NBER WORKING PAPER SERIES

TRADE SHOCKS AND THE SHIFTING LANDSCAPE OF U.S. MANUFACTURING

Katherine Eriksson
Katheryn Russ
Jay C. Shambaugh
Minfei Xu

Working Paper 25646
http://www.nber.org/papers/w25646

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2019, Revised January 2020

Trade Shocks and the Shifting Landscape of U.S. Manufacturing
Katherine Eriksson, Katheryn Russ, Jay C. Shambaugh, and Minfei Xu
NBER Working Paper No. 25646
March 2019, Revised January 2020
JEL No. F10,F16,F43

ABSTRACT

Using data over more than a century, we show that shifts in the location of manufacturing industries are a domestic reflection of what the international trade literature refers to as the product cycle in a cross-country context, with industries spawning in high-wage areas with larger pools of educated workers and moving to lower-wage areas with less education as they age or become "standardized." We exploit the China shock industries as a set of industries that were in the late-stage product cycle by 1990 and show how the activity in those industries shifted from high-innovation areas to low-education areas over the 20th century. The analysis also suggests that the resilience of local labor markets to manufacturing shocks depends on local industries' phase in the product cycle, on local education levels, and on local manufacturing wages. The risk of unemployment and detachment from the labor force rises most when a shock hits in areas where an industry already has begun phasing out, wages are high, or education levels are low. The results are consistent with the belief that there are long-term, secular trends in U.S. industrial structure driving the movement of industries, which shocks may mitigate or accelerate.

Katherine Eriksson
Department of Economics
University of California, Davis
One Shields Avenue
Davis, CA 95616
and NBER
kaeriksson@ucdavis.edu

Katheryn Russ
Department of Economics
University of California, Davis
One Shields Avenue
Davis, CA 95616
and NBER
knruss@ucdavis.edu

Jay C. Shambaugh
George Washington University
Elliot School for International Affairs
1957 E Street, N.W. Suite 502D
Washington, D.C. 20052
and NBER
jshambaugh@gwu.edu

Minfei Xu
One Shields Avenue
Davis, CA 95616
United States
mfxu@ucdavis.edu

1. Introduction

Manufacturing employment in the United States has been declining as a share of employment for decades and in absolute terms since 1979. Yet this decline has been quite uneven across the country, with both the level and type of manufacturing shifting across the country in predictable ways. Early manufacturing centers experienced declines long before the rest of the country, in particular in those products that would face competition from low-wage countries in the late 20th century. We show that these shifts are a domestic reflection of what the international trade literature refers to as the product cycle in a cross-country context (Vernon (1966), Krugman (1979), Grossman and Helpman (1991), Antràs (2005), Matsuyama (2019)). Industries spawn in high-wage areas with larger pools of educated workers and move to lower-wage areas with less education as they age or become "standardized." Beyond the location of manufacturing, the analysis in this paper suggests that the resilience of local labor markets to manufacturing shocks depends on local industries' phase in the product cycle, on their education levels, and their manufacturing wages, with the greatest risk of unemployment and detachment from the labor force occurring when a shock hits areas where an industry already is phasing out, wages are high, or education levels are low. The results are consistent with the belief that there are long-term, secular trends in U.S. industrial structure driving the movement of industries, which shocks may mitigate or accelerate.

We arrive at this result in three steps. First, to put the shifting geography of U.S. manufacturing in perspective, we map the movement of manufacturing employment across the United States at intervals between 1910 and 2011. Many papers have demonstrated the dispersal of manufacturing activity from the "manufacturing belt" concentrated in the Northeast and Great Lakes region into the Southeast and West within various periods. We find it useful to map this over the entire 20th century using 1990 commuting zones so that we can provide context and contrast with the movement of the subsets of manufacturing industries subject to import competition in the late 20th century. We show that early 20th century manufacturing was in high-education, high-patenting locations with historically low market access costs, but by the late 20th century the locations were spread and no longer concentrated in those areas.

Second, we pinpoint where the subset of industries subject to the surge in imports from China between 1991 and 2001, also known as the "China shock" (Autor, Dorn, and Hanson (2013) and

Acemoglu, Autor, Dorn, Hanson, and Price (2016)), were located over the course of the 20th century.[1] The advantage of studying this shock is it delineates a set of industries that were in a late stage of the product cycle by 1990. These were industries facing competition in advanced economies by countries with low-wage and lower-skilled workers, especially China.

Two stylized facts emerge. In particular, the industries eventually hit by the China shock originated in areas with higher average market access, patents per capita, wages, and education but had been moving away from these locations by 1990. By 1990, employment in the China-Shock industries was concentrated in areas with less innovative capacity, lower wages, less education, and higher unemployment rates. Holmes and Stevens (2014) provide a third and important observation that industries subject to the ADH China shock from 1990 were characterized by high average plant size, which Vernon (1966) and Klepper (1996) depict as a characteristic of industries in the late stage of the product cycle, where standardization has occurred. Together, these stylized facts are consistent with movement through a Vernon product cycle, such that by 1990 the industries were aging out of the places they originated and as their production processes became standardized and no longer at the technological frontier requiring immediate access to large pools of skilled labor and specialized inputs for ongoing development, they moved to areas with lower wages.

As points of comparison, we compute an analogous "Japan shock" for the period from 1975-1985 and "Tiger shock" from 1975-1988 and find that the regions most directly affected were quite different from those hit by the China shock. In particular, exposure to the China shock is correlated with lower educational attainment, lower incomes, and higher unemployment rates. In contrast, exposure to the Japan shock shows no such pattern, nor do areas with high concentrations in China-Shock industries in 1910 through 1960. Thus, the China shock was concentrated in areas that look distinctly different from regions hit by earlier shocks to manufacturing. We argue that the China shock hit industries late in their product cycle, while the Japan shock did not.

Finally, we examine the implications of product-cycle related variables for the severity of labor market effects when the China shock occurred. While locations where the import-competing

[1] This paper builds off the influential and growing literature around the China shock. Autor et al. (2013) create a measure of exposure to imports from China that is based on the share of manufacturing employment that is in those industries that China was exporting to the United States. To ensure that the imports are not simply filling a declining output that is shrinking for other reasons, they use the increase in imports to other advanced economies as an instrument. The sharp, and plausibly exogenous, increase in Chinese manufacturing exports beginning in 1990 as first China opened to the world economy and then entered the WTO, were an unusually large shift in the location of production and thus are an important natural experiment to explore.

industries were moving in may have been more exposed to the shock overall, once again consistent with the product cycle theory, locations where China shock industries were *already leaving* had more adverse labor-market outcomes conditional on their level of exposure. Areas where the shock-affected industries had been reducing employment the most between 1960 and 1980—which we interpret as a characteristic of local industries being in a late stage of the product cycle—experienced a roughly 0.25 basis point additional increase in the unemployment rate above that attributable to the shock by itself. Locations with high manufacturing wages also felt more pain conditional on their level of exposure. This could occur if firms had been holding on in a location due to sunk costs as in Fillat and Garreto (2015) or adjustment costs as in Rodriguez-Lopez (2014) amidst increasing pressures to move or exit, then a large shock jolted them out of the range of inaction. Areas with a greater fraction of workers with college degrees had somewhat less adverse labor-market outcomes conditional on the shock, suggesting that a highly educated workforce may be better able to achieve resilience through innovation or expansion in different sectors along the lines of Feenstra, Ma, and Xu (2017), for instance.

The shifting landscape of China-Shock industries within the United States is likewise consistent with the wage-reversal theory of economic geography in Krugman (1991) and Krugman and Venables (1995), which shares some features of the product cycle. As transport costs fall enough, the low wages in the periphery become more important and production shifts there. This in many way describes the shock to manufacturing in the United States, illustrated well by Jaworski, Kitchens, and Nigai (2018) in the context of the expansion of the interstate highway system. Krugman (1991) mentions the possible relationship between agglomeration and information or knowledge spillovers, but Vernon's enormous emphasis on the initial core regions requiring more capacity for innovation, while compatible with Krugman and Venables (1995) and later related work, is somewhat distinct.[2] Vernon also actually mentions the relationship of his product cycle theory to the observed dispersal of manufacturing activity across U.S. regions, in addition to its more widely noted cross-country interpretation. He emphasizes the need for product development (innovation) to be near consumers – richer areas – and near pools of skilled people equipped to innovate. For Vernon, economies of scale and innovation are inextricable.

Staiger and Skinner (2007) demonstrate that the same areas in the U.S. have been more capable

[2]Krugman (1991) seems to purposefully avoid an emphasis on innovation, declaring that an attractive feature of his framework "is that it requires no appeal to elusive concepts such as pure technological externalities" and preferring instead to focus on pecuniary externalities related to market access.

of incorporating innovations over time and these are chiefly areas with higher levels of education and social capital, which supports the idea that innovation tends to emanate from some areas and spread to others as it becomes more standardized. The initial (1910) core regions for the China shock industries were in fact highly educated locations with a high level of patents per capita. Over time, as the industries matured, activity shifted to locales with lower wages and levels of education. As such, when the China shock hit, it hit communities with less education and less capacity for innovation prior to the shock. These areas were less able to pivot to new industries.

Bloom, Handley, Kumar, and Luck (2018) find evidence that as the China shock hit, firms in areas with high levels of human capital were better able to expand output and employment in new industries when facing increasing import competition. Bernard, Smeets, and Warzynski (2017) show that as manufacturing employment declined in Denmark 1980-2013, many manufacturing firms switched industries, engaging in either design or process innovation as they did so. They document that these firms either began with a higher-educated pool of employees or shifted to more highly-skilled hires. Fort, Pierce, and Schott (2018) find similar industry switching in the U.S. 1977-2015.

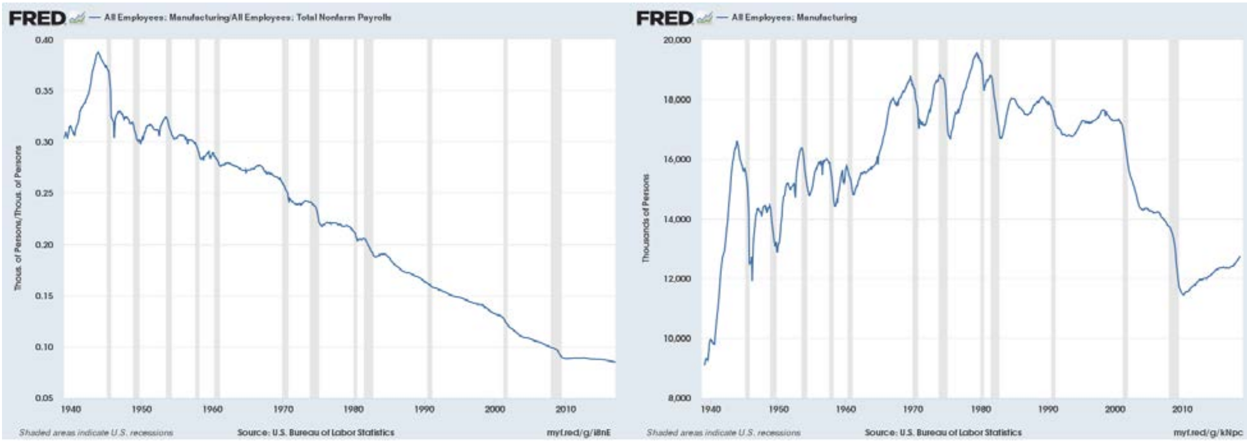
For our purposes, the exogeneity of the timing of the shock – largely based on transitions in political leadership in China and decisions to more actively engage the world economy – is nearly as important as the exogeneity of the regional impacts. We demonstrate that the timing of the China shock largely determined the location of the shock, and definitely determined the nature of the regions hit by the shock. In addition, by identifying industries in a late-stage of the production cycle from the international context, we avoid the contamination of industries' skill composition based on where they are located. China shock industries are considered late-stage in the production cycle based on their prior spread to low-wage countries and we find that even within the United States, over the 20th century, they follow a product-cycle path. The regions specializing in products that made up the China shock in 1910 were the leading manufacturing regions of the day. They were the richer and more educated parts of the United States. Over time, the location of production of these goods shifted towards less and less educated regions of the country, such that the eventual shock hit some of the weakest local economies in the United States.

The most closely targeted paper to this is that of Charles, Hurst, and Schwartz (2018) who examine the impact of declines in U.S. manufacturing on total employment. They do not focus on differences of the regions hit at different periods of time, but they do explore differences in impact from manufacturing shocks in the 1980s and 2000s. Much like ADH, they find that manufacturing shocks have sizable impacts on local labor market outcomes. The manufacturing share of employment and shocks to sectoral manufacturing specialization have significant negative impacts on overall local labor market employment. In other words, losses to manufacturing employment are not offset either by out-migration or shifts to other sectors. They also find the shocks to manufacturing in the 1980s had less of an overall impact on employment compared to those shocks in the 2000s.[3] Our findings support these results and help explain them by noting the stark differences in the types of places facing shocks in these two eras. Batistich and Bond (2018) also create a "Japan shock" to test the impact of the 1970s-1980s shock to manufacturing from Japanese imports on different racial and educational groups. While our results do not directly comment on their findings of differential impacts across race, their findings that the summed impact on a region is minimal is consistent with our work, as is their finding that the shock hit less educated workers harder.

A number of authors note that manufacturing was expanding in some regions as manufacturing employment fell overall, including Norton and Rees (1979), Holmes and Stevens (2004), Kim and Margo (2004), and Ju, Lin, and Wang (2015). Kim (1995) argues that this movement of manufacturing out of the Manufacturing Belt and into the South in the second half of the 20th century, referred to as regional convergence by economic historians, occurred due to changes in the mobility of factors and goods associated with declining transportation cost. Studies of economic history like Crafts and Klein (2017) view it as an example of core-periphery reversal modeled by Krugman and Venables (1995), while studies like Norton and Rees (1979), Erickson and Leinbach (1979), and Rees, Briggs, and Oakey (1984) in the regional studies literature interpret it as a manifestation of the product cycle as described by Kuznets (1930), Burns (1934), and Vernon (1966).

Section 2 maps the shifts in manufacturing in the United States since 1910, Section 3 formalizes the product cycle and examines its manifestation in U.S. manufacturing using the lens of Krugman (1979). Section 4 looks at the shifts in the location of exposure to shocks over time. It discusses the influence of product-cycle factors on local vulnerability to different types of

[3]Charles et al. (2018) use national shifts in manufacturing sectors combined with local specialization as a measure of their shocks (also know as shift-share or Bartik instruments).



(a) Manufacturing/Total Non-Farm Payrolls

(b) Manufacturing Employment

Figure 1: National Decline in manufacturing employment in shares and levels

trade shocks, contrasting the Japan shock with the China shock. Section 5 illustrates that these product-cycle factors matter for the severity of local labor market effects from the China shock, which hit late-stage industries in the United States.

2. The Decline – and shift – of U.S. manufacturing employment

The most commonly viewed figure of U.S. manufacturing – that of manufacturing employment as a share of non-farm workers – is shown in Figure 1a. This depicts a slow and steady decline beginning prior to 1950. Two other figures, though, show a slightly later downturn in U.S. manufacturing employment. The first is the simple level of U.S. manufacturing employment, in Figure 1b. This peaks later, in 1979 and does not show a sharp downturn until almost 2000. Clearly, population growth contributes to the continued growth in the series. But the use of non-farm employment as a denominator can also be misleading. During the 1940s and 1950s, there was a rapid shift from agricultural labor to services labor which increases the denominator in Figure 1a. If instead one examines manufacturing employment as a share of total employment as measured by the current population survey, U.S. manufacturing employment as a share of the labor force remained fairly level with some small fluctuations until the late 1960s. In 1967, it begins to decline and remains on a steady downward path, as in Figure 2.

The decline in manufacturing employment has multiple causes. On the one hand, continued productivity growth in the sector has allowed output to increase despite declining employment.

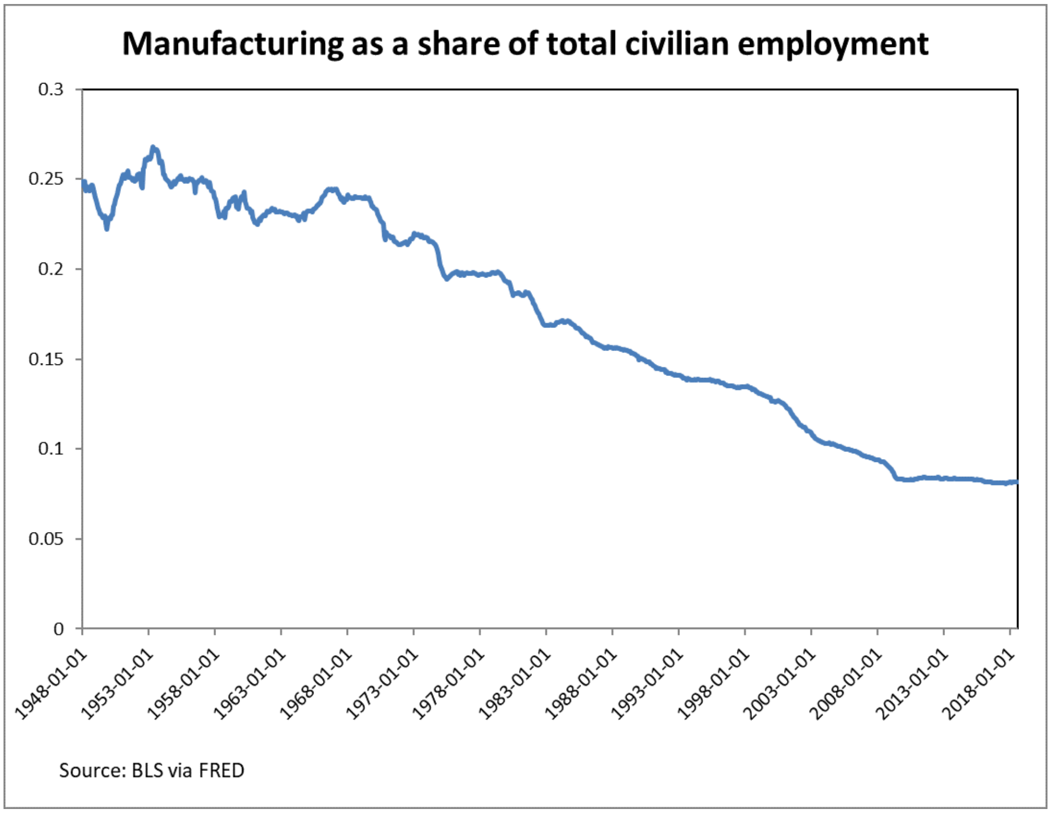


Figure 2: Manufacturing as a share of total civilian employment declined after 1950

At the same time, increased imports of manufactured goods have reduced the need for production relative to consumption. Fort et al. (2018) provide an excellent summary of the interlocking causality; see also Houseman (2018) who places less weight on technology, and Bailey and Bosworth (2014) for a balanced discussion.[4]

Yet this decline has not been even across geography. Even in periods where the share of manufacturing in total employment is trending down nationally, there are some places rising and some sharply falling.[5] To illustrate the lack of uniformity in the evolution of the manufacturing sector across local labor markets, we map it over the century beginning in 1910. We use employment counts in manufacturing industries by county from the full-count Census for 1910, 1940, and the IPUMS 5 percent sample for 1960, categorized using the IND1950 designations. For 1910 and 1940, we use NHGIS county shape files to adjust historical county borders to 1990 county borders, which we then match to 1990 commuting zones using the crosswalk from Dorn (2009) so that our

[4]Houseman (2018) emphasizes that rapid quality increases in computers and high-tech goods may make it seem their prices are falling quickly and hence output rising rapidly. This could bias towards putting too much weight on technology. Bailey and Bosworth (2014) show how changes in imported inputs and price indices may overstate who extent to which manufacturing output levels have remained strong as employment declined.

[5]See Helper, Krueger, and Wial (2012) for a discussion of the geographical shifts in U.S. manufacturing in recent decades, for example.

maps fit within the context of recent discussions of local labor market shocks.[6]

In 1910, Figure 3 shows that manufacturing had still not advanced far outside of its initial locations in New England, Pennsylvania, and near the coast of the Great Lakes, the region known as the Manufacturing Belt.

Between 1910 and 1940, Figure 4 illustrates how manufacturing declined as a share of employment most acutely in parts of New England, coastal Washington, and the northern Great Lakes region (especially northern Michigan, Wisconsin, and Minnesota), while expanding rapidly across the southern Great Lakes region (especially Illinois, Indiana, and southern Michigan) down through the northern Ohio river valley, and throughout most of the Appalachians from northeastern Alabama through Virginia and parts of Pennsylvania and upstate New York.

Between 1940 and 1960, manufacturing activity shown in Figure 4 declined in only a handful of localities, expanding across the United States and most rapidly throughout the eastern half of the country– including the Northeast, the Ohio river valley, the Great Lakes region, and the South—as well as California, Utah, and the Pacific Northwest. As Figure 1b showed, manufacturing employment nearly doubled over this period. Much of that increase took place during the industrialization surrounding World War II, before our total labor force statistics start (WWII can also distort those statistics depending on how one views those serving in the military). By 1948, much of the increase has taken place, thus, the roughly flat national share of employment from 1948-60 is not surprising relative to the large jump across locations from 1940-60.

By 1960 (see Figure 3), manufacturing employment shares in the United States were highest around the southern Great Lakes region, the Ohio River Valley, and through much of the Appalachians, as well as in parts of the Deep South and coastal Pacific Northwest. Manufacturing was 30-50 percent of employment in these regions, demonstrating the massive influence it had on overall economic outcomes. Manufacturing employment shares were still low throughout much of the country, below 10 percent across the Great Plains. The wide variation in employment shares already suggests that developments in manufacturing over the next decades would have

[6] In 1960, mini-PUMAs are the smallest geographic unit identified, so we overlay a NHGIS 1990 county shape file with a mini-PUMA shape file from IPUMS, reweighting mini-PUMAs overlapping with counties by the fraction of area of the mini-PUMA that falls within the county border. We then map counties to 1990 commuting zones, again using the Dorn (2009) crosswalk. We use employment counts from County Business Patterns database from 1974-2011. In all years, we take the manufacturing employment counts from these datasets as a fraction of the total civilian laborforce reported in the County Data Books from ICPSR-2896, interpolating the laborforce counts between available years where needed.

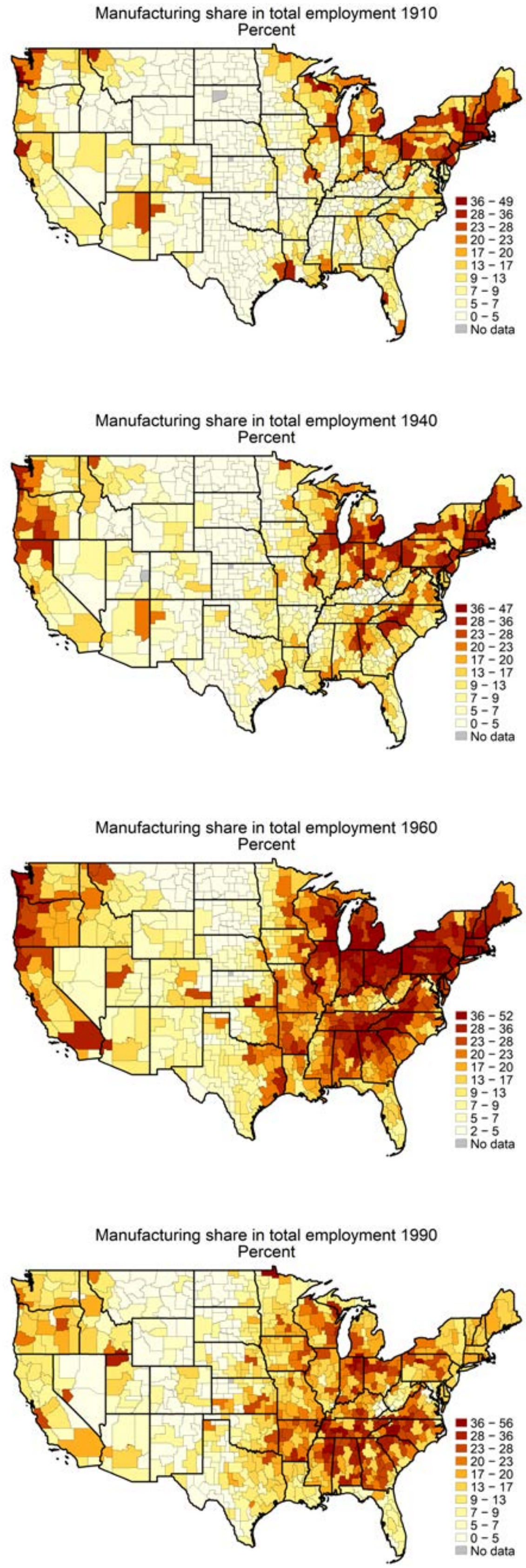


Figure 3: Local manufacturing employment shares 1910-1990, by commuting zone

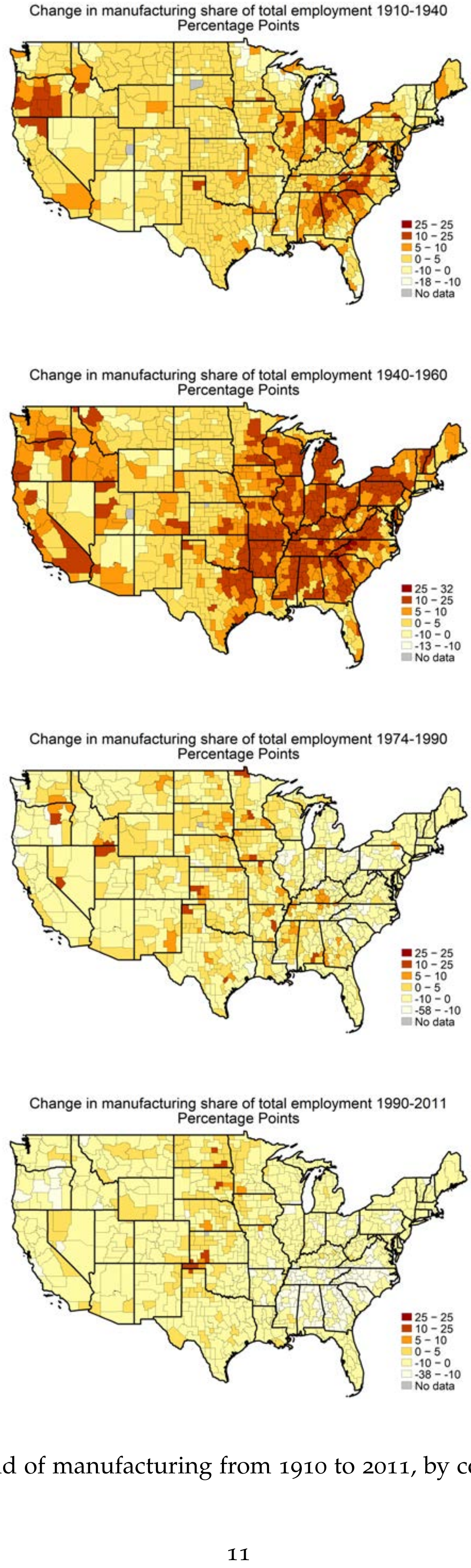


Figure 4: Spread of manufacturing from 1910 to 2011, by commuting zone

distinctly different impacts across regions.

Between 1974 (which marks the beginning of our County Business Patterns Data, while industry measures through 1960 were from the Census) and 1990, we see in Figure 4 declining or stable employment shares in manufacturing across much of the country. The national share of employment shown in Figure 2 drops relatively sharply – from an average of 21 percent in 1974 to an average of 15 percent in 1990. Yet there are still many exceptions where the manufacturing share is expanding rapidly, particularly in the Midwest, central Kentucky, the Deep South, and the Pacific Northwest. The manufacturing share declines most sharply across parts of the mid-Atlantic states, northern Ohio River Valley, and coastal Pacific Northwest. Fort et al. (2018) also discuss the geographical shifts in U.S. manufacturing during this period, in particular the shift towards the south. In total, in 251 out of the 720 commuting zones for which we have data in both 1974 and 1990, manufacturing rose as a share of employment despite the national decline in both share and total employment.

From 1990 through 2011, the era of the "China shock," the manufacturing share in total employment declines throughout the United States, except for a notable strip of expansion stretching from the Dakotas through northern Texas (see bottom panel in Figure 4). The manufacturing share holds steady in a number of zones scattered across the southern Ohio river valley, along the Mississippi River, and the far West. It falls most sharply across the Southeast, the northern Ohio River Valley, and parts of the Pacific Northwest.

The declines in New England and Pennsylvania, as well as in other early manufacturing centers was nothing new at this point for these regions, as they had experienced declining employment shares for decades, but the reversal across many newer manufacturing locations, especially in the South, was a distinct switch from the 1970s and 1980s. Furthermore, the decline in this era is less correlated with the level of manufacturing.

3. Product cycle redux

Krugman (1979) provides the first formalization of Vernon's (1966) product cycle hypothesis. The crux of his model lies in assumptions about the location of innovation and the timing of diffusion. The world, or in our U.S. example, the country, is split into two regions, "North" and "South." The North innovates and produces new goods. With time, goods become standardized to the degree that production can take place in the South. Workers in either region can produce standardized goods.

3.1 *A simple model*

Krugman starts with Dixit and Stiglitz (1977) preferences—utility increasing in the number of varieties n of goods c, including expansion in the number of goods due to ongoing innovation, Δn,

$$U = \left[\sum_{i=1}^{n+\Delta n} c(i)^{\theta} \right]^{\frac{1}{\theta}},$$

with $0 < \theta < 1$. Producing one unit of any good requires one unit of labor and the market for each is perfectly competitive, so that the price of any good equals the wage. Thus, whenever the Northern wage exceeds the Southern wage, only the South produces standardized goods.

Demand and perfect competition imply that the ratio of production of any two goods picked from the North and the South is given by

$$\frac{c_N}{c_S} = \left(\frac{P_N}{P_S} \right)^{-\frac{1}{1-\theta}} = \left(\frac{w_N}{w_S} \right)^{-\frac{1}{1-\theta}}. \tag{1}$$

In the simple case where only the South produces the standardized goods, combining Equation (1) with labor-market clearing equations ($L_N = n_N c_N$,$L_S = n_S c_S$) yields an expression for the relative wage in terms of the ratio of varieties produced in each region and the relative labor supply:

$$\frac{w_N}{w_S} = \left(\frac{n_N}{n_S} \right)^{1-\theta} \left(\frac{L_N}{L_S} \right)^{-(1-\theta)}. \tag{2}$$

Suppose that new products come on line at a rate defined by $\dot{n} = in$ and standardize at a rate $\dot{n}_S = t n_N$ (so that the average time it takes before the South can manufacture a brand-new product is $1/t$). Then, the North ends up producing a fraction of all goods in the economy equal to $\frac{i}{i+t}$ and the geographic variety split is given by

$$\frac{n_N}{n_S} = \frac{i}{t} \tag{3}$$

The relative wage in Equation (2) then reduces to a function of the rates of innovation and standardization, and the relative workforce size,

$$\frac{w_N}{w_S} = \left(\frac{i}{t} \right)^{1-\theta} \left(\frac{L_N}{L_S} \right)^{-(1-\theta)}. \tag{4}$$

Equation (4) indicates that the relative wage in the North is increasing in the rate of innovation relative to the rate of technology transfer or standardization.

To summarize, Krugman (1979) cleanly portrays an economy with two regions, new goods spawning in the North and gradually moving South, but continually replenished by innovation. In the world Krugman assumes where wages are higher in the North, speeding the rate of technology transfer can reduce wage inequality across regions, while increasing the rate of invention of new goods can increase inequality.

3.2 The product cycle in the United States

Table 1 demonstrates the shifts in manufacturing locations over time by examining correlations of the share of manufacturing employment in a commuting zone with various characteristics. The effects are somewhat muted because manufacturing as a sector combines both newly innovative and older standardizing industries. Yet we can see the movement of manufacturing employment generally into high-wage areas between 1910 and 1960, then away from them between 1960 and 1990, with progressively decreasing concentration of manufacturing employment in highly innovative areas as measured by patents per capita between 1910 and 1990. These shifts in manufacturing across the landscape of the United States appear to follow a product cycle. As seen in Table 1, early 20th century manufacturing locations were locations with higher levels of primary education and also more likely to patent. Consistent with the Krugman and Venables (1995) theory, these locations had historically lower market access costs, as well. Over time, though, the location of manufacturing employment in the United States was no longer correlated with education and became progressively less correlated with the location of patenting activity. Manufacturing is, of course, a mixture of industries at both early and late stages of the product cycle. There are older products that have shifted location, as well as new advanced manufacturing taking place in the same location where it spawned.

We argue that products exported to advanced economies by the much poorer Chinese economy must have been at a late stage in the product cycle and therefore will exhibit a more clear shift away from innovative areas over the 20th century. In fact, we will see shifts even more extreme than for manufacturing overall.

Table 1: Correlation of economic indicators with historical manufacturing employment shares

	(1) 1910	(2) 1960	(3) 1990
Farm value per acre	0.257***	0.109***	0.080**
Population density	-0.197***	0.279***	0.069*
Patents per capita 1890-1910	0.361***	0.291***	0.094**
Patents per capita 1970-1975	0.386***	0.329***	0.098***
Education			
% 6-14-year-olds enrolled in school	0.214***	.	.
% pop. age 25+ with HS or college	.	-0.050	0.026
% pop. foreign born	0.226***	0.020	-0.200***
Median income	.	0.224***	0.200***
Mnfg production wages per worker	0.090**	0.311***	0.027
Mnfg value added per worker	-0.300***	0.174***	0.016
Unemployment rate	.	0.136***	0.181***
Donaldson-Hornbeck market access in 1890	0.364***	0.602***	0.534***

Note: Asterisks ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels.

3.3 *Manufacturing intensity and vulnerability to trade shocks*

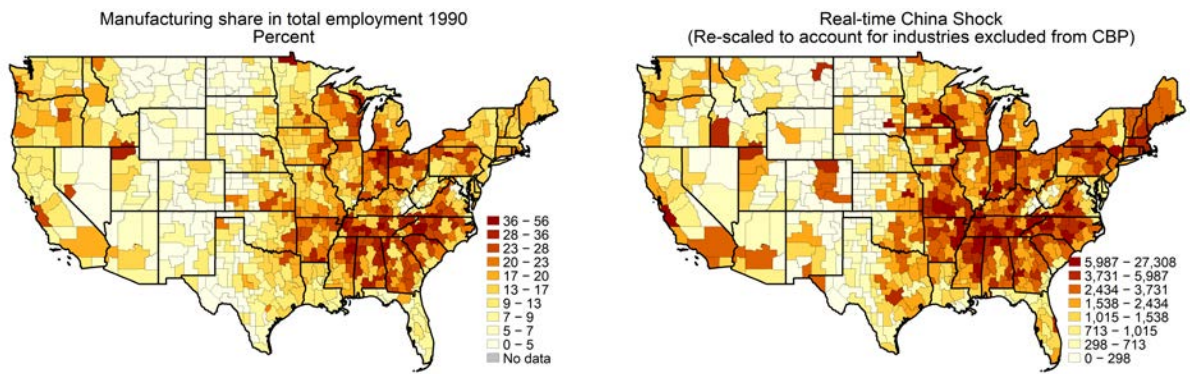
The large external shock prompted by China's rapid incorporation into the world economy in the last few decades of the 20th century triggered a bigger adjustment for U.S. manufacturing in some places relative to others. We use products exported by China as an example of goods that are, by Vernon's definition, late-stage in the product cycle in the international context by 1990, being exported by a low-wage country. The severe local labor market impacts identified by ADH highlight the uneven nature of the shock. Table 2 below shows that variation in overall manufacturing intensity across commuting zones in 1990 accounts for about 40 percent of the variation in exposure to the increase in U.S. imports from China between 1991 and 2007 measured in dollars per worker. So manufacturing intensity accounts for a large portion—but not all—of which localities felt the strongest import competition.

About 9 percent of commuting zones had manufacturing employment shares above the median level of 13.6 percent, but were concentrated in industries where the increase in U.S. imports from China 1990-2007 per worker (the China shock) amounted to less than the median commuting zone's level of $1550. The same fraction had manufacturing employment shares below the me-

Table 2: Change in U.S. imports from China per worker 1990-2007 on share of manufacturing in total employment 1990

	(1)
CZ manufacturing share 1990	171.500***
	(7.815)
Constant	-247.521*
	(134.256)
N	721
R^2	0.401

Note: Data by 1990 commuting zone. Standard errors in parentheses with ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels.



(a) Concentration of manufacturing in 1990

(b) China shock 1991-2007

Figure 5: Manufacturing employment versus import competition during the China shock

dian, but experienced a China shock above the median intensity. Two commuting zones in Texas, visible in Figure 5, illustrate this divergence. In 1990, manufacturing accounted for more than 20 percent of employment in the Dallam-Hartley-Moore commuting zone in the north-western-most corner of the Texas panhandle, but this zone experienced a China shock amounting to only $186 per worker. In contrast, the manufacturing share was about half as large in the El Paso-Hudspeth commuting zone at the westernmost tip of Texas (bordering Mexico), but it experienced a China shock of $3,501 per worker, nearly 20 times the intensity in the Dallam-Hartley-Moore zone.

Thus, whether an area was hit hard by this trade shock depended not just on whether it was a manufacturing-oriented place, but also on the product mix of their manufacturing output.

3.4 *Shifts in product specialization over time*

Crucially, there has been a change in the location of these product specializations over time. Below, we create synthetic "China shock" exposure at different points in time. To create these alternate-timeframe shocks, we use the same real-time imports per worker by industry at the national level as in the actual (1991-2007) ADH China shock, but identify the geographic concentrations of these industries at different points in time in the United States using industry employment statistics by county and total civilian labor force by county from these earlier years. If China had started exporting the same set of products it exported in the 1990s at some other point in time, these simulated shocks show which regions would have been affected as well as how intensively employment was concentrated in those sectors.

In Figure 6, we show how the rank of exposure to the China shock industries moves around the country during the 20th century.

Initially, the China shock industries were concentrated in the vanguard manufacturing locations in the United States: Massachusetts and across the Great Lakes. Over time, the greatest level of exposure drifted down towards the central southern region of the United States.

4. The product cycle and the China shock

The shifts in China shock industries across locations do not appear to be random. Table 3 shows that in 1910, commuting zones with higher employment shares in industries that later (from 1990) would face more import competition from China also had higher manufacturing production wages, higher manufacturing value added per worker, and a greater fraction of the population enrolled in school.[7] The higher farm values combined with higher manufacturing wages suggests they were also more wealthy. Perhaps most striking, we see that exposure to the China shock industries in 1910 was highly correlated with the locations of patent activity in 1890-1910, but that these industries move away from the locations with high patent activity by 1990. Thus, the locations of these industries made them consistent in 1910 with the description of innovative or high-tech industries within Vernon's product cycle hypothesis Vernon (1966). The same held true in 1960, though the correlation with the level of education and manufacturing value added

[7] We focus on the available census enrollment category that most nearly overlaps with the primary-school-aged population in 1910, to avoid anomalies generated by the political economy of high-school enrollment in the early 20th century discovered by Goldin (1998).

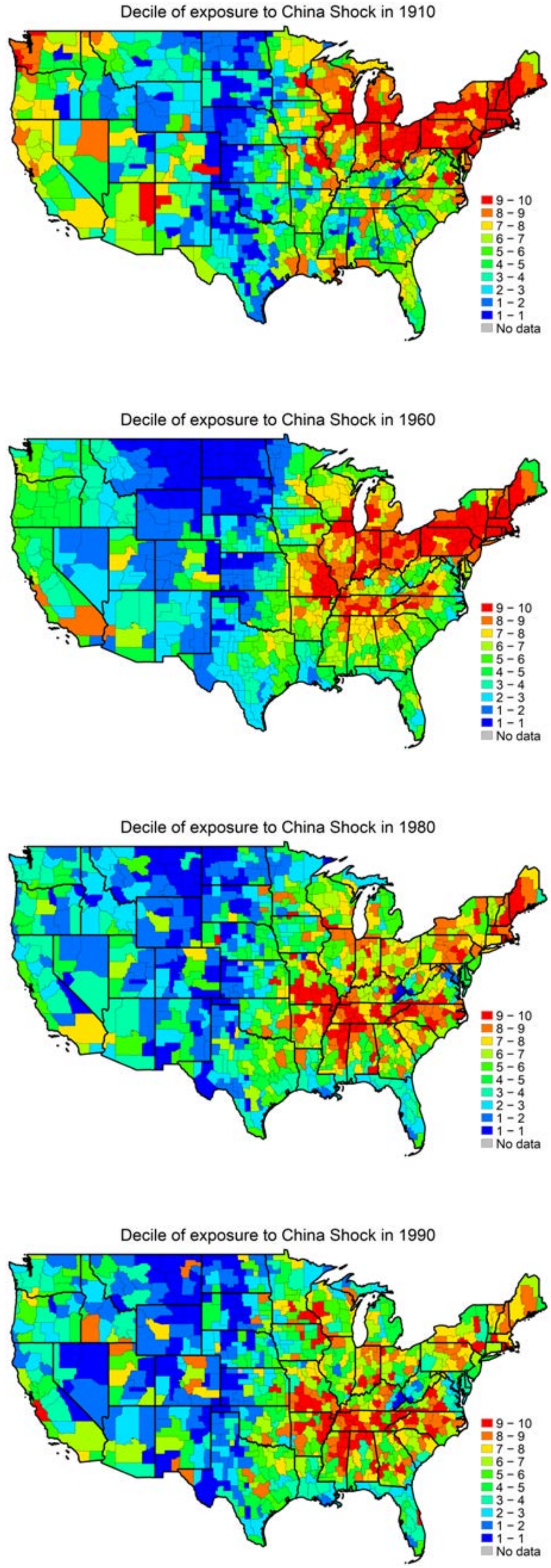


Figure 6: Rank of exposure to China shock 1910-1990, by commuting zone

weakened. Production of these goods had spread more evenly across the country, they were no longer entirely located in the vanguard locations. Because of the way this geographic shift in exposure to the China shock correlates with contemporary local wages in manufacturing, we argue that it reflects the Vernon product cycle.

Table 3: Correlation of economic indicators with historical exposure to the China shock

	(1) 1910	(2) 1960	(3) 1990
Farm value per acre	0.345***	0.107***	0.001
Population density	-0.190***	0.254***	0.078***
Patents per capita 1890-1910	0.477***	0.343***	0.061
Patents per capita 1970-1975	0.435***	0.324***	0.050
Education			
% 6-14-year-olds enrolled in school	0.287***	.	.
% pop. age 25+ with HS or college	.	-0.048	-0.185***
% pop. foreign born	0.170***	0.029	-0.109***
Median income	.	0.156***	0.091**
Mnfg production wages per worker	0.123***	0.179***	-0.105***
Mnfg value added per worker	-0.230***	0.148***	0.034
Unemployment rate	.	0.031	0.138***
Donaldson-Hornbeck market access in 1890	0.472***	0.517***	0.286***
Δ China shock exposure 1960 minus 1910	0.342***	0.930***	0.579***
Δ China shock exposure 1980 minus 1960	-0.291***	-0.245***	0.319***

Note: Asterisks ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels.

The pattern is also consistent with Krugman and Venables (1995), who place less of an emphasis on ability to innovate and more on how a random first-mover endowment might generate first a concentration in that area, followed by a move to lower-wage areas when transport costs fall. Exposure to the China shock industries in 1910 is also highly correlated with market access in 1890 as derived by Donaldson and Hornbeck (2016) based on the connectivity of places to markets using waterway and railroad routes. Those places with better connectivity may have had the better opportunity to build up manufacturing capacity, which would have left them a first-mover advantage later on as transportation costs continued to fall. A number of papers in the literature on regional studies and geography have also made the observation connecting the evolution of manufacturing across the United States to product cycles including Norton and Rees (1979), Kim (1995), and Holmes and Stevens (2004). Some, such as Kim and Margo (2004) and Holmes and Stevens (2004), call it regional convergence reflecting the Krugman-Venables core-periphery reversal and some an expression of a regional product cycle (Erickson and Leinback 1979; Norton and Rees (1979), Rees, Briggs, and Oakey 1984; Romo and Schwartz 1995).

By 1990, though, the China shock regions were less educated, less likely to have sizable foreign born populations, and had lower manufacturing wages. They also already had higher unemployment rates at the time the shock struck. Notably, they also have a higher-than-average median income. The correlation of income and the China shock for 1990 is smaller than in 1960, but is still positive. It may be that in 1990 the higher level of manufacturing associated with the China shock industries was still good for overall income even if these counties had slightly lower than average education.

The correlations by 1990 suggest that the China shock industries were no longer leading industries concentrated in high-education areas, but had moved through the product cycle. The lower education and higher unemployment also suggests these areas were likely more vulnerable to shocks and less able to pivot to other industries. Lastly, Cadena and Kovak (2016) show that low-skilled immigrants are more likely to move following a local labor market shock, so the lower share of immigrants and the lower level of education (also correlated with mobility) may mean these areas were more likely to suffer persistent local labor market impacts from a shock.

The results in Table 3, compared to those in Table 1, show that China shock industries followed a product cycle process more than manufacturing overall. China shock industries' locations in 1910 were more correlated with eduction, farm values, patents per capita, and market access in 1890 than overall manufacturing activity in 1910. But, by 1990 all of those orderings had reversed. While manufacturing in 1990 is still positively correlated with patenting activity, that is no longer true for China shock industries. By 1990, employment in China shock industries is negatively correlated with education, while manufacturing overall has zero correlation with education (seen in Table 1.

If one constructs deciles of exposure for CZs in 1910 and keeps them the same, tracing the change in their relative exposure over time as in Figure 7, we see that the areas that were initially most exposed in 1910 were still the most exposed as late as 1974. The gap between these regions

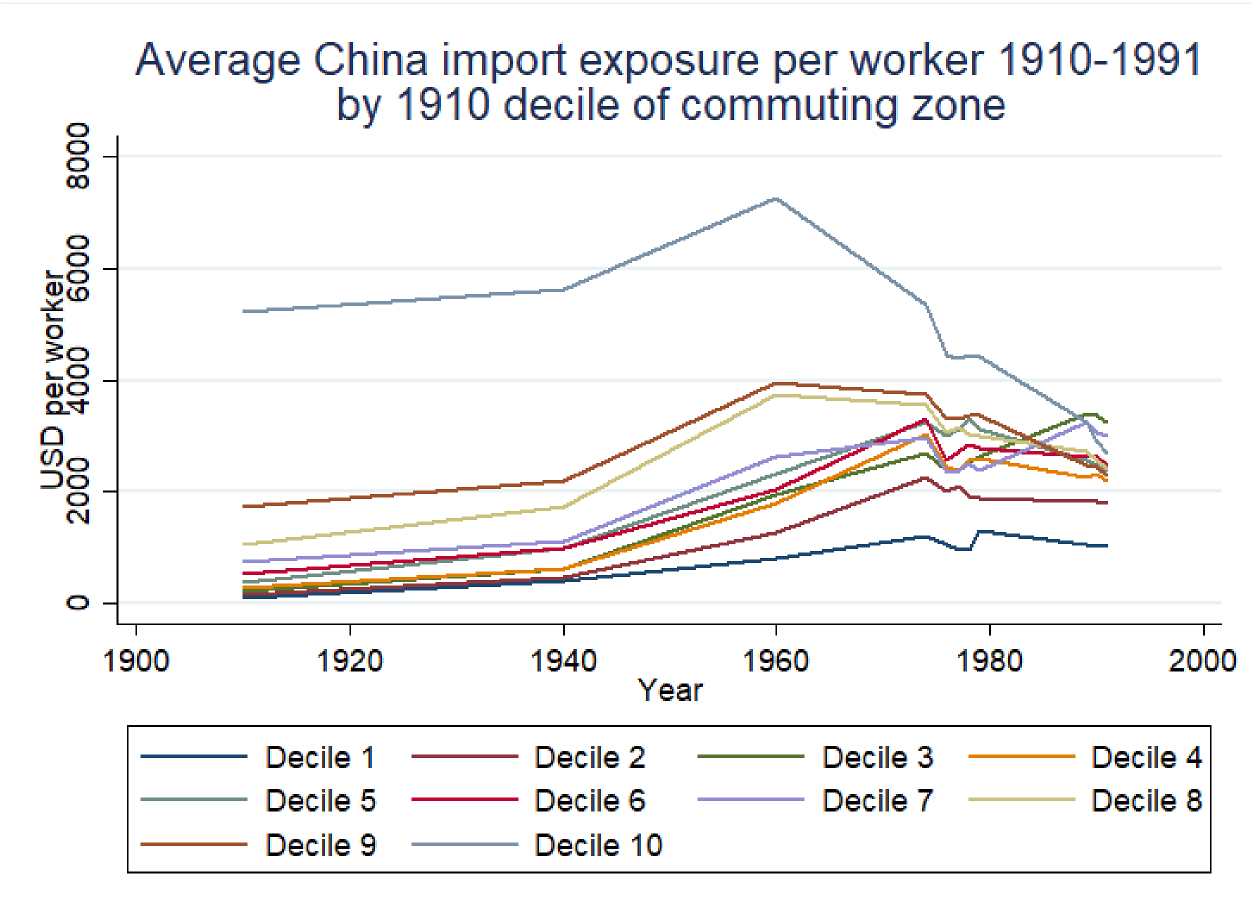


Figure 7: Exposure to China shock by 1910 exposure bin

and the rest of the country had shrunk, but they were still the main regions exposed. By 1991, these first-mover regions in 1910 were phasing out, becoming the 4th-most exposed decile, having rapidly shed exposure. Interestingly, the set of regions that were only 7th-most exposed in 1910 had moved to being the most exposed by 1991. Even as recently as 1974, they were only the 5th-most exposed. Had China opened to the world earlier exporting a similar set of products, these late-cycle regions that were eventually hit so hard by the shock would have been far less exposed. These patterns once again reinforce the product cycle view of the shifts in U.S. manufacturing as the initial leaders in these goods had shifted out of them to some extent by 1990 and areas that were much later adopters were the ones most heavily exposed by the time the shock begins in earnest.

We explore the origin of the first-mover status in Table 4 below. We regress the simulated 1910 China shock exposure on Donaldson-Hornbeck's 1890 market access, and historical patent data from Petralia, Balland, and Rigby (2016). We find that the DH market access measure can account for nearly a third of the variation, with patents per capita in 1890 and farm values in 1910 each underlying roughly one eighth.

Below we will focus on this differential shift from 1960 to 1980 seen in Figure 7 to study places that were increasing their exposure or decreasing their exposure during that time. We stop in 1980 as opposed to 1990 to make sure any shifts that were a response to the beginning of the China shock are not mixed into our analysis.

A negative value suggests a place was becoming less exposed. We show correlations with key indicators in Table 5. First, the China shock industries were migrating to more rural or less dense commuting zones. The places with increasing China shock industry exposure from 1960-80 were not less educated in 1960, but by 1990, they had substantially lower fractions of the adult population with 12+ years of education. They were also poorer, had lower manufacturing wages and value added per worker. The places that were seeing increased exposure were also places that had worse market access in 1890. Perhaps most striking, the industries were moving away from areas with the highest concentration of patent activity, whether measured in 1890-1910 or contemporaneously, in 1970-1975. In short, the places with rapidly growing exposure were weaker economically and fit the pattern of a late-stage product adopter.

Table 4: Exposure to 1991-2007 China shock in 1910 on historical measures of market access, innovation, population density, and wealth

	(1) Coefficient	(2) Beta
DH 1890 Market access	0.0001***	0.321***
	(0.000)	.
Patents per capita 1890	78389***	0.129***
	(22004)	.
Population density 1910	67.413	0.017
	(138.290)	.
Farm value per acre 1910	0.312***	0.123***
	(0.074)	.
Mfg. production wages per worker 1900	0.484	0.056
	(0.328)	.
Census division fixed effects	Yes	.
N	678	.
R^2	0.584	.

Notes: Standard errors in parentheses with ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels. Regression includes a constant. Level coefficients reported with standard errors in Column (1); beta coefficients reported in Column (2) to illustrate relative importance of each variable in explaining observed variation in 1910 exposure.

Table 5: Correlation of exposure to China shock in 1980 minus exposure in 1960 (positive = moving in) with economic indicators

	(1) 1960 levels	(2) 1990 levels
Farm value per acre	-0.050*	0.073***
Population density	-0.089***	-0.098***
Education		
% pop. age 25+ with HS or college .	-0.024	-0.161***
% pop. foreign born	-0.187***	-0.093
Median income	-0.250***	-0.144***
Mnfg production wages per worker	-0.121***	-0.125***
Mnfg value added per worker	-0.072***	-0.125***
Unemployment rate	-0.022	-0.019***
Donaldson-Hornbeck market access in 1890	-0.087***	
Patents per capita 1890-1910	-0.190***	
Patents per capita 1970-1975	-0.196***	
Δ China shock exposure 1960 minus 1910	-0.165***	

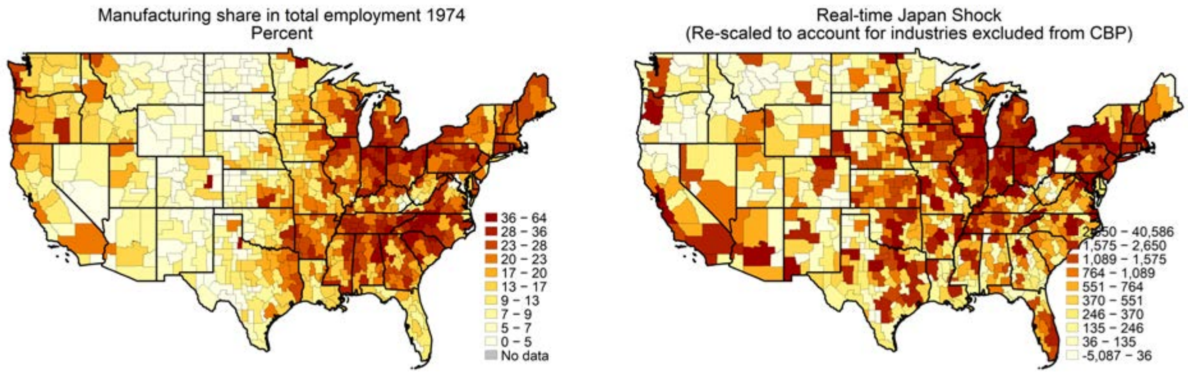
Note: Asterisks ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels.

4.1 Contrast with the Japan shock

While not as large or as discontinuous as the China shock, the rapid increase of Japanese imports into other advanced economies in the 1970s and 1980s was also seriously disruptive (see Batistich and Bond (2018) for discussion).

We create an analogous Japan shock, which uses increases in U.S. imports from Japan per worker in the corresponding U.S. industry. We also create a "Tiger shock" in the same way, but using U.S. imports from Taiwan, South Korea, Singapore, Thailand, and Hong Kong. Table 6 compares the Japan shock to the China shock, the simulated China shock for 1974, and the Tiger shock. Given that Japan had a GDP per capita in the 1970s much closer to that of the United States than China did in the 1990s, the fact that Japan was exporting a good was less indicative of being in the late stage of the product cycle, consistent with the U.S. evidence below.

The table first reinforces the shifting nature of the China shock. The correlation between the real-time China shock and the simulated 1974 China shock is only 0.64. Perhaps more surprising



(a) Concentration of manufacturing in 1974 (b) Japan shock 1975-1985

Figure 8: Manufacturing employment versus import competition during the Japan shock

Table 6: Correlation of exposure to different waves of import competition and the manufacturing share of total employment

	(1) 1974 China shock exposure	(2) 1990 China shock exposure (real-time)	(3) 1974 manufacturing share of employment
1974 exposure to Japan shock (real-time)	0.373***	0.147***	0.174***
1974 exposure to Tiger shock (real-time)	0.411***	0.289***	0.151***
1974 China shock exposure	1.000***	0.6453***	0.525***
1990 China shock exposure (real-time)	0.645***	1.000***	0.509***

Note: Data are based on employment at the commuting zone level in industries matched to U.S. imports from Japan 1975-85, Tigers 1975-88, and China 1990-2007. Asterisks ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels.

is the relatively low correlation of the 1974 China shock and the 1974 Japan shock. The two shocks involve distinctly different intensities across products, such that had the Japan and China shocks both occurred in 1974, they would have hit different places. The most stark finding, though, is that the real-time Japan shock (computed with local industry employment shares in 1974 and the increase in U.S. imports from Japan per worker 1975-85) has a low correlation, only 0.15, with the real-time China shock (computed with local employment shares in 1990 and the increase in U.S. imports from China per worker 1991-2007). The two actual shocks, one in 1975 through 1985 and the other 1991 through 2007, hit with vastly different intensity across the country.[8]

The lower correlation with manufacturing intensity for the Japan shock may also appear puzzling. Looking at maps of the real-time Japan shock and manufacturing intensity in 1974, it is clear that the lack of correlation stems from the fact that the heavily manufacturing intensive Southeast – the area that was hit full force by the China shock – was simply not as intensively engaged in the products Japan was exporting to the world. Conversely, the Japan shock overlaps somewhat more with initial areas of manufacturing development and in particular the synthetic China shock for 1910.

Perhaps more important than the lack of correlation across these shocks is the fact that the shocks hit such different types of places. Table 7 shows that the places hit by the Japan shock were higher-income (median income and manufacturing wages were significantly higher than the rest of the country), they were more educated, and they had higher farm value per acre. Notably, unemployment rates were not correlated with the shock, unlike the 1991 China shock that hit areas that had higher unemployment rates at the start. One surprising feature that the table highlights is that production of the goods in question was actually shifting towards more educated areas over time (or the areas producing these goods were becoming more educated) in stark contrast to the shifts in correlation with education for the simulated China shocks over time. Moreover, in 1910 exposure to the Japan shock overlaps with areas of patent activity quite substantially, and quite similarly in comparison with exposure to the China shock. However,

[8]Top-ten industries hit by the Japan shock, if we exclude industries with less than 200 workers, include household video and audio equipment, motor vehicles, printed circuit boards, photographic equipment an supplies, magnetic and optical recording media, electromedical equipment, semivitreous table and kitchenware, search and navigation equipment, electronic connectors, medicinals and botannicals. The top-ten industries hit by the China shock reflect a greater prevalence of lower-tech production, especially toys, footwear, and apparel: household video and audio equipment; games, toys, and children's vehicles; printing trades machinery; luggage; footwear, except rubber; electronic computers; waterproof outerwear; rubber and plastic footwear; women's handbags and purses; leather and sheep-lined clothing.

when we look at exposure later in the 20th century, exposure to the Japan shock continues to be highly correlated with areas of patent activity, while the China shock industries have no special geographic affinity to patent-heavy areas by the time the shock hit.

Table 7: Correlation of economic indicators with historical exposure to the Japan shock

	(1) 1910	(2) 1960	(3) 1990
Farm value per acre	0.220***	0.116***	0.083***
Population density	-0.094***	0.216***	0.165***
Patents per capita 1890-1910	0.376***	0.417***	0.147***
Patents per capita 1970-1975	0.375***	0.407***	0.234***
Education			
% 6-14-year-olds enrolled in school	0.188***	.	.
% pop. age 25+ with HS or college	.	0.004	0.136***
% pop age 25+ with 4+ years college	.	.	0.161***
% pop. foreign born	0.143***	0.145***	0.034
Median income	.	0.121***	0.298**
Mnfg production wages per worker	0.121***	0.266***	-0.199***
Mnfg value added per worker	-0.104***	0.171***	-0.097
Unemployment rate	.	-0.026	-0.031
DH Market access 1890	0.234***	0.412***	0.311***

Note: Asterisks ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels.

Table 8 shows that the Tiger shocks are somewhat in between the China and Japan shock with largely no correlation with education and slightly lower wages.

Thus, the Japan shock was on average hitting communities that had a population with a higher level of education. This may have given those communities a better opportunity to pivot to other industries and tasks. It does not mean there were no communities hurt by the Japan shock, but the average impact should be mitigated by the fact that the areas hit had a higher level of education in the workforce. This is established further in Section 5, which shows that conditional on the size of the China shock, the impacts were worse in areas with a lower average level of education.

Table 8: Correlation of economic indicators with historical exposure to the Tiger shock

	(1) 1910	(2) 1960	(3) 1990
Farm value per acre	0.180***	0.095***	0.090***
Population density	-0.101***	0.182***	0.130***
Patents per capita 1890-1910	0.317***	0.363***	0.133***
Patents per capita 1970-1975	0.268***	0.360***	0.187***
Education			
% 6-14-year-olds enrolled in school	0.128***	.	.
% pop. age 25+ with HS or college	.	-0.015	-0.064***
% pop. foreign born	0.101***	0.122***	-0.030
Median income	.	-0.061	0.067***
Mnfg production wages per worker	0.028***	0.229***	-0.091**
Mnfg value added per worker	-0.140***	0.114***	-0.085
Unemployment rate	.	0.027	0.012
DH Market access 1890	0.247***	0.378***	0.239***

Note: Asterisks ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels.

5. Employment effects and the product cycle

Just as manufacturing employment shares do not correlate one-to-one with local exposure to the China shock, employment effects do not correlate one-to-one with exposure. In Section 3, we note that the areas hit by the China shock were in some sense more vulnerable economically than other parts of the country – lower education, lower manufacturing wages, higher unemployment. In this section, we turn to the question of how hard the shock hit measured in terms of unemployment or detachment from the labor force, conditional on the size of the shock measured in terms of national imports per worker weighted by local industry employment shares.

Vernon's hypothesis has been applied most broadly to movement of product specialization across countries. Our simple correlations and maps above suggests several variables that may matter when predicting the effect that a trade shock may have on domestic local labor markets within the context of the product cycle framework—whether an industry had already been moving into or out of the area; the local prevailing wage rate; and the capacity for innovation or adoption of new technologies, which is how we interpret education-related variables and patents per capita. We find that the stage at which localities found themselves in the product cycle influenced the intensity of employment effects. The manufacturing wage and education variables could have impacts outside of the product cycle framework if education allows an area to innovate and shift to new industries (even outside of manufacturing) more easily (Staiger and Skinner (2007)) or low manufacturing wages simply signal that an area is more ready to compete with Chinese imports.

We can expand Krugman (1979) to include a third country which we call China for illustrative purposes. Again for simplicity, we assume that this third country can produce goods as they standardize but does not invent new goods. While technology transfer to the South still occurs at rate t, technology transfer to the third country occurs with more hangups, at a rate $t_C < t$. Like Krugman does for the South, we now assume that conditions prevail such that wages in China are lower than in the South. If wages are flexible, the first result with the entry of the third country into trade with the U.S. is an increase in wage inequality, as the wage ratio is now given by

$$\frac{w_N}{w_S} = \left(\frac{i}{t - t_C}\right)^{1-\theta} \left(\frac{L_N}{L_S}\right)^{-(1-\theta)}, \tag{5}$$

increasing in technology transfer to China. Arkolakis, Ramondo, Rodriguez-Clare, and Yeaple (2018) do not mention the product cycle, but have a rich quantitative model where trade integration has implications for the location of innovation and production, as well as wage inequality within and across countries. Our purpose with the stylized model here is merely to fix ideas in terms of why variables related to innovation (including education) and wages may tie in with product-cycle timing during the 20th century to understand how severe local labor market effects are in the event of a trade shock.

In Krugman's stylized world, the economy always attains full employment due to wage adjustment. We note that if one assumes that wages do not adjust immediately—so that employment can dip below full employment levels in transition until wages adjust as in Dornbusch, Fischer, and Samuelson (1977)—then a slight rearrangement of Equation (4) implies that any change in the rate of innovation or the speed of technology transfer (standardization) can reduce employment in the region where the ratio of varieties decreases. In particular, if we denote $\tilde{L}_r$ a level of employment in region r that may be less than full employment before wages adjust, in the new world where the U.S. trades with China, we have

$$\frac{\tilde{L}_N}{\tilde{L}_S} = \frac{i}{t - t_C} \left(\frac{w_N}{w_S}\right)^{-\frac{1}{(1-\theta)}}. \tag{6}$$

In the short run, a drop in the rate of innovation or an increase in the rate of technology transfer may depress employment in the North relative to the South, and vice versa. In addition, products phasing out of the U.S. altogether and offshored to China ($t_C > 0$) may depress employment in the South. If China offers additional skilled labor or incentives for firms to set up foreign affiliates in China and accelerate standardization more generally—an increase in t—we may also see depressed employment in the North, especially in a richer setting where some parts of the North are less innovative than others. The relative wage also can exacerbate the employment effect if wages do not adjust quickly.

From this point, we show that product-cycle-related variables matter for the severity of local impacts from the China shock. The employment effects from the China shock have been carefully studied in a framework refined by many authors, so we depend on existing empirical specifications below as a benchmark. However, Krugman's simple model suggests that looking at the direction in which industries already were moving from "North" to "South" within the United States before the China Shock hit can help one understand which areas were likely to experience bigger effects on local labor market conditions. We therefore measure the direction of China-shock industry movements into or out of local labor markets *before the China shock hit* as an indicator of both (1) the product-cycle age of the industries operating in the area (standardizing/aging if they were moving out) and (2) the proximity to innovation relevant to the invention of the China-competing products (lower if the industries were moving in from somewhere else). We mark areas with the biggest swings into or out of China shock industries—the upper and lower quintile of the change in exposure to the China shock in 1980 relative to 1960—and interact these variables with the ADH measure of the severity of the shock by CZ.

We run regressions based on ADH Table 5 Panel B Columns (3) and (4), which shows the impact of the China shock on the share of unemployed and on the share of the working age population not in the labor force (NILF). We include all the same controls and China shock measure as ADH[9] and include an interaction term with the China shock measures and a set of variables that we think might affect the resilience of the local labor market based on the above discussion. For each variable, we use a CZ-level dummy variable to signal being in the top or

[9]In particular, we use CBP total employment by county to construct the local industry employment shares as in Acemoglu et al. (2016). This is in contrast to our prior discussions and simulated historical trade shocks, where we used instead Census total employment by county to account for non-manufacturing employment when constructing local manufacturing-sector and manufacturing-industry employment shares.

bottom quintile among all CZs. We show the core China shock impact, the uninteracted dummy variable, and the interaction term.

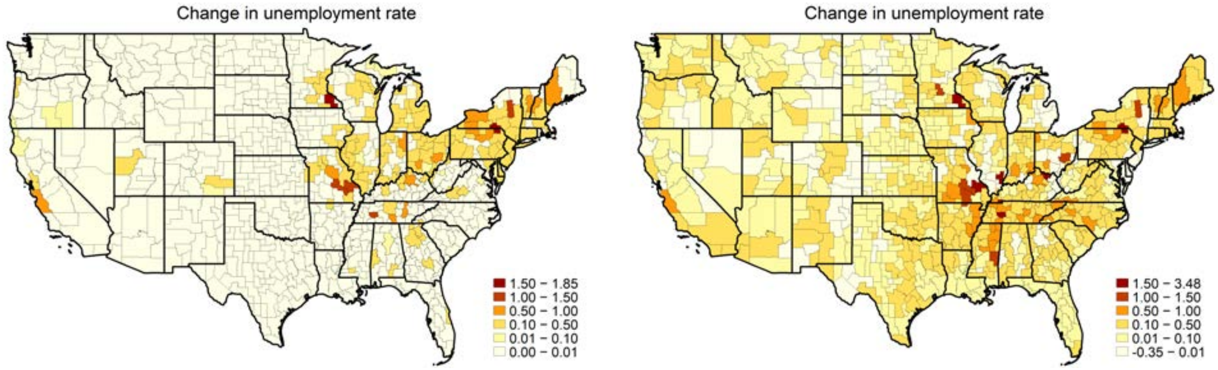
5.1 *Areas with Increasing or Decreasing Exposure*

Continuing with the example of China shock industries, we break down the ADH regression sample by these product-cycle indicators. First, we look at whether an industry had been moving into or out of an area between 1960 and 1980, before China initiated its outward focus as a marker for whether an area was a late adopter of producing these goods or if it had already started to transition out of them. Columns (1)-(2) of Table 9 below replicate the basic ADH result. Columns (3) and (4) show that areas where China shock industries had been *moving in* between 1960 and 1980 (top quintile of exposure in 1980 minus exposure in 1960, measured by dollars of increased Chinese imports per worker between 1991 and 2007 weighted by 1960 or 1980 local employment shares) on average experienced no greater or lower impact for a given level of the shock. In contrast, areas where the industries had been *moving out* (bottom quintile of exposure in 1980 minus exposure in 1960, all negative values) experienced increases in unemployment, shown in Columns (5) and (6). The China shock variable is virtually the same in Columns (3) and (4) as it is in Table 5 of ADH, but the shock itself has smaller coefficients in Columns (5) and (6), suggesting that areas that were not already moving out of these industries did not experience as much pain for a given level of shock as in the initial ADH results.

Table 9: Change in share of unemployed, not-in-the-labor-force 1990-2007 on 1960-80 shift and ADH controls

	1990-2007 stacked first differences					
	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Sh. unempl.	Δ Sh. NILF	Δ Sh. unempl.	Δ Sh. NILF	Δ Sh. unempl.	Δ Sh. NILF
ADH China shock	0.221***	0.553***	0.273***	0.530*	0.137*	0.399*
	(0.058)	(0.150)	(0.063)	(0.219)	(0.058)	(0.175)
Moving in 1960-80 × ADH China shock			-0.087	0.143		
			(0.056)	(0.231)		
Moving in 1960-80			0.063	-0.848		
			(0.165)	(0.600)		
Moving out 1960-80 × ADH China shock					0.241*	0.442**
					(0.108)	(0.152)
Moving out 1960-80					-0.357	-0.731
					(0.222)	(0.445)
ADH controls	Yes	Yes	Yes	Yes	Yes	Yes
N	1444	1444	1444	1444	1444	1444
R^2	0.404	0.386	0.398	0.383	0.343	0.424

Notes: Standard errors in parentheses with ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels. Regressions include a constant and a dummy for the 2000-2007 period. ADH controls are Census division fixed effects and lags of the CBP manufacturing employment share, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women, percentage of employment in routine occupations, average offshorability index of occupations, and a squared time trend.



(a) "Move-out effect" amplified trade shock in areas industries left 1960-1980

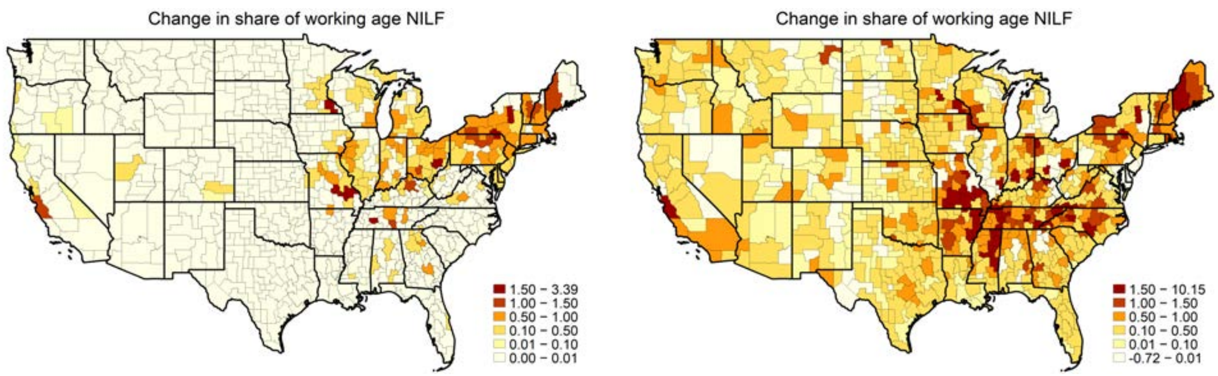
(b) Combined effects of trade shock and move-out indicator across all areas

Figure 9: Predicted increase in unemployment rate 1991-2007 from Table 8, Col (5)

We can use the estimated coefficients from the regression in Table 9 to compute the size of this "move-out effect" on labor market responses to the increase in import competition during the China shock. Figures 9a and 10a map the locations of commuting zones where China shock industries were aging out between 1960 and 1980, amplifying the impact of the shock on unemployment rates and detachment from the labor force beyond what the degree of exposure to the shock by itself would have implied. Figures 9b and 10b in each figure shows the overall effect of the shock, including the moveout effect, to make the distinction between the overall predicted effect of the shock versus the moveout effect on its own. In many cases, areas with the greatest overall impact were those where the industries had been moving in 1960-80, simply because they had greater exposure. However, for a given level of exposure, places where the industries had been *moving out* before the shock hit had more adverse impacts on the unemployment rate and the share of workers detached from the labor force.[10]

An alternative way to measure the product cycle theory would be to look at the areas that were initial adopters (based on exposure in 1910) or those that had excellent market access in 1890 and could be expected to see strong initial development in these industries under both the product cycle and Krugman-Venables wage-reversal hypotheses, as in Tables 10 and 11.

[10]This moveout effect does not seem driven by differences in the presence of upstream industries. We computed the 1990 share of local employment in upstream industries exposed indirectly to the China shock as suppliers to industries directly competing with Chinese imports. In unreported regressions, we included this as an additional control and as an additional interaction term with the China shock variable, with no substantial change in this moveout effect. We also create a move-in/moveout set of variables for these upstream industries 1960-80 and find more adverse effects on unemployment rates conditional on the trade shock where they were already moving out.



(a) "Move-out effect" amplified trade shock in areas industries left 1960-1980

(b) Combined effects of trade shock and move-out across all areas

Figure 10: Predicted increase in share of working age not in the labor force 1991-2007 from Table 8, Col (6)

Table 10: Change in share of unemployed and not-in-the-labor-force 1990-2007 on 1910 simulated exposure to China shock and ADH controls

	1990-2007 stacked first differences			
	(1)	(2)	(3)	(4)
	Δ Sh. unempl.	Δ Sh. NILF	Δ Sh. unempl.	Δ Sh. NILF
ADH China shock	0.162**	0.412*	0.223***	0.562***
	(0.061)	(0.162)	(0.057)	(0.152)
High 1910 exposure × ADH Ch shock	0.266*	0.634*		
	(0.129)	(0.294)		
High 1910 exposure	-0.457*	-1.135*		
	(0.209)	(0.565)		
Low 1910 exposure × ADH Ch shock			-0.194**	-0.171
			(0.074)	(0.153)
Low 1910 exposure			0.232	0.780
			(0.129)	(0.461)
ADH controls	Yes	Yes	Yes	Yes
N	1444	1444	1444	1444
R^2	0.421	0.401	0.406	0.386

Notes: Standard errors in parentheses with ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels. Regressions include a constant and a dummy for the 2000-2007 period. ADH controls are Census division fixed effects and lags of the CBP manufacturing employment share, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women, percentage of employment in routine occupations, average offshorability index of occupations, and a squared time trend.

Table 11: Change in share of unemployed, not-in-the-labor-force 1990-2007 on Donaldson-Hornbeck 1890 Market Access and ADH controls

	1990-2007 stacked first differences			
	(1)	(2)	(3)	(4)
	Δ Sh. unempl.	Δ Sh. NILF	Δ Sh. unempl.	Δ Sh. NILF
ADH China shock	0.159**	0.407**	0.269***	0.757***
	(0.060)	(0.157)	(0.078)	(0.215)
High DH 1890 Mkt Access $\times$ ADH Ch shock	0.262*	0.642*		
	(0.132)	(0.295)		
High DH 1890 Market Access	-0.629**	-1.277*		
	(0.244)	(0.562)		
Low DH 1890 Mkt Access $\times$ ADH Ch shock			-0.231**	-0.977***
			(0.087)	(0.274)
Low DH 1890 Market Access			0.434**	1.741***
			(0.166)	(0.395)
ADH controls	Yes	Yes	Yes	Yes
N	1444	1444	1444	1444
R^2	0.416	0.395	0.402	0.401

Notes: Standard errors in parentheses with ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels. Regressions include a constant and a dummy for the 2000-2007 period. ADH controls are Census division fixed effects and lags of the CBP manufacturing employment share, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women, percentage of employment in routine occupations, average offshorability index of occupations, and a squared time trend.

Much like those places that saw a shrinking share in the China shock industries from 1960-1980, those that had high initial exposure in 1910 or good market access in 1890 saw a larger increase in the unemployment rate conditional on the size of the China shock. Again, the non-interacted terms suggest these places were doing better over this time period. Places with high early exposure and market access had fundamentally lower increases in the unemployment rate and the share of the population out of the labor force, but conditional on the size of the shock, they experienced a more adverse impact.

5.2 *Manufacturing Wages*

Second, we consider local wage rates. While ADH show that low-wage workers were particularly hard hit by the China shock, and while low-wage areas became more exposed to the China shock in the decades before it hit, Column (1) in Table 12 below shows that the employment effects have been more intense in areas of the United States with the highest manufacturing wages. Column (2) provides additional evidence that increases in the share of those not in the labor force associated with the trade shock were greater in the highest-wage areas. The low-wage areas were no different in their effects from the rest of the country. The greater impact for high-wage areas could be seen as consistent with the product cycle theory, or simply with the idea that these areas were least able to compete with Chinese imports on price.

It is worth emphasizing the un-interacted variable coefficients. Having high wages is unambiguously good for a place. On average over 1991-2007, they have increased labor-force participation (relative to the rest of the country) and lower unemployment. The issue is that conditional on the size of the shock, these places have worse outcomes.

5.3 *Innovation and education*

Aside from being an area where affected industries already were being pulled into by low wages or other factors, the product cycle hypothesis suggests that countries, or in our case local economies, can adapt to competition from late adopters by innovating to stay ahead of them or to advance other sectors. As noted, this is consistent with the findings in Staiger and Skinner (2007) that note that some areas of the country consistently move to new innovations faster, and

Table 12: Change in share of unemployed, not-in-the-labor-force 1990-2007 on 1987 manufacturing production wages per worker and ADH controls

	1990-2007 stacked first differences			
	(1)	(2)	(3)	(4)
	Δ Sh. unempl.	Δ Sh. NILF	Δ Sh. unempl.	Δ Sh. NILF
ADH China shock	0.135*	0.436**	0.227***	0.535***
	(0.056)	(0.154)	(0.057)	(0.151)
High-wage × ADH Ch shock	0.253**	0.336*		
	(0.095)	(0.161)		
High-wage	-0.405*	-0.625*		
	(0.186)	(0.410)		
Low-wage × ADH Ch shock			-0.060	0.067
			(0.064)	(0.142)
Low-wage			0.091	0.790
			(0.113)	(0.408)
ADH controls	Yes	Yes	Yes	Yes
N	1444	1444	1444	1444
R^2	0.430	0.406	0.404	0.392

Notes: Standard errors in parentheses with ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels. Regressions include a constant and a dummy for the 2000-2007 period. ADH controls are Census division fixed effects and lags of the CBP manufacturing employment share, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women, percentage of employment in routine occupations, average offshorability index of occupations, and a squared time trend.

these areas have higher education levels.[11] Table 13 shows parallel results for areas with higher or lower levels of education.[12]

We find in Table 13 that areas with a higher percentage of college-educated workers experienced less of a blow to the labor force participation rate, though they still experienced a comparable increase in the share of unemployed workers (the interaction term is negative but not statistically different from zero). Again, the non-interacted variables are also of interest. The commuting zones in the lowest quintile for education (largest percentage with no high school degree) experienced an increase in the share of the working-age population not in the labor force regardless of the China shock, but while the coefficient is large, the result is not statistically significantly different from zero. Thus, it is possible that the shock was hitting these areas that were already struggling for quite different reasons. ADH had already controlled for similar factors and the coefficients on the uninteracted shock, so this does not cast doubt on their results as much as highlight the sense that the shocks were hitting areas that were already struggling. The fact that controls are already in the regression may also make it far less likely that the uninteracted dummy variable for lowest quintile of education would have a statistically significant coefficient.

5.4 Combined impacts

We combine these different strands of the theory into a broader analysis in Table 14. In Columns (1) and (2), we include the ADH trade shock interacted with the dummy variables for being in the top quintile of education, the top quintile of manufacturing wages, and the commuting zones in top quintile of industrial shift into China shock exposure ("moving in") from 1960 to 1980. In Columns (3) and (4), we include the interaction with the dummy variables indicating the lowest quintile for education and wages, and the quintile indicating the greatest shift out of China shock exposure from 1960 to 1980. We find that despite the relatively high levels of correlation across some of the variables, the same broad patterns persist that were seen in the variable by variable regressions. The areas with growing exposure look no different from all other regions, but the ones with shrinking exposure do face larger losses in both the share of workers employed

[11] Staiger and Skinner (2007) also argue these areas have higher social capital as well.

[12] As one possible mechanism to support innovation, a supplemental table in Appendix B, TableB.1, suggests that the presence of Research I universities also can mitigate detachment from the labor force associated with the shock and that the presence of a Research I university may entirely prevent increases in unemployment in low-wage areas, conditional on the size of the shock.

Table 13: Change in share of unemployed, not-in-the-labor-force 1990-2007 on education and ADH controls

	1990-2007 stacked first differences			
	(1)	(2)	(3)	(4)
	Δ Sh. unempl.	Δ Sh. NILF	Δ Sh. unempl.	Δ Sh. NILF
ADH China shock	0.293***	0.972***	0.209***	0.561***
	(0.080)	(0.186)	(0.060)	(0.158)
High fraction college × ADH Ch shock	-0.112	-0.726***		
	(0.096)	(0.194)		
High fraction college	-0.100	0.855		
	(0.146)	(0.445)		
Low fraction HS × ADH Ch shock			0.080	-0.131
			(0.255)	(0.682)
Low fraction HS			0.091	0.790
			(0.113)	(0.408)
ADH controls	Yes	Yes	Yes	Yes
N	1444	1444	1444	1444
R^2	0.403	0.383	0.406	0.401

Notes: Standard errors in parentheses with ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels. Regressions include a constant and a dummy for the 2000-2007 period. ADH controls are Census division fixed effects and lags of the CBP manufacturing employment share, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women, percentage of employment in routine occupations, average offshorability index of occupations, and a squared time trend.

and attached to the labor force conditional on the shock. Again, higher education areas face a smaller impact on the share of the population not in the labor force, and areas with higher initial manufacturing wages faced larger losses in both the share of workers employed and attached to the labor force conditional on the shock.

Two substantial changes to the results occur once all adverse circumstances are imposed together. First, we see in Table 14 that areas with a fraction of the population 25 and older with 12+ years of education in the lowest quintile face a much larger increase in the unemployment rate conditional on the size of the shock. Second, the shock by itself loses significance, the only instance in which this happens in any of our specifications. We interpret this not as refuting the ADH results, but rather as indicating that a combination of high dropout rates and having industries in the process of aging out in the product cycle can make local labor markets acutely vulnerable to a trade shock, to a degree that even having a low prevailing wage in manufacturing production activities cannot mitigate.

The results beg the question of whether a high dropout rate, aging-out industries, and high wages makes local labor markets more vulnerable to other shocks, as well. It is conceivable that they may also be more vulnerable to other types of supply shocks, like credit or oil price shocks, as well as to demand shocks.

6. Additional Discussion

These results may help explain some puzzles regarding the U.S. economy over the last several decades. Influential work by Blanchard and Katz (1992) famously showed that unemployment rates in 1975 across states in the United States were not correlated with those in 1985, suggesting a convergence across regions after shocks. This was in part accomplished by mobility—as unemployed workers moved to find alternative employment.[13] More recent work has shown less mobility in response to different economic circumstances (Ganong and Shoag (2017)) and more persistent economic losses following shocks (Autor et al. (2013)). Austin, Glaeser, and Summers (2018) demonstrate that in particular with regards to employment rates, the prior convergence results of Blanchard and Katz (1992) no longer apply. Regions with low employment rates

[13] See for example Feyrer, Sacerdote, and Stern (2007)

Table 14: Change in share of unemployed, not-in-the-labor-force 1990-2007 on 1960-80 industrial shift, education, 1987 manufacturing production wages per worker and ADH controls

	1990-2007 stacked first differences			
	(1)	(2)	(3)	(4)
	Δ Sh. unempl.	Δ Sh. NILF	Δ Sh. unempl.	Δ Sh. NILF
ADH China shock	0.251**	0.802***	0.114	0.365
	(0.078)	(0.228)	(0.059)	(0.196)
Moving in 1960-1980 × ADH Ch shock	-0.028	0.162		
	(0.065)	(0.223)		
High fraction college × ADH Ch shock	-0.154	-0.775***		
	(0.105)	(0.193)		
High-wage × ADH Ch shock	0.253*	0.462**		
	(0.102)	(0.151)		
Moving out 1960-1980 × ADH Ch shock			0.257*	0.486**
			(0.109)	(0.159)
Low fraction HS × ADH Ch shock			0.196**	-0.071
			(0.062)	(0.172)
Low-wage × ADH Ch shock			-0.117	0.123
			(0.078)	(0.154)
ADH controls	Yes	Yes	Yes	Yes
N	1444	1444	1444	1444
R^2	0.427	0.410	0.430	0.325

Notes: Standard errors in parentheses with ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels. Regressions include a constant and a dummy for the 2000-2007 period. ADH controls are Census division fixed effects and lags of the CBP manufacturing employment share, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women, percentage of employment in routine occupations, average offshorability index of occupations, and a squared time trend. Variables in interaction terms in the table also included independently in the regression.

remain with low employment rates over time.[14] Dao, Furceri, and Loungani (2017) also show that labor has become relatively immobile in response to labor demand shocks. Mobility has declined for many reasons, and Ganong and Shoag (2017) make a compelling case that land use restrictions in rapid-growth regions have helped generate housing cost increases in successful regions, preventing some migration into these regions. The regional targeting of these shocks is also important.

Less educated workers are far less likely to move across states (see Molloy, Trezzi, Smith, and Wozniak (2016) for discussion). Less educated regions are also less likely to shift to new industries and take on new innovations (Staiger and Skinner (2007)). A combination of skill-biased technological change and rising positive agglomeration effects for educated workers in skilled cities (Glaeser and Saiz (2004)) have meant that more-skilled regions had strong positive shocks hitting them over the last few decades supporting their growth. Thus, the clustering of more recent manufacturing shocks in these less educated regions may have greatly magnified the impact and persistence of the economic effects of the shocks.

Over a much longer horizon, Eckert and Peters (2018) document that the decline in the share of agricultural employment happened *within* labor markets and was *not* accomplished primarily by moving workers from agricultural regions to non-agricultural regions. This is not due to lack of mobility. Rather, the flows of workers simply were not disproportionately from agricultural to non-agricultural regions. Allen and Donaldson (2018) map local population growth and economic activity in the United States 1800-2000. In a structural analysis, they show that while path dependence could be important in determining the level of economic activity, initial population shares do not appear to be important drivers of aggregate welfare. We interpret this as again suggestive that labor was reasonably mobile over the last two centuries. In a more recent context, Nunn et al. (2018) show that people from regions characterized by low economic performance do not typically move to thriving regions when they do move.

The relatively stark shifts in the location of production that we document are an interesting counterpoint to the notion of path dependence in the economy. While Allen and Donaldson (2018) find the conditions for path dependence in the U.S. economy are met, their simulations also show that changes in initial conditions have relatively small impacts on the eventual structure of the

[14] See also Nunn, Parsons, and Shambaugh (2018) for discussion of the reduced convergence in regional outcomes since 1980.

U.S. economy. This fits with the idea that the location of production has moved substantially. At the same time, they find that different shocks would have mattered a great deal. This in a sense is consistent with our finding that the timing of the China shock had nontrivial implications for its ultimate effects on the economy.

Also related to these timing issues, several papers have made progress examining the Bartik share methodology, showing that controlling for industry-specific pre-trends or comovement between areas with similar sectoral composition can affect measured impacts on these industries from the China shock (Goldsmith-Pinkham, Sorkin, and Swift (2018); Adao, Kolesar, and Morales (2018); and Borusyak, Hull, and Jaravel (2018)). Our paper suggests that the pre-trends and comovement may be systematically linked to a product cycle with persistent geographical roots stretching back to U.S. industrial development as it took shape more than a century ago.

7. Conclusion

Manufacturing has declined as a share of employment over a long stretch of time in the United States. That decline was neither smooth nor universal in its pace across places in the United States. In addition, the location of production of certain types of products has shifted substantially over time. This means that when targeted shocks have hit the economy, they affect different parts of the country to different degrees, and the location of this pain is a function of when the shocks actually hit.

In this paper, we demonstrate that the evolution of manufacturing in the United States follows a within-county product cycle pattern. Early manufacturing was in more educated, more innovative places with activity spreading over time. We are able to use the China shock industries as an example of late-stage product cycle industries and show their evolution from 1910-1990 follows the product cycle predictions even more clearly than the manufacturing sector as a whole.

When the China shock hit the United States from 1990-2007, the areas most exposed had lower wages, lower levels of education, less innovative capacity as measured by patents per capita, and higher unemployment rates prior to the shock. Yet at the beginning of the 20th century, these same industries were concentrated in areas with high wages, education, and patent activity. The location of production in many ways fits with a within national theory of the product cycle. This fact may help explain why the shock hurt in these areas to the extent that it did. People in these areas were less likely to move, firms less likely to innovate or switch into different industries. At the same time, the impact of the shock – conditional on the size of the shock – also broadly fits the product cycle theory. It was worse in those areas that were already shedding exposure to these industries.

The non-random distribution of the shocks is important for our understanding of the extent to which we should expect trade to cause sizable local labor market disruptions and the extent to which policies to cushion their impacts would have been warranted. The fact that industry specialization has both been shifting over time and is distributed based on important characteristics of places also may have important implications for papers that use shift-share methodologies and the burgeoning literature studying that issue.

References

Acemoglu, D., D. H. Autor, D. Dorn, G. H. Hanson, and B. Price (2016): "Import Competition and the Great US Employment Sag of the 2000s," *Journal of Labor Economics*, 34.

Adao, R., M. Kolesar, and E. Morales (2018): "Shift-Share Designes: Theory and Inference," .

Allen, T. and D. Donaldson (2018): "The Geography of Path Dependence," Unpublished manuscript.

Antràs, P. (2005): "Incomplete Contracts and the Product Cycle," *The American Economic Review*, 95, 1054–1073.

Arkolakis, C., N. Ramondo, A. Rodriguez-Clare, and S. Yeaple (2018): "Innovation and Production in the Global Economy," *American Economic Review*, 108, 2128–2173.

Austin, B., E. Glaeser, and L. Summers (2018): "Saving the Heartland: Place-based Policies in 21st Century America," Tech. rep., Brookings Papers on Economic Activity.

Autor, D. H., D. Dorn, and G. H. Hanson (2013): "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *The American Economic Review*, 103, 2121–68.

Bailey, M. N. and B. P. Bosworth (2014): "U.S. Manufacturing: Understanding Its Past and Potential Future," *Journal of Economic Perspectives*, 28, 3–26.

Batistich, M. K. and T. Bond (2018): "Symptoms Before the Syndrome? Stalled Racial Progress and Japanese Trade in the 1970s and 1980s," Purdue University.

Bernard, A. B., V. Smeets, and F. Warzynski (2017): "Rethinking Deindustrialization," *Economic Policy*, 32, 5–38.

Blanchard, O. J. and L. Katz (1992): "Regional Evolutions," *Brookings Papers on Economic Activity*, 1–75.

Bloom, N., K. Handley, A. Kumar, and P. Luck (2018): "The Impact of Chinese Trade: The Good, the Bad, and the Apocryphal," Unpublished manuscript.

Borusyak, K., P. Hull, and X. Jaravel (2018): "Quasi-Experimental Shift-Share Research Designs," .

Burns, A. (1934): *Production Trends in the United States*, New York: National Bureau of Economic Research.

Cadena, B. and B. Kovak (2016): "Immigrants Equilibrate Local Labor Markets: Evidence from the Great Recession," *American Economic Journal: Applied Economics*, 8.

Charles, K. K., E. Hurst, and M. Schwartz (2018): "The Transformation of Manufacturing and the Decline in U.S. Employment," Working Paper 24468, National Bureau of Economic Research.

Crafts, N. and A. Klein (2017): "A Long-Run Perspective on the Concentration of Manufacturing Industries in the United States," Working Paper 1715, University of Kent School of Economics Discussion Papers.

Dao, M., D. Furceri, and P. Loungani (2017): "Regional Labor Market Adjustment in the United States: Trend and Cycle," *Review of Economics and Statistics*, 99, 243–257.

Dixit, A. K. and J. E. Stiglitz (1977): "Monopolistic Competition and Optimum Product Diversity," *The American Economic Review*, 67.

Donaldson, D. and R. Hornbeck (2016): "Railroads and Economic Growth: A "Market Access" Approach," *The Quarterly Journal of Economics*, 131, 799–858.

Dorn, D. (2009): "Essays on Inequality, Spatial Interaction, and the Demand for Skills," Ph.D. thesis, University of St. Gallen.

Dornbusch, R., S. Fischer, and P. A. Samuelson (1977): "Comparative Advantage, Trade, and Payments in a Ricardian Model with a Continuum ofGoods," *The American Economic Review*, 67, 823–839.

Eckert, F. and M. Peters (2018): "Spatial Structural Change," Unpublished Manuscript.

Erickson, R. and T. Leinbach (1979): "Characteristics of branch plants attracted to nonmetro areas," in *Nonmetropolitan Industrialization*, ed. by R. Lonsdale and H. Seyler, Washington, D.C.: Winston, 57–78.

Feenstra, R. C., H. Ma, and Y. Xu (2017): "US Exports and Employment," Working Paper 24056, National Bureau of Economic Research.

Feyrer, J., B. Sacerdote, and A. Stern (2007): "Did the Rust Belt Become Shiny? A Study of Cities and Counties That Lost Steel and Auto Jobs in the 1980s," *Brookings-Wharton Papers on Urban Affairs*, 48–89.

Fillat, J. L. and S. Garreto (2015): "Risk, Returns, and Multinational Production," *Quarterly Journal of Economics*, 130.

Fort, T., J. Pierce, and P. Schott (2018): "Perspectives on the Decline of U.S. Manufacturing Employment," *Journal of Economic Perspectives*, 32.

Ganong, P. and D. W. Shoag (2017): "Why Has Regional Income Convergence in the U.S. Declined?" *Journal of Urban Economics*, 102, 76–90.

Glaeser, E. L. and A. Saiz (2004): "The Rise of the Skilled City," *Brookings-Wharton Papers on Urban Affairs*, 47–105.

Goldin, C. (1998): "America's Graduation from High School: The Evolution and Spread of Secondary Schooling in the Twentieth Century," *Journal of Economic History*, 58, 345–374.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2018): "Bartik Instruments: What, When, Why, and How," .

Grossman, G. and E. Helpman (1991): "Endogenous Product Cycles," *The Economic Journal*, 101, 1214–1229.

Helper, S., T. Krueger, and H. Wial (2012): "Why Does Manufacturing Matter? Which Manufacturing Matters? A Policy Framework," Discussion paper, Metropolitan Policy Program at Brookings.

Holmes, T. J. and J. J. Stevens (2004): "Spatial Distribution of Economic Activities in North America," in *The Handbook of Regional and Urban Economics*, ed. by J. Henderson and J. Thisse, vol. 4, chap. 63, 2797–2839.

——— (2014): "An Alternative Theory of the Firm-Size Distribution, with Geography and Intra- and International Trade," *Journal of Political Economy*, 122.

Houseman, S. (2018): "Understanding the Decline of U.S. Manufacturing Employment," Working Paper 18-287, Upjohn Institute Working Paper.

Jaworski, T., C. T. Kitchens, and S. Nigai (2018): "The Interstate Highway System and the Development of the American Economy," Unpublished Manuscript, University of Colorado, Boulder, http://eh.net/eha/wp-content/uploads/2018/06/Kitschens.pdf.

Ju, J., J. Y. Lin, and Y. Wang (2015): "Endowment structures, industrial dynamics,and economic growth," *Journal of Monetary Economics*, 76, 244–263.

Kim, S. (1995): "Expansion of Markets and the Geographic Distribution of Economic Activities: The trends in U.S. Regional Manufacturing Structure: 1860–1987," *The Quarterly Journal of Economics*, 110, 881–908.

Kim, S. and R. A. Margo (2004): "Historical Perspectives on U.S. Economic Geography," in *The Handbook of Regional and Urban Economics*, ed. by J. Henderson and J. Thisse, vol. 4, chap. 66, 2981–3014.

Klepper, S. (1996): "Entry, Exit, Growth, and Innovation over the Product Life Cycle," *The American Economic Review*, 86, 562–583.

Krugman, P. (1979): "A Model of Innovation, Technology Transfer, and the World Distribution of Income," *Journal of Political Economy*, 87, 253–266.

——— (1991): "Increasing Returns and Economic Geography," *Journal of Political Economy*, 99, 483–499.

Krugman, P. and A. J. Venables (1995): "Globalization and the Inequality of Nations," *The Quarterly Journal of Economics*, 110, 857–880.

Kuznets, S. (1930): *Secular Movements in Production and Prices*, Boston: Houghton Mifflin.

Matsuyama, K. (2019): "Engel's Law in the Global Economy: Demand-Induced Patterns of Structural Change, Innovation, and Trade," *Econometrica*, 87, 497–528.

Molloy, R., R. Trezzi, C. L. Smith, and A. Wozniak (2016): "Understanding Declining Fluidity in the U.S. Labor Market," *Brookings Papers on Economic Activity*, 183–259.

Norton, R. and J. Rees (1979): "The Product Cycle and the Spatial Decentralization of American Manufacturing," *Regional Studies*, 13, 141–151.

Nunn, R., J. Parsons, and J. C. Shambaugh (2018): "The Geography of Prosperity," in *Place Based Policies for Shared Economic Growth*, ed. by R. Nunn and J. Shambaugh, Washington, D.C.: The Hamilton Project.

Petralia, S., P.-A. Balland, and D. L. Rigby (2016): "Data Descriptor: Unveiling the Geography of Historical Patents in the United States from 1836 to1975," *nature.com*.

Rees, J., R. Briggs, and R. Oakey (1984): "The adoption of new technology in the American machinery industry," *Regional Studies*, 18, 489–504.

Rodriguez-Lopez, A. (2014): "What Drives Offshoring? Selection and Escape-Competition Mechanisms," Unpublished Manuscript, University of California, Irvine.

Schott, P. K. (2008): "Chinese Exports," *Economic Policy*, 5–49.

Staiger, D. and J. Skinner (2007): "Technology Adoption from Hybrid Corn to Beta Blockers," in *Hard-to-Measure Goods and Services: Essays in Honor of Zvi Griliches*, ed. by E. R. Berndt and C. R. Hulten, Chicago, IL: University of Chicago Press and NBER.

Vernon, R. (1966): "International Investment and International Trade in the Product Cycle," *The Quarterly Journal of Economics*, 80, 190–207.

Appendix A. Data

A.1 Historical manufacturing data

To compute historical manufacturing employment shares, we use employment counts in manufacturing industries by county from the full-count Census for 1910, 1940, and the IPUMS 5 percent sample for 1960, categorized using the IND1950 designations. For 1910 and 1940, we use NHGIS county shape files to adjust historical county borders to 1990 county borders, which we then match to 1990 commuting zones using the crosswalk from Dorn (2009) so that our maps fit within the context of recent discussions of local labor market shocks.[15]

A.2 Historical exposure to 1991-2007 China shock

To compute which local labor markets would have been most exposed to a surge in imports in the same industries as occurred in 1991-2007 (to the extent that these industries yet existed), we matched the NAICS categories of affected industries to IND1990 using Dorn's matching, then IND1990 to IND1950, which is used for the industry categories in the 1910 and 1940 employment count data available from IPUMS. To measure the national-level import surge by industry, we use the imports per worker given industry employment in 1990, as computed in ADH. Then we use the CZ industry-level employment counts as a share of the total CZ employment as weights, multiplying these weights by the surge in imports per worker 1991-2007 in each corresponding industry and summing the total by CZ according to the formula laid out by ADH:

$$\Delta IPW_{CZ,t} = \sum_j \frac{L_{CZ,j,t}}{L_{CZ,t}} \frac{\Delta M_{j,1991-2007}}{L_{j,1990}},$$

where j represents the industry, L is the size of the workforce in the area or industry, and M U.S. imports from China. In ADH, t is 1990. We also compute synthetic historical exposure to the 1991-2007 China Shock industries, with t=1910, 1940, 1960, 1974-90 For charts and tables of correlations, we use Census total civilian employment from the County Data Books (available in ICPSR-2896) for all t in $L_{CZ,t}$, including 1974-1990. This departs from ADH, who use the summ

[15] In 1960, mini-PUMAs are the smallest geographic unit identified, so we overlay a NHGIS 1990 county shape file with a mini-PUMA shape file from IPUMS, reweighting mini-PUMAs overlapping with counties by the fraction of area of the mini-PUMA that falls within the county border. We then map counties to 1990 commuting zones, again using the Dorn (2009) crosswalk. We use employment counts from County Business Patterns database for years from 1974-2011 to maintain consistency with ADH and also due to having only 1 percent samples available for census data after 1960. In all years, we take the manufacturing employment counts from these datasets as a fraction of the total civilian laborforce reported in the County Data Books from ICPSR-2896, interpolating the laborforce counts between available years where needed.

of employment in CBP, which does not include agricultural production and some other categories of employment that is captured in the numbers for total civilian employment. To construct our "moving in" and "moving out" variables for regressions in Section 5, we use this definition of exposure in 1960 and 1980 and take the difference. Otherwise, in the regressions for Section 5, we do not depart from the ADH definitions and use data exactly as in their replication package to keep our results nested within theirs for comparability.

A.3 Other historical variables

All other historical variables are taken from ICPSR-2896, except for patents, which are from Petralia et al. (2016), and trade data used to construct the Japan and Tiger shocks, which are from Schott (2008), available on his website at https://spinup-000d1a-wp-offload-media.s3.amazonaws.com/faculty/wp-content/uploads/sites/47/2019/06/xm_sic87_72_105_20120424.zip.

Appendix B. Supplemental Table

Table B.1: Change in share of unemployed, not-in-the-labor-force 1990-2007 on presence of Research I university, lowest quintile manufacturing wages per worker

	1990-2007 stacked first differences			
	(1)	(2)	(3)	(4)
	Δ Sh. unempl.	Δ Sh. NILF	Δ Sh. unempl.	Δ Sh. NILF
ADH China shock	0.201***	0.807***	0.166***	0.796***
	(0.060)	(0.176)	(0.066)	(0.182)
Res I × ADH Ch shock	0.060	-0.748***	0.018	-0.732**
	(0.054)	(0.278)	(0.063)	(0.292)
Research I	-0.132	1.325**	-0.127	1.276**
	(0.118)	(0.542)	(0.152)	(0.567)
Low-wage × ADH Ch shock			0.029	0.036
			(0.040)	(0.107)
Low-wage			-0.072	0.113
			(0.151)	(0.429)
Res I × Low-wage × ADH Ch shock			-1.137***	-0.593
			(0.172)	(0.717)
Research I × Low-wage			1.920**	3.132***
			(0.850)	(0.807)
ADH controls	Yes	Yes	Yes	Yes
N	1444	1444	1444	1444
R^2	0.403	0.350	0.369	0.351

Notes: Standard errors in parentheses with ***, **, and * respectively denoting significance at the 1%, 5% and 10% levels. Regressions include a constant and a dummy for the 2000-2007 period. ADH controls are Census division fixed effects and lags of the CBP manufacturing employment share, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women, percentage of employment in routine occupations, average offshorability index of occupations, and a squared time trend. Low-wage indicates lowest quintile of manufacturing wages per worker among all CZs. Research I indicates presence of a university designated as such by the Carnegie Endowment located in the CZ.