle-wage workers see substantial drops in cumulative earnings without a decline in years of employment implies that their earnings per year of work have fallen. Among low-wage workers, the implied 75/25 differential loss in earnings per year amounts to 7.8% (-1.2×6.7) annually, while for middle-wage workers, the in-year earnings losses are only approximately half as large. Finally, for high-wage workers, no adverse earnings effects are evident.⁴⁶ We conclude that trade adjustment is particularly costly for less attached, lower tenure, and lower wage workers.

⁴⁶It is likely that some of the reduced earnings among low-wage and middle-wage workers is due to reduced work hours rather than reduced hourly pay, although unfortunately, our data do not allow us to explore this margin further.

5.4 Trade Shocks Seen Through the Lens of Mass Layoffs

Our results make evident that workers with low earnings are differentially impacted by trade shocks. No such distinctions between low and high-wage workers appear in the literature on mass layoffs, where low and high-skill workers are found to fair equally poorly subsequent to large contractions in their initial firms. How do we reconcile our results on adverse trade impacts for low-wage workers with the absence of differential outcomes following mass layoffs?

In Table 8, we examine when and how workers separate from their initial employer in response to changes in trade exposure, and also consider the wage changes associated with these separations. The dependent variable in columns 1 to 4 is an indicator for exit from the initial firm. In column 1, exit is defined as separation from the initial employer any time during the 1992 to 2007 period. The positive and significant coefficient, consistent with results in Table 3, shows that more trade exposed workers are more likely to separate from their initial place of work. Reading down the rows for column 1, the effects are about one-and-a-half-times larger for low-wage workers (panel B) as for middle or high-wage workers (panels C and D). Columns 2 to 4 divide exits into three mutually exclusive categories according to their timing, such that the coefficients in columns 2 to 4 sum to that in column 1: exits that occur within two years after the start of the first mass layoff at the initial firm (column 2), exits within two years *before* a mass layoff at the initial firm (column 3), and exits that did not occur just before or during a mass layoff (column 3).⁴⁷

For the full sample in panel A, separations during the two years of the first recorded mass layoff episode at the firm (column 2) account for about three-fourths of the total trade-induced separation effect (column 1). The contribution of mass layoff separations to total separations is highest among low-wage and middle-wage workers (panels B and C), at 85% (.430/.508) and 92% (.325/.352), and lowest among high-wage workers, at 60% (.216/.355). Separations from the initial employer immediately *before* a mass layoff have the opposite pattern, accounting for over a quarter of trade-induced separations for high-wage workers but less than one-fifth of separations among low-wage workers. While trade exposure significantly increases the likelihood that a low-wage or middle-wage workers leaves the initial firm during a mass layoff, the only significant effect among high-wage workers is for separations *before* mass layoffs.

How a worker separates from a firm appears to be associated with the accompanying wage loss, as shown in columns 5 to 7 of Table 8, which display the change in earnings from a worker's penultimate

⁴⁷A mass layoff is defined as in von Wachter, Song and Manchester (2009): an event in which employment at a firm with at least 50 initial employees contracts by at least 30% over the course of two years, with less than half of the displaced workers moving to a common new employer. Column 3 in Table 8 includes separations from initial firms that had no mass layoffs during the sample period.

year at the initial firm to the second year after the separation, measured as a fraction of an initial annual wage. For low-wage workers (panel B), the impact of trade on wage loss from a pre-mass layoff separation (column 5) or post-mass layoff separation (column 6) is identical up to two decimal places. Yet, for high-wage workers (panel D), the pattern differs sharply. Trade-induced separations from the initial employer that occur *during* a mass layoff have negative wage repercussions for high-wage workers (column 5), but there is zero wage effect from their separations that occur *before* a mass layoff (column 6). Thus, high-wage workers are relatively likely to separate from initial employers before a mass layoff occurs and to see no negative wage effects from such exits. One interpretation for this pattern is that high-wage workers anticipate impending cuts at their initial firms, and proactively search for alternative employment opportunities that allow them to leave the initial firm without a loss in earnings. Low-wage workers, by contrast, suffer significant wage hits whether they separate from initial employers before or during a mass layoff, reflecting their poor prospects for discovering or matching with new employers that provide comparable earning opportunities.

The difference in pre-mass layoff separations between low and high-wage workers is, naturally, absent in the mass layoff literature. Referring to Table 8, an analysis applying the Jacobsen-LaLonde-Sullivan approach would only capture the relatively similar earnings hits to low and high-wage workers that occur after a mass layoff, shown in column 5, and would miss the contrasting experiences between these two groups prior to such a layoff, seen in column 6. Putting all separations together, exits from the initial firm appear to be scarring for low-wage workers no matter when they occur, whereas for high-wage workers the exits that are most painful are those that occur as part of a major contraction at their initial employer. The inclusion in our data of separations that occur prior to mass layoffs therefore contribute to explaining the relatively large differences that we find in the impact of adverse shocks on the earnings of low-wage versus high-wage individuals.

6 Heterogeneity in Trade Adjustment by Firm Characteristics

While the labor literature focuses on whether worker heterogeneity is important for understanding adjustment to labor market shocks, the trade literature treats firm heterogeneity as an essential feature in how industries respond to import competition. Do the characteristics of the initial firm matter for how workers adjust to trade exposure? In the influential Melitz (2003) model, larger, more productive firms are more likely to export and less likely to exit production in response to a reduction in import barriers. These predictions are supported by a substantial body of evidence

that documents a positive correlation between exporting and measures of firm size, average wages, TFP, skill intensity, and capital intensity (Bernard, Jensen, Redding, and Schott, 2007). Next, we examine whether workers in larger or higher-paying firms fare better in response to import growth.

Table 9 considers the impact of exposure to trade on cumulative earnings, cumulative years of employment, and cumulative earnings per year worked for individuals based on the characteristics of their employer in 1991. The first two panels separate firms by whether average earnings per employee in 1991 was below the median (panel A1) or above the median (panel A2) in the employment-weighted sample of firms that are represented in our data extract; the second two panels separate initial employers by size, with the first group having 1 to 999 employees in 1991 (panel B1) and the second group have 1000 or more employees in that year (panel B2).⁴⁸

Column 1 shows that for a given trade shock, workers employed in low-wage firms suffer losses in cumulative earnings that are 2.5 as large as do workers in high-wage firms (column 1 of panels A1 and A2). These differences arise primarily because workers who are initially employed at low-wage firms experience a greater trade-induced decline in earnings per year of employment during the outcome period (column 3), and specifically at their initial firm (column 6). By contrast, workers of high-wage firms experience comparatively smaller declines in earnings per year worked at the initial firm (column 6), though they have equally large reductions in their years of employment with that firm (column 5). The adverse outcomes for workers of low-wage firms, which stem from lower earnings per employment year rather than fewer years with employment, are consistent with the adverse results for low-wage workers in Tables 7 and 8.

Somewhat less expected is the pattern of worker adjustment by initial employer size. In panels B1 and B2 of Table 9, the trade impact on cumulative earnings is 2.4 times greater for workers initially employed in larger firms (column 1, panel B2) than for those initially employed in smaller firms (column 1, panel B1). Continuing to compare larger (panel B2) versus smaller (panel B1) employers, workers starting out in larger employers have greater trade-induced reductions in cumulative years worked (-1.7 versus 0.05, column 2) and substantially greater reductions in cumulative years worked at the initial firm (-15.5 versus -2.3, column 5), with the latter effects significant. Further, workers from larger employers endure greater trade-related reductions in cumulative earnings per year worked over both the entire sample (-0.8 versus -0.3, column 3) and while employed at the initial firm (-0.5 versus -0.2, column 6), with all coefficients significant. Across the board, the adverse consequences

⁴⁸Our sample contains information on total employment and total wage bill by firm that is drawn from the full population of the Social Security Master Earnings File. We use this information for the construction of control variables in the regression analysis, and for the sample split of firms by average wage level here.

of trade shocks are decidedly elevated for workers starting out in larger enterprises.⁴⁹

Combining the insights of sections 5 and 6, we see that workers differ in their adjustment to increased import competition according both to variation in their initial earnings, job tenure, and attachment to the labor force and to variation in the average pay and employment size of their initial employers. The last of these results seems at odds with Melitz (2003). We are however not the first to show that workers in larger firms are more affected by labor-market shocks. Following mass layoffs, Jacobsen, LaLonde, and Sullivan (1993) and von Wachter and Bender (2006) find that earnings losses are greatest for workers separated from the largest employers. Biscourp, and Kramarz (2007), using French data, report that in large firms (but not small firms), import growth at the firm level is positively correlated with job destruction. Holmes and Stevens (2010) obtain similar results in U.S. data, based on a calibrated model that allows for one group of firms that produce standard goods subject to heterogeneous productivity as in Melitz (2003), and a second group of specialty firms that produce customized goods for particular clients. Standard firms are both relatively large and more exposed to trade competition, resulting in their contracting more sharply in response to a surge in imports. Whether one adopts Holmes and Stevens or some other framework, a departure from the basic Melitz model appears necessary to account for the vulnerability of workers initially employed in larger employers to increases in import competition.

7 Alternative Specifications

In this section, we describe alternative measures of industry exposure to import growth from China or other low-wage countries. Using these measures, we re-estimate the regressions for cumulative earnings, cumulative employment years, and earnings per year of employment from panel A of Table 2. Table 10 contains the results, with baseline estimates from Table 2 reproduced in panel A. The alternative measures of trade exposure are the following:

(i) *Gravity-based measure of trade exposure.* Our strategy for identifying the impact of trade exposure as measured in equation (3) is based on the assumption that growth in imports from China in high income countries is due to supply shocks in China, or global changes in trade policy toward China, rather than due to import demand shocks in these countries. As an alternative to instrumenting for observed U.S. imports from China with other wealthy countries' imports from China, we determine the supply shock component of import growth from China using the gravity

⁴⁹We have also explored a four-way split of the sample by firm size and average wage. Consistent with the results reported in Table 9, trade-induced earnings losses are largest for workers in large low-wage firms and smallest in small high-wage firms, though results are less precisely estimated in the smaller samples resulting from a four-way split.

model of trade. With data on bilateral imports by high income countries at the industry level over 1991 to 2007, we estimate a gravity model in which the dependent variable is log industry imports from China minus log industry imports from the United States and the regressors are dummy variables for the importing country, dummy variables for the industry, and standard controls for trade costs. Taking the China-U.S. difference in log imports removes from the data variation in trade associated with import demand shocks in the destination market that are common across sources of supply. Changes over time in the residuals from this regression represent the change in China’s comparative advantage and trade costs in an industry relative to the United States, which is directly analogous to the term, $(\hat{A}_{cj} - \theta \hat{\tau}_{ncj})$, in equation (2). Following the procedure described in the appendix to Autor, Dorn, and Hanson (forthcoming), we use these residuals to construct an alternative measure of import growth. This approach, shown in panel B of Table 10, allows us to estimate the impacts of trade exposure under weaker identifying assumptions. Since we have neutralized market-level import demand in the gravity estimation, the new identifying assumption is that changes in China’s comparative advantage are uncorrelated with U.S. product demand shocks (to the extent that any covariation remains in the data, it would tend to bias coefficients on import penetration in the cumulative earnings regressions toward zero).

(ii) *Other low-income countries.* Changes in import penetration from China may overstate the change in trade exposure for U.S. workers if China competes with other low-wage countries in the U.S. market. One worry is that imports from China simply displace other countries’ exports to the United States. To address this concern, we add to imports from China imports from all other low-income countries. Given that China accounts for over 90 percent of recent growth in U.S. imports from low-wage economies, this modification is unlikely to materially affect the trade penetration measure. Results using this measure of trade exposure are shown in panel C of Table 10.

To provide further comparisons with alternative low-wage-country sources of U.S. imports, we replace import penetration from China with import penetration from Mexico and Central America. Results for this outcome are in Panel D of Table 10. Over the sample period, Mexico had minimal industrial productivity growth (Hanson, 2011), making U.S. demand shocks a relatively important driver for growth in U.S. imports from Mexico, especially when compared to China. We would therefore expect our instrumentation strategy to perform poorly for Mexico, as absent strong export supply shocks its shipments to high income countries would be particularly subject to idiosyncratic demand shocks in these markets. Below, we confirm that growth in import penetration from Mexico and Central American has effects that are economically small and statistically insignificant.

(iii) *Other destination markets.* Growth in China’s exports affects U.S. industry output not just

through intensifying competition in the U.S. consumer market but also in foreign markets in which U.S. firms compete with China. Following this logic, we expand the definition of import penetration in equation (3) to include all destination markets to which U.S. industries export goods. Results using this measure of trade exposure are shown in panel E of Table 10.

(iv) *Net imports.* China's growth causes an increased supply of goods to the U.S. market but may also increase demand for U.S. exports. To account for U.S. exports to China, we also measure trade exposure using *net* imports rather than gross imports, which allows U.S. exports to China to offset some of the loss in production from greater import penetration. Because U.S. manufacturing imports from China are six times larger than U.S. manufacturing exports to China, this change is unlikely to have a large effect on the trade exposure measure. Results using this measure of trade penetration are shown in panel F of Table 10.

(v) *Factor content of trade.* If the labor content of production varies across goods that China ships to the U.S. market, measuring trade in dollar terms may not accurately capture the impact of import growth on U.S. workers (Deardorff and Staiger, 1988; Borjas, Freeman, and Katz, 1997; Burstein and Vogel, 2011). To account for differences in labor intensity across sectors, we measure net imports in worker equivalent units, using direct and indirect labor usage in the production of industry outputs, based on the 1992 U.S. input-output table. Our measure calculates industry exposure to trade by imputing labor services embodied in net imports using net imports times employment per dollar of gross shipments in U.S. industries (\tilde{L}_{j0}/Y_{j0}), where we measure L_{j0} based on the *direct plus indirect* employment of labor used to manufacture goods in an industry.⁵⁰ Results using this measure of trade exposure are shown in panel G of Table 10.

(vi) *Intermediate inputs.* Growth in exports by China represents not just greater competition for U.S. producers but also greater supply of inputs that U.S. industries require, which may positively affect U.S. productivity (Goldberg, Khandelwal, Pavcnik, and Topalova, 2010). To account for input supply effects, we adjust total industry imports for imports of intermediate inputs by netting out the latter. Results using this measure of trade exposure are in panel H of Table 10.

Table 10 documents that each of these alternative measures of trade exposure has a negative impact on cumulative earnings of workers over the 16-year sample period, consistent with the main results in Table 2. The estimated effects are statistically significant in all setups except for panel D, where import penetration is measured for Mexico and Central America and not for China. Results for

⁵⁰That is, \tilde{E}_{uj0} is the component for industry j of the vector $\mathbf{E}(\mathbf{I}-\mathbf{C})^{-1}$, where \mathbf{E} is the vector of direct employment in each industry, \mathbf{C} is the industry input-output matrix, and \mathbf{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.

cumulative years with positive earnings and for cumulative earnings per year worked also reflect the pattern of our main specification in Table 2, which documented particularly strong negative effects of exposure to Chinese imports on earnings per year, and more modest effects on employment years. The estimates in Table 10 add substantial credibility to the robustness of our results to alternative specifications of rising import competition from China.

8 Conclusion

China’s spectacular export growth in recent decades provides a rare opportunity to examine how workers adjust to trade shocks. Changes in trade flows typically have myriad causes and are jointly determined with other outcomes of interest. In the case of China, its economically backward state at the time the country began to open to foreign trade and investment meant that its subsequent export growth would be driven by the convergence of its economy toward the global technology frontier rather than by idiosyncratic shocks in its trading partners. We exploit this feature of recent Chinese history to examine how U.S. workers adjust to a surge in imports in their initial industries of employment. Data from the Social Security Administration give us a unique longitudinal perspective over an extended period of time to observe how workers respond to greater import competition.

Workers who in 1991—prior to China’s rapid growth—were employed in an industry that was subsequently exposed to greater import competition from China experienced over the 1992 to 2007 period lower cumulative earnings, weakly lower cumulative employment, lower earnings per year worked, and greater reliance on Social Security Disability Insurance. Exposure to trade induces workers to move between employers and between industries. Workers initially employed in industries with larger increases in import competition were more likely to leave their initial employer, more likely to leave their initial two-digit industry, and more likely to leave manufacturing overall.

There is considerable heterogeneity across workers in adjustment to import competition, which distinguishes our work from previous analyses that examine the labor market consequences of mass layoffs or intensifying import competition. Reductions in cumulative earnings are concentrated among workers with low initial wages, workers with low tenure at their initial firm, workers with weak attachment to the labor force, and those employed at large firms with low wage levels. Trade competition also affects the careers of high-wage workers, who are able to rapidly separate from their initial employers and move to other firms, often outside manufacturing. High-wage workers frequently make these adjustments prior to large-scale layoffs at their initial firm, and without notable declines in earnings. Low-wage workers instead stay longer in their initial trade-exposed

firms and industries, are more likely to separate from their initial firm during mass layoffs, and incur greater losses of earnings both at the initial firm and after moving to other employers. Our results are robust to including a large set of worker, firm and industry controls, to using alternative measures of trade exposure, and to falsification tests which verify that future increases in trade exposure do not predict past changes in worker outcomes by industry.

We focus on import growth from China while recognizing that China actively participates in global production networks. Goods exported by China use inputs produced in other developing economies and in high-income countries. Still, China's enormous size and its rapid rate of technology convergence means that its own growth has been a major impulse for the expansion of global production networks in recent decades. Our findings do not preclude a role for other countries in the recent growth in U.S. imports of labor-intensive manufactures.

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Data appendix

Social Security Data

Our main source of data is the Annual Employee-Employer File (EE), an extract from the Master Earnings File (MEF) of the U.S. Social Security Administration that provides longitudinal earnings histories for a randomly selected one percent of workers in the United States. This data provides annual earnings, an employer identification number (EIN), and a Standard Industrial Classification (SIC) code for each job that a worker held. Our analysis draws on information covering the years 1972 through 2007. For workers who have multiple jobs in a given year, we aggregate earnings across all jobs and retain the EIN of the employer that accounted for the largest share of the worker's earnings. Earnings data is inflated to 2007 using the Personal Consumption Expenditure Index, and annual uncapped earnings are Winsorized at the 99th percentile of each year's wage distribution in order to mitigate the impact of outliers on the empirical analysis. We augment the EE data with individual-level information on birth year, sex, race and immigrant status (U.S. or foreign born) from the SSA's NUMIDENT file which records information from Social Security card application forms. We code race as non-white if the race indicator is missing in the data, which is the case for about 3.5% of all observations. We also add information on annual uncapped self-employment earnings from the MEF (available since 1992), and on Social Security benefit entitlement and benefit amounts from the Master Beneficiary Record (MBR). The Social Security program that is most relevant for our study of working-age individuals is Disability Insurance.

For about 97% of all employees in 1991, we are able to match the EIN of the employer to firm data that provides information on industry and firm size, measured by total employment and payroll in the complete MEF data. The industry classification is based on firms' registration with the Internal Revenue Service (IRS). Coders at the Social Security Administration transform the write-in information from the IRS form to a four-digit SIC code, or to a three-digit or two-digit SIC code if the description of firm activity is not sufficiently detailed to permit a preciser classification. The IRS switched from a paper-based application for obtaining an EIN to an online application procedure in the year 2000 and the Standard Industrial Classification was replaced by the North American Industry Classification System (NAICS) starting in 1997. For a large portion of new firms that have been incorporated as of these years, we are no longer able to observe industry codes.

Our main sample comprises workers who were born between 1943 and 1970. We use this sample to study outcomes during the period 1992 to 2007 when these workers were between 22 and 64 years old. The sample is restricted to workers who were earning at least \$8,193 per year in each of the four

years 1988 to 1991, prior to the outcome period. The value of \$8,193 (in 2007 dollars) corresponds to the earnings of a worker who was employed during 1,600 annual hours at the Federal minimum wage of 1989. The sample size of this main sample is 508,129. We also show additional results for an extended sample that includes workers with a weaker labor force attachment. This alternative sample comprises the 880,465 workers who had positive earnings (and a valid industry code) during at least one year in each of the three-year periods 1987 to 1989 and 1990 to 1992.

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 four-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. We also aggregate the trade data to three-digit and two-digit SIC industries in order to construct measures of import exposure for firms whose industry is not identified at the four-digit level in the Social Security Administration data. Details on our industry classification are available on request. Second, we combine the HS-SIC 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 SIC industries. All import amounts are inflated to 2007 US\$ using the Personal Consumption Expenditure deflator.

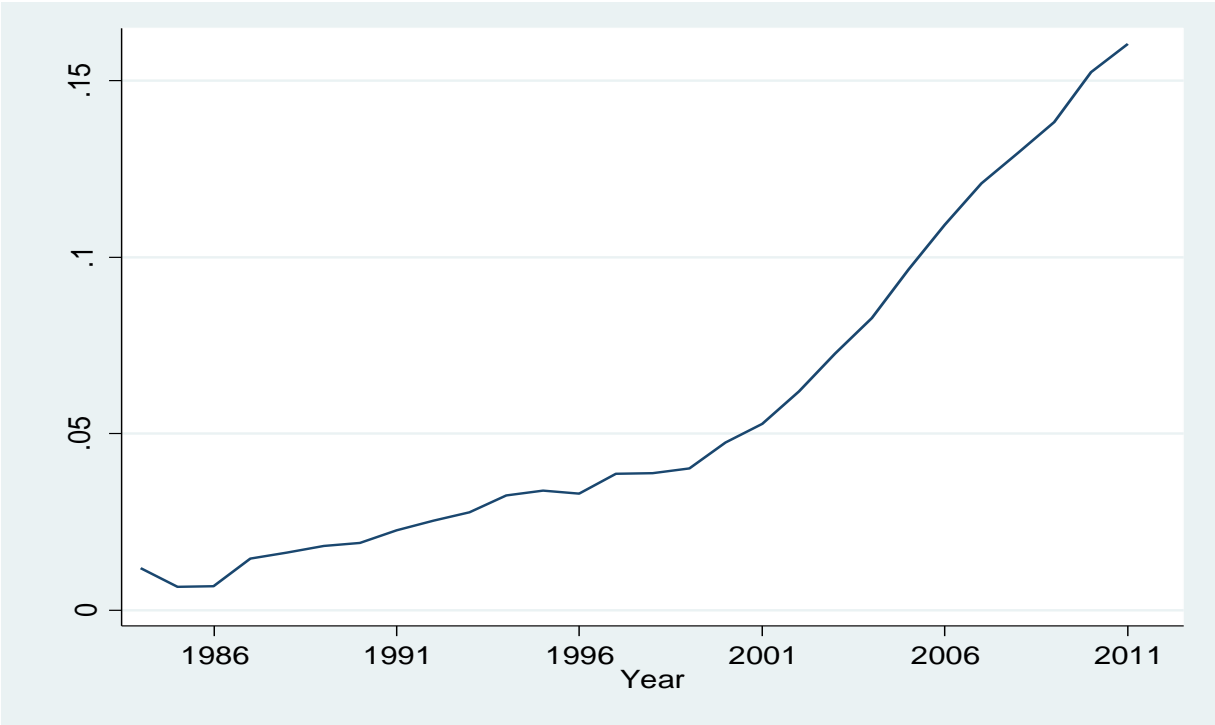


Figure 1.
China Share of World Manufacturing Exports, 1984-2011.

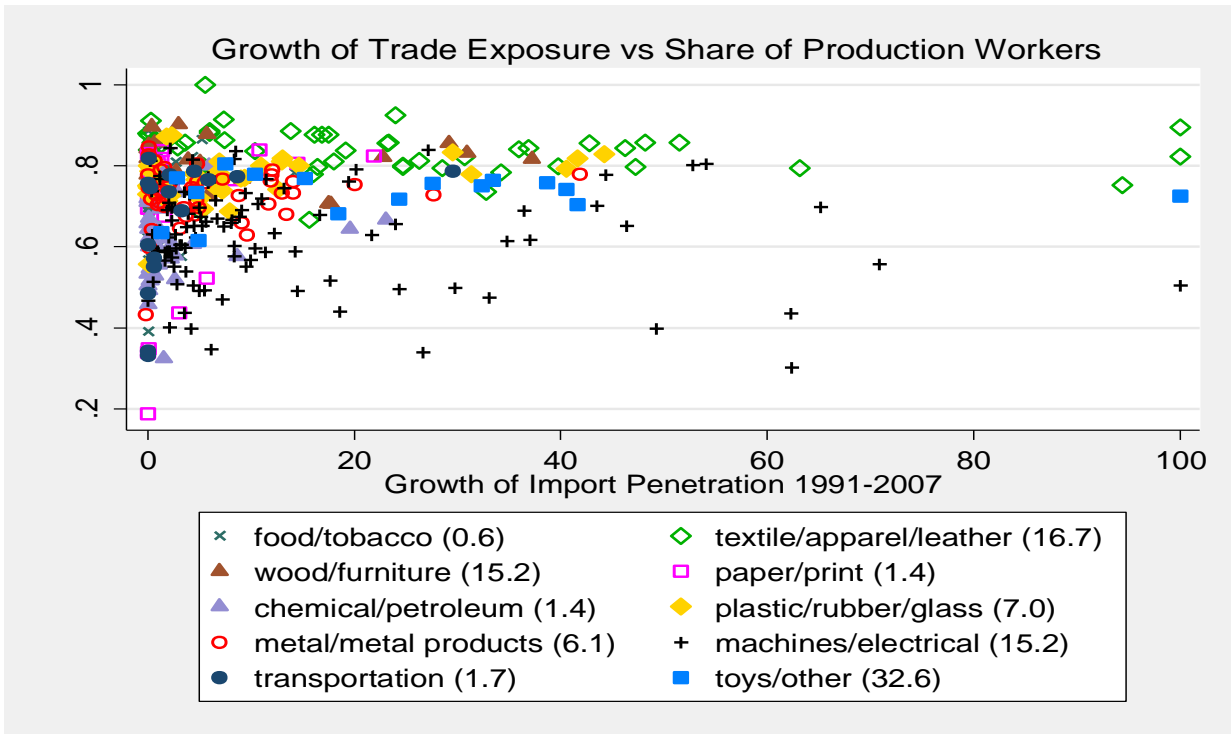


Figure 2.
Trade Exposure and Production Worker-Intensity by Industry.

Notes: Numbers in parentheses in the legend indicate average growth of import penetration within industry group, weighted by 1991 employment. Values for growth of import penetration are winsorized at 100.

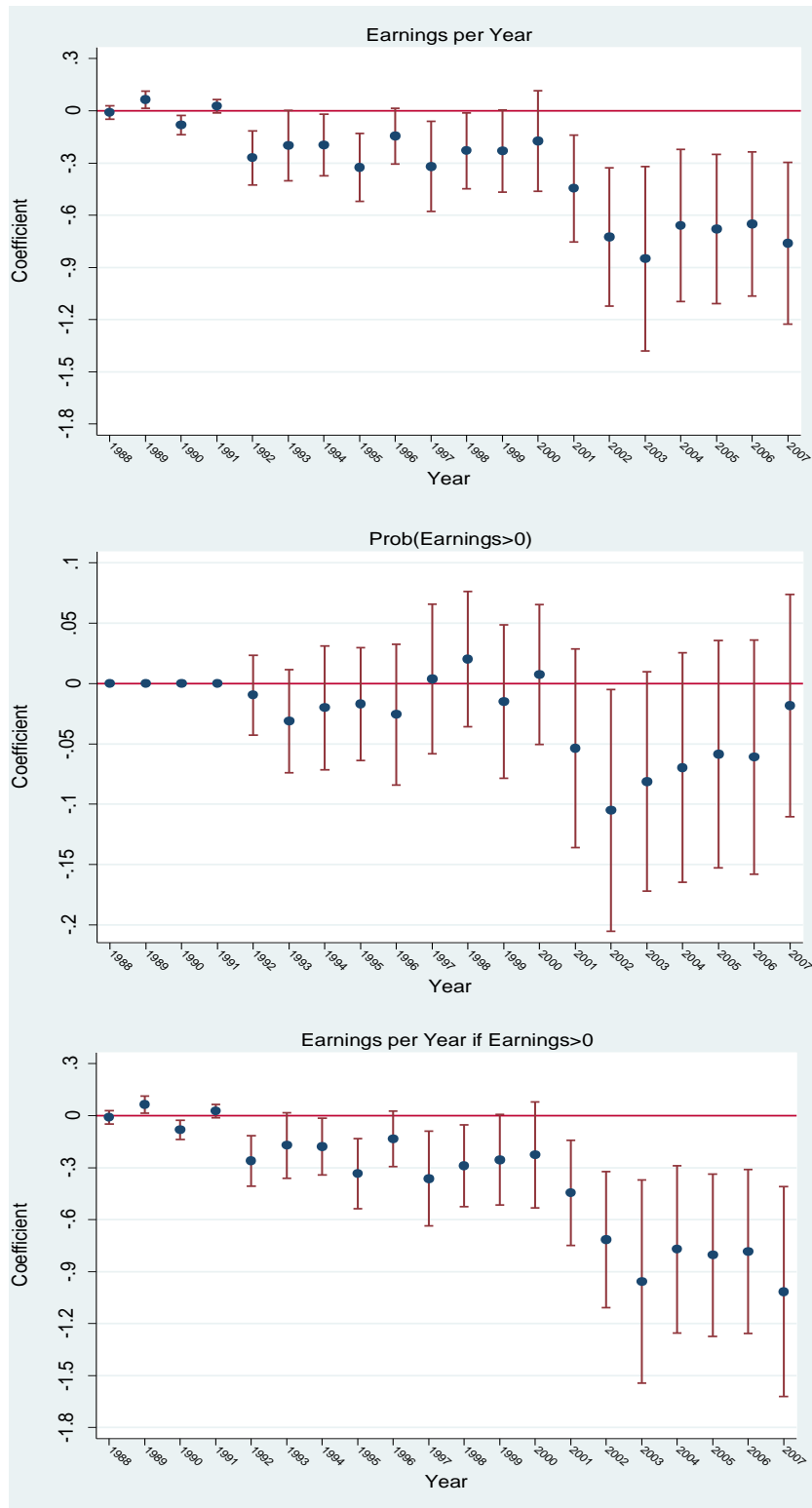


Figure 3.
Year-by-Year Regression Results for Main Outcomes.

Notes: Each panel plots the regression coefficients and 90% confidence intervals obtained from up to 20 regressions. The regressions relate the outcome indicated at the top of each panel, and measured during the year indicated on the x-axis, to the trade exposure of workers' 1991 industry. All regressions include the vector of control variables from column 9 of Table 1. Note in the second panel that all workers have positive earnings during the years 1988 to 1991 due to sample construction.

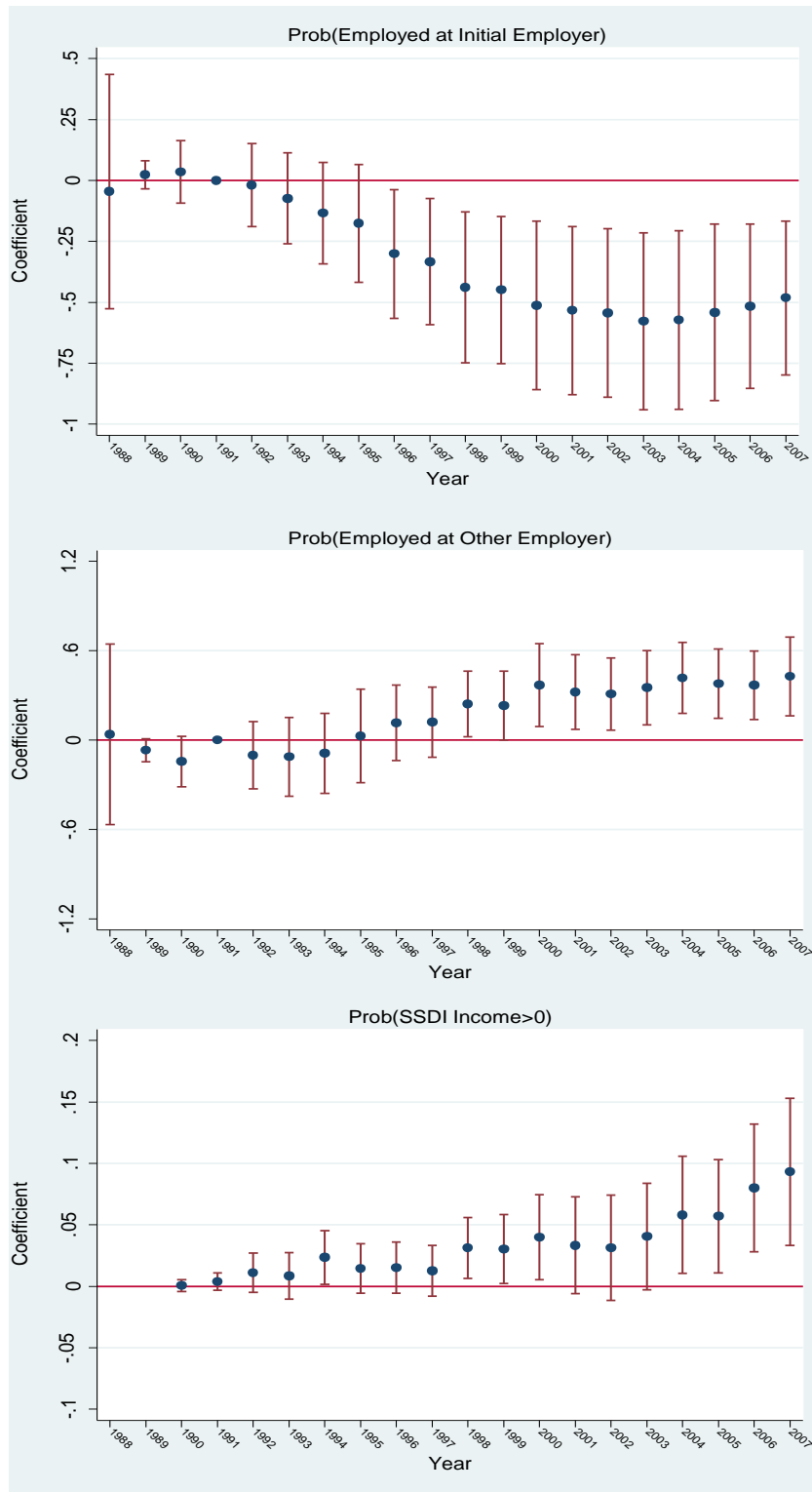


Figure 4.
 Year-by-Year Regression Results for Probability that Worker is (a) Employed by Initial Employer, (b) Employed with a New Employer; (c) Receiving SSDI Income

Notes: Each panel plots the regression coefficients and 90% confidence intervals obtained from up to 20 regressions. The regressions relate the outcome indicated at the top of each panel, and measured during the year indicated on the x-axis, to the trade exposure of workers' 1991 industry. All regressions include the vector of control variables from column 9 of Table 1. Note that our data set contains SSDI payments only since 1990.

Table 1. Imports from China and Cumulative Earnings, 1992-2007: OLS and 2SLS Estimates.
 Dependent Var: 100 x Earnings 1992-2007 (in Multiples of Initial Annual Wage)

	2SLS								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Δ China Imports)/ US Consumption ₉₁	-2.939 * (1.150)	-5.726 * (1.425)	-6.017 ** (1.475)	-6.099 ** (1.395)	-6.883 ** (1.351)	-6.436 ** (2.450)	-5.695 * (2.326)	-6.728 ** (2.392)	-6.864 ** (2.477)
(China Imports ₉₁)/ US Consumption ₉₁						13.134 (9.308)	22.089 ** (7.544)	21.739 ** (7.103)	21.760 ** (7.287)
(Non-China Imports ₉₁)/ US						-1.841 (1.390)	1.495 (1.121)	1.995 ~ (1.201)	1.975 (1.216)
Birth year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Demographic controls			yes	yes	yes	yes	yes	yes	yes
Employment history				yes	yes	yes	yes	yes	yes
Earnings history					yes	yes	yes	yes	yes
10 mfg industry							yes	yes	yes
Industry characteristics								yes	yes
Pretrends ind emp and wage									yes

Notes: N=508,129. All regressions include a constant and a full set of birth year dummies. Demographic controls in column 3 include dummies for female, non-white and foreign-born. Employment history controls in column 4 include dummies for tenure at 1991 firm (0-1, 2-5, 6-10 years), experience (4-5, 6-8, 9-11 years), and size of 1991 firm (1-99, 100-999, 1000-9999 employees). Earnings history controls in column 5 include the worker's annual log wage averaged over 1988-1991, an interaction of initial wage with age, and the change in log wage between 1988 and 1991, as well as the level and trend of the 1991 firm's log mean wage for the period 1988-1991. Columns 6-9 add controls for a worker's 1991 manufacturing industry, starting with initial trade penetration by Chinese and non-Chinese imports in column 6 (coefficients indicated in the table). Column 7 add dummies for 10 manufacturing sub-industries, column 8 adds 1991 levels for employment share of production workers, log average wage, capital/value added, and 1990 levels for computer investment, share of investment allocated to high-tech equipment, and fraction of intermediate goods among imports in 1990, and column 9 additionally controls for changes in industry employment share and log average wage level during the preceding 16 years (1976-1991). Robust standard errors in parentheses are clustered on start-of-period 3-digit industry. ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

Table 2. Imports from China 1992-2007 and Cumulative Earnings, Years with Earnings, and Earnings per Year 1992-2007 and 1976-1991: 2SLS Estimates.

Dep Vars: 100 x Cumulative Earnings; 100 x Years with Earnings; 100 x Earnings per Year of Employment (in Multiples of Initial Annual Wage)

	Cumulative Earnings		Years w/ Earnings>0		Earnings/ Year	
	(1)		(2)		(3)	
<u>A. Treatment Period 1992-2007</u>						
(Δ China Imports)/ US Consumption ₉₁	-6.864 (2.477)	**	-0.535 (0.505)		-0.393 (0.140)	**
<u>B. Pre-Period 1976-1991</u>						
(Δ China Imports)/ US Consumption ₉₁	-0.432 (1.996)		0.695 (0.856)		-0.064 (0.112)	

Notes: N=508,792 in Panel I and N=301,490 in Panel II, except N=506,339 and N=300,239 in column 3 where the dependent variable is not defined for individuals who are never employed during the entire outcome period. Regressions in Panel I include the full control vector from column 9 of Table 1. Regression in Panel II include the same controls except tenure, experience and firm size; and industry-level controls are measured either for 1975 or for 1972 (intermediate imports, computer investment and high tech equipment). Robust standard errors in parentheses are clustered on start-of-period 3-digit industry. $\sim p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$

Table 3. Imports from China and Earnings and Employment by Firm, Industry and Sector, 1992-2007: 2SLS Estimates.

Dep Vars: 100 x Cumulative Earnings; 100 x Years with Earnings; 100 x Earnings per Year of Employment (in Multiples of Initial Annual Wage)

Same 2-digit Industry? Same Firm?	All Em- ployers	Same Sector			Other Sect	N/A
		Yes	Yes	No	No	N/A
		Yes	No	No	No	No
	(1)	(2)	(3)	(4)	(5)	(6)
<u>A. Cumulative Earnings (in Initial Annual Wage*100)</u>						
(Δ China Imports)/ US Consumption ₉₁	-6.864 ** (2.477)	-9.107 ** (3.395)	-2.998 ~ (1.671)	5.914 * (2.326)	-2.253 (3.049)	1.579 * (0.800)
<u>B. Cumulative Employment (in Years*100)</u>						
(Δ China Imports)/ US Consumption ₉₁	-0.535 (0.505)	-6.204 * (2.566)	-2.036 (1.278)	4.654 ** (1.655)	1.451 (1.983)	1.600 * (0.625)
<u>C. Earnings per Year of Emp (in Initial Annual Wage*100)</u>						
(Δ China Imports)/ US Consumption ₉₁	-0.393 ** (0.140)	-0.283 ** (0.093)	-0.543 ~ (0.304)	-0.551 ~ (0.300)	-0.655 * (0.291)	-0.606 * (0.245)

Notes: N=508,129 in panels A and B. N=506,339/424,027/155,993/263,158/112,002/119,989 in columns 1-6 of panel C. Column 6 measures employment and earnings in firms with missing industry information. A large majority of these firms are new firms that have been incorporated between the years 2000 and 2007. All regressions include the full vector of control variables from column 9 of Table 1. Robust standard errors in parentheses are clustered on start-of-period 3-digit industry. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Table 4. Imports from China and Non-Wage Income, 1992-2007: 2SLS Estimates.
 Dep Vars: 100 x Cumulative Years of Indicated Status or Income 1992-2007

	A. Cumulative Years with Main Income from:			
	Wage Earnings	Self-Emp Income	SSDI Income	No Recorded Income
	(1)	(2)	(3)	(4)
(Δ China Imports)/ US Consumption ₉₁	-0.493 (0.498)	-0.127 (0.207)	0.562 (0.268)	* 0.057 (0.367)
	B. Cumulative Income (in Initial Annual Wage*100)			
	Wage Earnings	Self-Emp Income	SSDI Income	No Recorded Income
(Δ China Imports)/ US Consumption ₉₁	-6.864 (2.477)	** -0.007 (0.348)	0.352 (0.164)	* n/a
	C. Years with SSDI Income: Intensive vs Extensive Margin			
	100*Dummy (Yrs SSDI>0)	100*Yrs SSDI if Yrs SSDI>0		
(Δ China Imports)/ US Consumption ₉₁	0.082 (0.035)	* 0.687 (1.298)		

Notes: N=508,129, except N=32,426 in the second column of panel C. The dependent variable in the first column of Panel C is a dummy for individuals who received SSDI benefits in at least one year during 1992 to 2007 and the dependent variable in the second column of Panel C is the number of calendar years with SSDI benefits conditional on receiving benefits in at least one year. All regressions include the full vector of control variables from column 9 of Table 1. Robust standard errors in parentheses are clustered on start-of-period 3-digit industry. $\sim p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Table 5. Imports from China and Cum. Years of Emp and SSDI Receipt by Worker Sample: 2SLS Estimates. Dep Vars: 100 x Cum. Years with Inc from Indicated Sources and 100 x Dummy for SSDI Inc, 1993-2007.

	Cumulative Years with Main Income from:				100*Dummy (Yrs SSDI>0)
	Wage Earnings	Self-Employmt	SSDI Benefits	No Income	
	(1)	(2)	(3)	(4)	
					(5)
<u>A. Main Sample: High LF Attachment</u>					
(Δ China Imports)/ US Consumption ₉₁	-0.613 (0.415)	-0.152 (0.157)	0.438 * (0.202)	0.327 (0.330)	0.056 * (0.026)
N=508,129					
<u>B. Extended Sample: High and Low LF Attachment</u>					
(Δ China Imports)/ US Consumption ₉₁	-0.991 (0.569)	~ -0.694 (0.301)	* 1.137 (0.431)	** 0.548 (0.426)	0.125 ** (0.043)
N=880,465					

Notes: Panel A includes workers who earned at least the equivalent of a full-time minimum wage job in each of the four years 1988 to 1991. Panel B adds workers with low annual incomes or interrupted careers who were employed at least in one year during 1987-1989, and one year during 1990-1992. All regressions include the full vector of control variables from column 9 of Table 1, except that all industry- and firm-related variables are averaged over those years in which a worker was employed during 1990 to 1992. Robust standard errors in parentheses are clustered on start-of-period 3-digit industry. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Table 6. Imports from China and Earnings and Employment by Firm Tenure and Age, 1992-2007: 2SLS Estimates. Dep Vars: 100 x Cum Earnings; 100 x Years with Earnings; 100 x Earnings per Year of Emp (in Multiples of Initial Annual Wage)

	Outcomes: Overall and by Employer				Outcomes: Overall and by Employer			
	All Firms	Initial Firm	Same Sector	Sect / NA	All Firms	Initial Firm	Same Sector	Sect / NA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<u>A1. Workers w/ Firm Tenure <5 Years</u>				<u>B1. Workers Born in 1957-1970</u>			
Cum Earnings	-15.06 ** (5.53)	-15.53 ** (5.77)	-1.28 (5.02)	1.75 (6.76)	-8.71 * (3.52)	-8.98 ** (3.40)	2.45 (3.37)	-2.18 (4.09)
Cum Yrs Emp	0.84 (0.99)	-9.03 * (3.88)	1.99 (3.14)	7.88 ~ (4.63)	0.94 (0.64)	-4.43 * (2.09)	2.49 (1.78)	2.88 (2.47)
Cum Earn/Yr	-0.95 ** (0.34)	-0.60 ** (0.20)	-1.65 ** (0.60)	-1.22 * (0.51)	-0.61 ** (0.23)	-0.56 ** (0.18)	-1.06 * (0.50)	-0.68 * (0.31)
	<u>A2. Workers w/ Firm Tenure ≥5 Years</u>				<u>B2. Workers Born in 1943-1956</u>			
Cum Earnings	-1.74 ~ (0.94)	-4.99 * (2.08)	0.06 (0.99)	3.20 (1.98)	-5.63 ** (2.03)	-8.39 ** (3.28)	-0.08 (1.94)	2.84 (2.67)
Cum Yrs Emp	-1.27 * (0.59)	-4.18 * (1.86)	0.17 (0.76)	2.74 (1.68)	-1.38 ~ (0.76)	-6.84 * (2.80)	1.42 (1.43)	4.04 (2.49)
Cum Earn/Yr	-0.05 (0.06)	-0.07 (0.06)	0.01 (0.08)	0.13 (0.11)	-0.25 ** (0.09)	-0.09 (0.08)	-0.47 * (0.21)	-0.25 (0.17)

Notes: N=293,816/214,313/236,136/249,921 for Panels A1/A2/B1/B2, except smaller samples for cumulative earnings per year of employment. Columns 4 and 8 report outcomes at firms outside the initial sector and at firms with missing industry information (most of which have been incorporated between 2000 and 2007). All regressions include a constant and the full vector of control variables from column 9 of Table 1. Robust standard errors in parentheses are clustered on start-of-period 3-digit industry. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Table 7. Imports from China and Earnings and Employment by Subgroup of Workers: 2SLS Estimates.

Dep Vars: 100 x Cum Earnings; 100 x Years with Earnings; 100 x Earnings per Year of Emp (in Multiples of Initial Annual Wage)

	<u>Worker Outcomes -- Overall and by Employer</u>			
	All Firms	Initial Firm	Oth Firm, Same Sector	Other Sector/NA
	(1)	(2)	(3)	(4)
<u>A. Initial Wage in Bottom Tercile of Cohort</u>				
Cum Earnings	-18.27 ** (5.76)	-8.78 * (3.84)	0.85 (5.21)	-10.34 * (4.52)
Cum Yrs Emp	-0.20 (1.30)	-4.10 ~ (2.23)	4.50 ~ (2.73)	-0.60 (2.68)
Cum Earn/Yr	-1.16 ** (0.34)	-0.44 ~ (0.24)	-2.71 ** (0.85)	-1.34 ** (0.45)
<u>B. Initial Wage in Middle Tercile of Cohort</u>				
Cum Earnings	-9.93 ** (3.65)	-8.50 ** (3.27)	2.73 (2.38)	-4.16 (3.17)
Cum Yrs Emp	-0.37 (0.65)	-4.43 * (2.03)	2.84 ~ (1.65)	1.22 (1.88)
Cum Earn/Yr	-0.61 ** (0.22)	-0.51 ** (0.17)	-0.67 ~ (0.35)	-0.67 * (0.31)
<u>C. Initial Wage in Top Tercile of Cohort</u>				
Cum Earnings	-0.22 (2.07)	-9.15 ~ (4.69)	2.24 (2.36)	6.69 (5.38)
Cum Yrs Emp	-0.41 (0.55)	-7.79 ~ (4.29)	1.10 (1.59)	6.28 (4.29)
Cum Earn/Yr	0.03 (0.14)	-0.04 (0.12)	0.07 (0.29)	0.03 (0.22)

Notes: N=169,386/169,357/169,386 for panels A/B/C, except smaller samples for cumulative earnings per year. Earnings and employment outcomes are reported cumulative over all firms that employ a worker during the outcome period (columns 1), and separately for the initial firm (column 2), other firms of the same sector (column 3), and firms that are either outside the initial sector or have missing industry information (column 4). All regressions include a constant and the full vector of control variables from column 9 of Table 1. Robust standard errors in parentheses are clustered on start-of-period 3-digit industry. ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

Table 8. Imports from China and Probability of Leaving Initial Firm by Timing of Departure: 2SLS Estimates. Dep Vars: Probability of Indicated Event in Percentage Points, 1992-2007.

	Probability of Exit Initial Firm			E(Δ Earn t-1 to t+2 Exit)		
	At Any Time (1)	w/in 2 yrs during Mass Layoff (2)	w/in 2 yrs before Mass Layoff (3)	w/in 2 yrs during Mass LO (5)	w/in 2 yrs before Mass LO (6)	not w/in 2yrs of Mass LO (7)
<u>A. All Workers</u>						
(Δ China Imports)/ US Consumption ₉₁	0.418 (0.169)	*	0.327 (0.127)	**	0.096 (0.057)	~ (0.099)
(Δ China Imports)/ US Consumption ₉₁	0.508 (0.157)	**	0.430 (0.177)	*	0.098 (0.119)	-0.006 (0.202)
<u>B. Workers with Initial Wage in Bottom Tercile of Cohort</u>						
(Δ China Imports)/ US Consumption ₉₁	0.352 (0.134)	**	0.325 (0.106)	**	0.074 (0.055)	-0.048 (0.101)
<u>C. Workers with Initial Wage in Middle Tercile of Cohort</u>						
(Δ China Imports)/ US Consumption ₉₁	0.355 (0.217)		0.216 (0.132)		0.093 (0.052)	~ (0.124)
(Δ China Imports)/ US Consumption ₉₁						
<u>D. Workers with Initial Wage in Top Tercile of Cohort</u>						
(Δ China Imports)/ US Consumption ₉₁						

Notes: N=508,129/169,386/169,386 for panels A/B/C/D. The first column measures the probability that a worker leaves the 1991 firm at any time during 1992-2007. The next three columns disaggregate the outcome into departures during the first mass layoff of the firm (column 2), departures right before the first mass layoff (column 3), and departures at any other time (column 4). A mass layoff is defined as an employment decline of >30% over two years at a firm with at least 50 employees, with less than half of the departing workers moving to the same new firm. Descriptive statistics in columns 5 to 7 provide the average change in annual earnings between years t-1 and t+2 for manufacturing workers who leave the initial firm between years t and t+1. The earnings change is expressed in multiples of initial annual earnings, and is conditional on positive earnings in t-1 and t+2. Robust standard errors in parentheses are clustered on start-of-period 3-digit industry. ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

Table 9. Imports from China and Earnings and Employment by Wage Level and Size of Initial Firm, 1992-2007: 2SLS Estimates.

Dep Vars: 100 x Cum Earnings; 100 x Years with Earnings; 100 x Earnings per Year of Emp (in Multiples of Initial Annual Wage).

	I. Overall Outcomes					II. Outcomes at Initial Firm				
	Cum		Yrs w/	Earn/		Cum		Yrs w/	Earn/	
	Earnings		Earn>0	Year		Earnings		Earn>0	Year	
	(1)		(2)	(3)		(4)		(5)	(6)	
<u>A1. Initial Employer: Avg Firm Wage < Sample Median</u>										
(Δ China Imports)/ US Consumption ₉₁	-12.63 (4.85)	**	0.73 (1.09)	-0.82 (0.29)	**	-9.29 (4.17)	*	-4.17 (2.55)	-0.45 (0.23)	~
<u>A2. Initial Employer: Avg Firm Wage \geq Sample Median</u>										
(Δ China Imports)/ US Consumption ₉₁	-5.16 (2.09)	*	-0.55 (0.50)	-0.29 (0.12)	*	-8.52 (3.85)	*	-6.53 (3.25)	-0.22 (0.08)	**
<u>B1. Initial Employer: Firm Size 1-999 Employees</u>										
(Δ China Imports)/ US Consumption ₉₁	-4.34 (1.85)	*	0.05 (0.43)	-0.27 (0.11)	**	-4.47 (1.85)	*	-2.31 (1.26)	~ (0.08)	**
<u>B2. Initial Employer: Firm Size 1000+ Employees</u>										
(Δ China Imports)/ US Consumption ₉₁	-14.93 (5.78)	**	-1.67 (1.32)	-0.81 (0.34)	*	-20.12 (8.49)	*	-15.47 (6.38)	-0.49 (0.22)	*

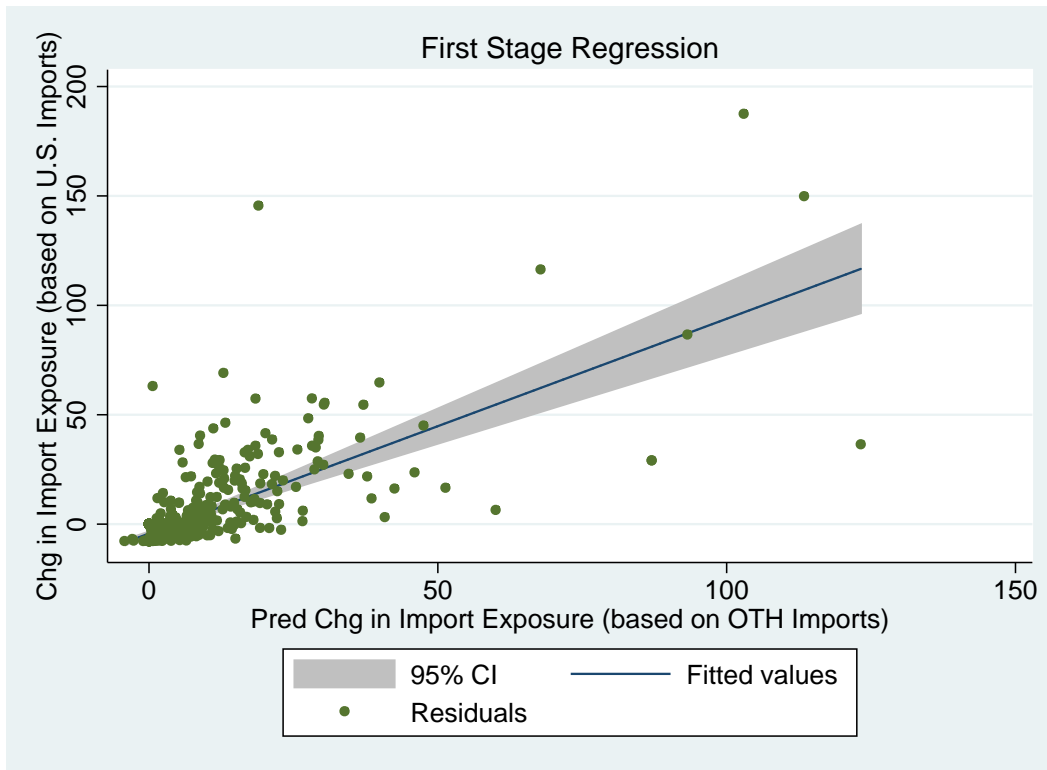
Notes: N=254,126/N=254,003/N=238,131/N=269,998 in panels A1/A2/B1/B2, except slightly smaller samples in in columns 3 and 6. All regressions include a constant and the full vector of control variables from column 9 of Table 1. Robust standard errors in parentheses are clustered on start-of-period 3-digit industry. ~ p \leq 0.10, * p \leq 0.05, ** p \leq 0.01.

Table 10. Alternative Measures of Import Exposure: 2SLS Estimates.

Dep Vars: 100 x Cumulative Earnings; 100 x Years with Earnings; 100 x Earnings per Year of Employment (in Multiples of Initial Annual Wage), 1992-2007

<i>Alternative Measure of Trade Exposure</i>	Cum Earnings	Years w/ Earn>0	Earn/Year	<i>Alternative Measure of Trade Exposure</i>	Cum Earnings	Years w/ Earn>0	Earn/Year
	(1)	(2)	(3)		(4)	(5)	(6)
<u>A. 2SLS Main Results</u>							
Δ Import Penetration, using Imports from China	-6.864 (2.477)	** -0.535 (0.505)	-0.393 (0.140)	Δ Import Penetration, using China Imports to U.S. and other Markets	-5.616 (2.029)	** -0.493 (0.442)	-0.321 (0.113)
<u>B. Reduced Form OLS</u>							
Δ China-US Productivity Differential (Gravity Residual)	-4.684 (1.494)	** -0.383 (0.378)	-0.270 (0.090)	Δ Net Import Penetration, using China Imports	-3.056 (1.348)	* -0.844 (0.384)	* -0.125 (0.079)
<u>C. 2SLS (Instr: Low-OTH Tr.)</u>							
Δ Import Penetration, using all Low-Income Country Imports	-6.836 (2.409)	** -0.489 (0.486)	-0.396 (0.138)	Δ Net Imports from China in Worker-Equivalent Units	-4.553 (1.808)	* -1.171 (0.517)	* -0.202 (0.104)
<u>D. 2SLS (Instr: Mex-OTH Tr.)</u>							
Δ Import Penetration, using Imports from Mexico/CAFTA	-0.118 (6.688)	1.583 (2.160)	0.029 (0.411)	Δ Import Penetration, using China Imp adj for Imported Inputs	-6.499 (2.386)	** -0.568 (0.514)	-0.368 (0.134)
<u>E. 2SLS (Instr: Chn-OTH Tr.)</u>							
<u>F. 2SLS (Instr: Chn-OTH Tr.)</u>							
<u>G. 2SLS (Instr: Chn-OTH Tr.)</u>							
<u>H. 2SLS (Instr: Chn-OTH Tr.)</u>							

Notes: N=508,129 in columns 1-2 and 4-5, N=506,339 in columns 3 and 6. Panel A repeats results from Tables 2 and 3. The mean (and standard deviation) of trade exposure among manufacturing workers is 1.24 (4.14) in Panel B, 8.56 (14.94) in Panel C, 3.20 (5.54) in Panel D, 8.62 (15.22) in Panel E, 6.14 (13.96) in Panel F, 5.91 (13.87) in Panel G, 5.77 (12.69) in Panel H. All models include the full vector of control variables from column 9 of Table 1, except that start-of-period import exposure levels are adjusted to reflect the alternative definitions of import exposure measures where feasible. Robust standard errors in parentheses are clustered on start-of-period 3-digit industry. $\sim p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.



Appendix Figure 1.
2SLS First Stage Regression.

Notes: The graph corresponds to the first stage regression for the model in column 2 of Table 1 (coefficient 0.713, s.e. 0.083), and partials out a dummy variable for workers employed in manufacturing industries. The shaded area indicated a 95% confidence interval around the fitted regression line. The scatterplot is displayed only for workers who did not change their industry of employment between 1988 and 1991.

Appendix Table 1. Descriptive Statistics

	Main Sample All Workers	Main Sample: Manuf Workers	Extended Sample: All Workers	Extended Sample: Manuf Workers
<u>A. Trade Exposure, 1991-2007</u>				
(Δ Imports from China to US)/US Consumption ₉₁	1.60 (7.05)	7.72 (13.85)	1.30 (5.85)	6.30 (11.59)
P90, P10 Interval	[2.72, 0.00]	[24.74, 0.06]	[1.99, 0.00]	[18.75, 0.04]
P75, P25 Interval	[0.00, 0.00]	[7.30, 0.62]	[0.00, 0.00]	[6.28, 0.38]
(1991 Imports from China to US)/US Consumption ₉₁	0.11 (0.94)	0.54 (2.00)	0.11 (0.88)	0.48 (1.78)
<u>B. Main Outcome Variables, 1992-2007</u>				
100*Cumulative Earnings (in Mult of Avg Annual Wage 88-91)	1918.4 (1181.7)	1808.9 (1025.7)	n/a	n/a
100*Number of Years with Earnings>0	1422.3 (342.1)	1428.6 (335.7)	1326.0 (428.3)	1355.8 (403.6)
100*Cum Earn/Yrs with Earn>0 (in Mult of Avg Ann Wage 88-91)	130.0 (69.9)	122.4 (59.7)	n/a	n/a
100*Number of Years with Main Income from SSDI	34.3 (168.3)	43.3 (188.6)	44.4 (200.0)	50.9 (211.4)
100*Number of Years with Main Income from Self-Employment	46.4 (175.9)	37.7 (152.2)	59.8 (200.4)	47.0 (170.2)
<u>C. Worker Characteristics in 1991</u>				
Female	0.431	0.312	0.475	0.359
Non-White	0.207	0.200	0.236	0.235
Foreign-Born	0.077	0.086	0.085	0.097
Employed in Manufacturing	0.208	1.000	0.173	0.836
Tenure 0-1 Years	0.269	0.236	0.418	0.425
Tenure 2-5 Years	0.368	0.355	0.301	0.283
Tenure 6-10 Years	0.169	0.187	0.129	0.134
Tenure 11+ Years	0.194	0.221	0.153	0.158
Firm Size 1-99 Employees	0.231	0.153	0.257	0.199
Firm Size 100-999 Employees	0.237	0.289	0.231	0.285
Firm Size 1000-9999 Employees	0.246	0.290	0.210	0.251
Firm Size 10000+ Employees	0.286	0.267	0.302	0.265
Average Log Wage 1988-1991	10.46	10.55	9.23	9.60
Sample Size	508,129	105,625	880,465	181,900

Notes: The main sample in the first two columns includes all workers who had at least full-time minimum wage earnings during each of the years 1988 to 1991. The extended sample in the second two columns includes all workers who had a positive income in at least one year between 1987 and 1989 and one year between 1990 and 1992. Trade exposure for this sample and control variables for manufacturing employment, tenure and firm size are computed and averaged over all years between 1990 and 1992 during which the worker is employed. Average log wage for this sample is computed based on years with positive earnings between 1988 and 1991. The outcome variables for main income sources are defined for the years 1993-2007 in the extended sample. Column B2 provides statistics for the subset of workers from the extended sample who were employed in manufacturing during at least one year between 1990 and 1992.

Appendix Table 2. Import Exposure by Subsample.

	Δ Import Exposure 1991- 2007	Δ Import Exposure 1991- 1999	Δ Import Exposure 1999- 2007
	<u>A. Full Sample</u>		
Full Sample	7.72	1.81	5.91
	<u>B. Sample Splits by 1991 Worker Characteristics</u>		
Initial Wage < Cohort Median	8.83	2.28	6.55
Initial Wage \geq Cohort Median	6.85	1.44	5.41
Firm Tenure < 5 Years	8.50	1.99	6.51
Firm Tenure \geq 5 Years	6.83	1.60	5.23
Workers Born in 1957-1970	7.85	1.88	5.97
Workers Born in 1943-1956	7.59	1.75	5.84
Male	7.02	1.58	5.45
Female	9.25	2.32	6.92
	<u>C. Sample Splits by 1991 Firm Characteristics</u>		
Avg Firm Wage < Sample Median	9.17	2.52	6.65
Avg Firm Wage \geq Sample Median	7.05	1.48	5.57
Firm Size 1-999 Employees	8.66	2.18	6.48
Firm Size 1000+ Employees	6.97	1.52	5.45

Notes: This table indicates the average trade exposure for manufacturing workers in the main sample and in subsamples. Trade exposure for subperiods in columns 2 and 3 sums to overall trade exposure in column 1, and indicates the distribution of the trade shock over time.