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**Working Paper**

## Why aren't people leaving Janesville? Industry persistence, trade shocks, and mobility

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## Why Aren't People Leaving Janesville? Industry Persistence, Trade Shocks, and Mobility

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## **Why Aren't People Leaving Janesville? Industry Persistence, Trade Shocks, and Mobility**

**Upjohn Institute Working Paper 22-365**

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### **ABSTRACT**

Particular industries have dominated many locations in the United States for more than a century. We show that individuals residing in such locations were systematically less likely to move away from there during the past few decades. By identifying locations with sizable employment shares in the same manufacturing industries in 1870 and 1980, we documented less out-migration in the decades following 1980 than earlier. In response to the largest shock affecting manufacturing employment since then, these locations adjusted differently: the “China shock” led to higher unemployment in their communities, but fewer people moved away. Drawing on rich data of social links across counties and surveys of individuals residing there, we document that these individuals have stronger local friendship networks than residents of more thriving communities and exhibit systematic differences in their job-market search behavior. We hypothesize that when local opportunities narrow, residents of these locations both lack information about job opportunities elsewhere and benefit from the amenity value of extended social networks in their location of origin. Instrumental variable results based on a historical shock to local industries’ chances of survival suggest that the effect of dominant manufacturing industries on migration is causal. Mediation analysis reveals that the emergence of strong local ties primarily drives such migration.

**JEL Classification Codes:** J23, N31, N32, N71, N72, R12, Z1

**Key Words:** Employment persistence, labor mobility, local ties

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# 1 Introduction

Janesville, Wisconsin, transformed itself from a vibrant agricultural community in the late nineteenth century into the manufacturing town it remained throughout the twentieth century. A General Motors plant, established in 1919, provided ample job opportunities for locals throughout multiple generations. As [Amy Goldstein \(2017\)](#) describes, life there was deeply intertwined with the plant. Thousands worked there, some families for generations. In 2008, the plant closed, leaving many residents without comparable employment opportunities in the community. However, despite the loss of a dominant employer, Janesville's population still grew after 2008. Janesville is just one piece of a puzzle scattered all across former manufacturing centers of the United States: hundreds of small towns have seen the closure of large plants in their dominant industry, yet their inhabitants stay. In a nation characterized by the mobility of its populace compared to Europe ([Molloy, Smith and Wozniak, 2011](#)), where most of the U.S. population came from in terms of its ancestry, this is surprising. Should we not expect a decline in population once a dominant employer shuts down and opportunities vanish?

In this paper, we argue that it is not primarily economic factors, such as durable investment (for instance, in housing), or the monetary costs of migration or job search, that are responsible for the lack of movement out of cities where employment opportunities are lacking. Instead, we argue, the long-time presence of specific industries, providing jobs (in particular, low-skilled ones) for generations of residents, has led to the emergence of strong local ties and has prevented weaker ties of locations at greater distance from luring residents away. These strong local ties not only inhibit community residents from gaining access to information regarding employment opportunities outside their vicinity, but also, by virtue of their having access to an extensive network of family and friends, provide them with a location-specific amenity.

We measure the presence and size of employment in disaggregated manufacturing industries across U.S. counties, State Economic Areas, and Commuting Zones (locations to follow) in 1870 and 1980, from the Census Bureau's Annual Survey of Manufactures and the County Business Patterns, respectively. From these statistics, we construct a measure of location-specific industry employment persistence (abbreviated to "industry persistence" in the rest of this paper) over more than a century. We document sizable variation in this measure across and within U.S. regions and show that it is driven by a wide variety of industries. Using migration data at the State Economic Area (hereafter, SEA) level, we use ordinary-least-squares (OLS) estimation to document lower out-migration rates relative to in-migration where industry persistence is high from 1960 to 2000. The main

concern in our analysis is reverse causality, as industries may be more likely to persist in locations with low out-migration rates, since firms can keep wages lower. We address this concern by using a major labor demand shock (comparable in magnitude to the contemporaneous “China Shock”) in the United States that stemmed from the introduction of convict labor in the 1870s, directly after we start recording measurement of industry persistence (Poyker, 2018). Competition with prison-made goods forced affected industries in affected locations to be more productive. As a result, compared to similar industries in unaffected locations, these industries were more likely to survive until 1980. We employ an instrumental variable (IV) estimation and use exposure to pre-convict-labor-era prison capacities as an instrument for industry persistence. Old prisons were built based on demographic factors, with no consideration given to their later use of convict labor. Indeed, the instrument is not correlated with pre-1870 growth in manufacturing wages, whether geographically or by industry. This indicates that, indeed, the geographic placement of prisons was unrelated to local economic conditions.

Low out-migration due to industry persistence is a general feature of these locations, but in addition is also strongly pronounced in Commuting Zones (hereafter, CZs) disproportionately affected by external labor demand shocks. China’s accession to the World Trade Organization (WTO) in 2001 and its domestically driven comparative advantage in low-skilled manufacturing industries increased competition in these industries, which once provided for the livelihoods of residents in small towns such as Janesville. We show that in such towns, while unemployment surged compared to other locations, their total population has not declined disproportionately. Figure 1 depicts this by comparing the adjustment to the China shock from 2000 to 2007 in CZs below and above median industry persistence.<sup>1</sup> In regression analysis resembling that of Autor, Dorn and Hanson (2013), we estimate the heterogeneous effect of industry persistence for commuting zones affected by the China shock. Our results reaffirm the main insight conveyed by the figure. Additionally, to alleviate concerns of endogeneity, we combine Autor, Dorn and Hanson’s instrument with the exposure to pre-convict-labor-era prisons’ capacity. Our causal estimates of the differential adjustment of CZs with persistent industries confirm our baseline results: not only are residents of locations with persistent industries less likely to out-migrate in general, but also their adjustment behavior to external shocks is different from that of other CZs affected similarly.

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<sup>1</sup>We discuss the construction of our industry persistence measure in detail in Section 2.

Figure 1: In CZs with Persistent Industries, Unemployment Increases at a Greater Rate, but Population Declines at a Slower Rate



Notes: Panel A shows that Commuting Zones above the median share of employment in persistent industries had larger increases in unemployment as a result of China's inclusion in the WTO in 2000–2008. Panel B shows that at the same time, Commuting Zones above the median share of employment in persistent industries had smaller declines in population.

Why have people stayed in places strongly affected by negative labor demand shocks? We proceed by showing that individuals there, on average, have fewer social connections to other locations throughout the United States. To show this, we use data recently made available on the social connectedness between locations. These data draw on Facebook friendship networks. Facebook is the dominant online social network for individuals around the world, covering almost all age groups and social backgrounds. We use this data, first introduced by [Bailey et al. \(2018\)](#), to count the friendship links across counties. We create a measure of a county's average connectedness to other counties in the United States and correlate it with industry persistence. We find that counties with stronger industry persistence are less connected to other counties on Facebook. Furthermore, we use mediation analysis ([Dippel et al., 2017](#)) to infer whether the effect of industry persistence on migration rates operates through this lack of social connectedness. Our results confirm that, indeed, almost two-thirds of the effect operates through this social connectedness channel. We corroborate this with evidence from the General Social Survey (GSS) by documenting that individuals in counties with higher industry persistence, yet within the same industry and occupation, and controlling for various demographic variables and college attendance, are less likely to have ever moved and have fewer friends in total but stronger connections to these friends. Furthermore, these respondents report different labor market search behavior, as evidenced by their lower willingness to learn new skills for a job or accept a temporary one.

Our paper contributes to several strands of the literature. First, we contribute to the literature related to long-run cycles in industrial development (e.g., [Eriksson et al., 2021](#)). We emphasize the social consequences of industrial structure and its persistence, and we show its direct effects on migration and relevant local labor market outcomes. Second, we contribute to the sociological and evolutionary anthropology literature on weak ties ([Granovetter, 1977](#)) and local kinship ([Enke, 2019](#)), and the economic literature on migrant networks and migration ([Battisti, Peri and Romiti, 2016](#); [Akram, Chowdhury and Mo-barak, 2017](#); [Mahajan and Yang, 2020](#)). We demonstrate how weak ties and local kinship can result from local industrial structure, and what their effect is on relevant economic and social behavior. Our results hint at the importance of persistent local industrial structure for low migration rates—e.g., in Europe ([Molloy, Smith and Wozniak, 2011](#)). Finally, we contribute to the literature on the effect of the China shock on the U.S. economy, and in particular on differences in locations’ ability to adjust to external shocks ([Kim and Vogel, 2018](#); [Bloom et al., 2019](#)). We show that these differences in adjustment are predetermined, and that they therefore provide insights on how to design and focus place-based policies aimed at mitigating the adverse effects of labor demand shocks.

The paper proceeds as follows. In [Section 2](#), we introduce our data sources and two main measures of industry employment persistence, and we discuss their spatial and industry-specific patterns. [Section 3](#) then provides evidence that locations with higher industry persistence have seen lower out-migration from 1960 to 2000 and have had differential labor market adjustment to the China Shock. [Section 4](#) in turn provides evidence on our mechanism by documenting that those locations are less connected to other locations in the U.S., and that their inhabitants differ in the strength of their social ties and their labor market behavior. [Section 5](#) concludes.

## 2 Industry Employment Persistence: Measurement and Patterns

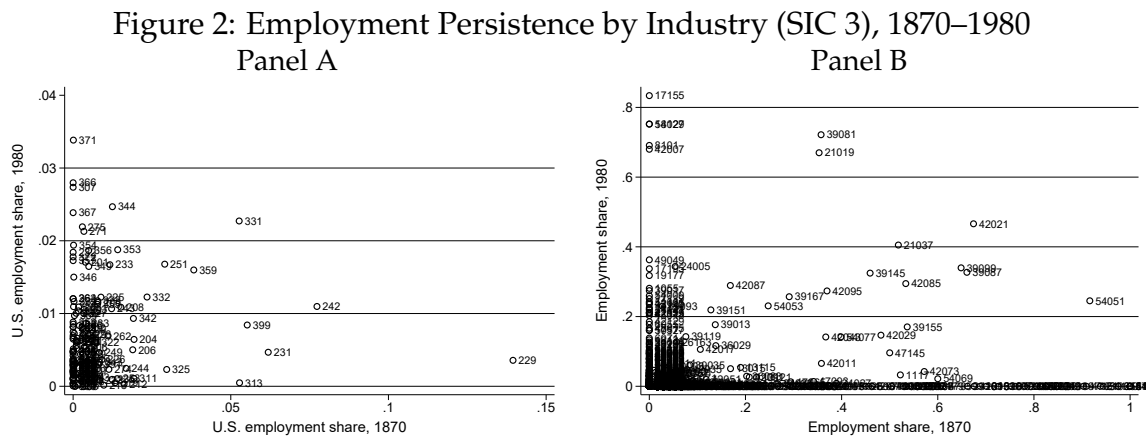
We use two sources of data to measure persistence of a particular manufacturing industry in a county, Community Zone, or State Economic Area. Throughout, we focus on manufacturing industries, as data on these are consistently available over the time period considered.<sup>2</sup> Our main data used are county-industry SIC 3-level employment counts for

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<sup>2</sup>We use manufacturing industries at the disaggregated Standard Industrial Classification (SIC 3), particularly the codes 200–399.



1870 and 1980.<sup>3</sup> We construct the measure at three levels of spatial aggregation. For one, we focus on the smallest unit available—counties—and whenever it is sensible to perform analysis or estimation at this level, we do so. In some instances, we follow the literature and perform our analysis at a more disaggregated level, namely CZ, which broadly captures regions in which people both work and live,<sup>4</sup> while for migration outcomes we make SEA our level of analysis, a choice enforced by data availability at that level. For the following description of the measure and its geographic patterns, we focus on counties, the most disaggregated level for which we have data.



Notes: Panel A is a scatter plot of U.S. employment shares in 1870 and 1980. In Panel A, each dot is an SIC three-digit industry code. Panel B is a scatter plot of U.S. counties' employment shares in 1870 and 1980 for SIC 331, Primary Metal Manufacturing. In Panel B, each dot is a county. We label FIPS codes in Panel B.

Panel A of Figure 2 depicts the national U.S. employment share of manufacturing industries in 1870 and 1980. Certain industries that employed large shares of the U.S. manufacturing labor force in 1870 have seen a decline over the following 110 years (e.g., Miscellaneous Textile Goods, SIC 229), while other industries, which only emerged during the late nineteenth century, have become major employers throughout the twentieth century, such as Motor Vehicles and Motor Vehicle Equipment (SIC 371). Various industries employ a comparable share of total manufacturing employment in both 1870 and 1980, such as Primary Metal Manufacturing (SIC 331) and Sawmills and Planing Mills (242).

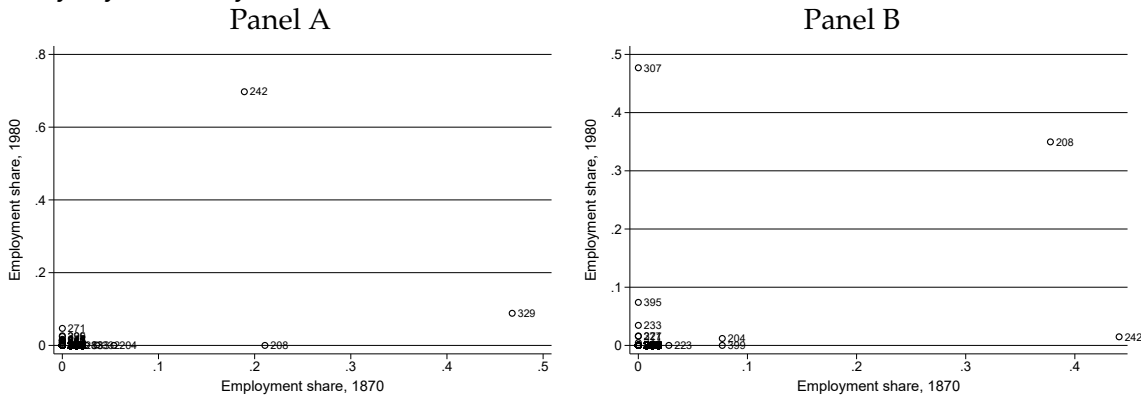
<sup>3</sup>The 1980 employment count comes from the County Business Patterns. These data (at the North American Industry Classification System [NAICS] 3-digit code level) come from the Census Bureau ([www.census.gov/programs-surveys/cbp.html](http://www.census.gov/programs-surveys/cbp.html)). The SIC 3–NAICS 3 crosswalk used is available in the Online Appendix. We rely on David Dorn's imputation algorithm for nondisclosed values, available on his website ([www.ddorn.net/data.htm](http://www.ddorn.net/data.htm)). The 1870 county-industry employment comes from the Table XI of the "Compendium of the Ninth Census."

<sup>4</sup>We use David Dorn's county-to-commuting-zone crosswalk to do so (Autor, Dorn and Hanson, 2013).



Panel B allows us to look within such an industry. For each county, we plot its employment share in “Primary Metal Manufacturing” in 1870 and in 1980. While many entries and exits of individual counties took place, a sizable number reported employment in both 1870 and 1980. An example is Cambria County, Pennsylvania (FIPS code 42021), where this industry has been a major employer for more than a century. It had a considerable manufacturing employment share (70%) in primary metals in 1870, and it still had an almost 45% share in the same industry in 1980.

Figure 3: Employment Persistence in Amador County, California, and Nelson County, Kentucky, by Industry (SIC 3), 1870–1980



*Notes:* Each dot represents an SIC three-digit industry code. Panel A is a scatter plot of employment shares in 1870 and 1980 in Amador County, California (FIPS 6005). Panel B is a scatter plot of employment shares in 1870 and 1980 for Nelson County, Kentucky (FIPS 21179).

Our analysis will rely on cross-county variation; hence, we next inquire into how persistent industries are within a county. Panel A of Figure 3 shows the manufacturing employment share for Amador County. There, two industries are persistent: 1) Sawmills and Planing Mills (SIC 242) and 2) Abrasive, Asbestos, and Miscellaneous (SIC 329). Panel B, by comparison, shows a similar scatter plot for Nelson County. There, only one industry, Beverages (SIC 208), in 1980 still employs a sizable share of the manufacturing labor force, as it did more than a century earlier. Compared to 1870, only a small share of manufacturing employment took place in Sawmills and Planing Mills (SIC 242) by 1980.

All of the outcomes we are interested in are at the location level. Naturally, the effect of even one persistent industry alone is not contained to workers within that industry, but extends, through family and community linkages, to the entire community. The comparison of Amador and Nelson Counties, above, demonstrates an ambiguity in measuring industry persistence in a certain location. How should we aggregate these county-industry employment shares to a county-level measure? Our measure could capture either of two

aspects: 1) whether in a county the same industries still exist and have comparable shares of employment, or 2) whether industries survived that became (or remained) dominant until 1980.

In answer, we introduce two measures that capture each of these aspects separately. The first measure focuses on the second aspect, emphasizing the importance of industry employment shares in 1980. It is defined as follows:

$$IP_c = \sum_{i \in I} (1 (Emp_{ic1870} > 0) \times \lambda_{ic1980}), \quad (1)$$

where  $\lambda_{ic1980} = \frac{Emp_{ic1980}}{\sum_i Emp_{ic1980}}$  is the employment share in industry  $i$  in county  $c$  (or CZ/SEA) in 1980,  $I$  is a set of three-digit SIC codes (200–399), and  $1 (Emp_{ic1870} > 0)$  is an indicator function equal to unity if industry  $i$  existed in 1870 in county  $c$  (i.e., had nonzero employment), and zero otherwise. This measure at the industry level ranges from 0 to 1, in which 0 indicates that neither in 1870 nor in 1980 did any individual in a county work in a particular sector, and 1 represents the hypothetical case in which all manufacturing workers in a county worked in that sector in 1870 and also 110 years later. Summing it up over industries, its bounds remain 0 and 1. As most of our outcomes are measured after 1980, this measure captures well the relative importance of persistent industries in 1980. But while it emphasizes the importance of persistent industries in 1980, it downplays their role in 1870. As an extreme case, consider two counties, both of which in 1980 have all local manufacturing workers employed in a single sector. Independent of their 1870 employment shares in this sector, they will exhibit the same value of industry persistence at the county level, as long as at least one worker was employed in this industry in 1870.<sup>5</sup>

Our second measure alleviates the issues arising from the extreme case discussed before, by explicitly considering 1870 and 1980 employment shares. It is defined as follows:

$$IP_c = \frac{1}{\sum_{i \in I} [(\lambda_{ic1870} - \lambda_{ic1980})^2]}, \quad (2)$$

where  $\lambda_{ic1870} = \frac{Emp_{ic1870}}{\sum_i Emp_{ic1870}}$  is the employment share in industry  $i$  in county  $c$  (or CZ/SEA) in 1870. The denominator  $(\lambda_{ic1870} - \lambda_{ic1980})^2$  measures the squared changes in industry employment shares between 1870 and 1980. Summing up these differences over all industries  $i \in I$ , a county with a smaller value exhibits higher persistence of industry employment shares. Making this second measure comparable with the first one computed in Equation (1), we take its inverse, so that larger values are associated with higher measures

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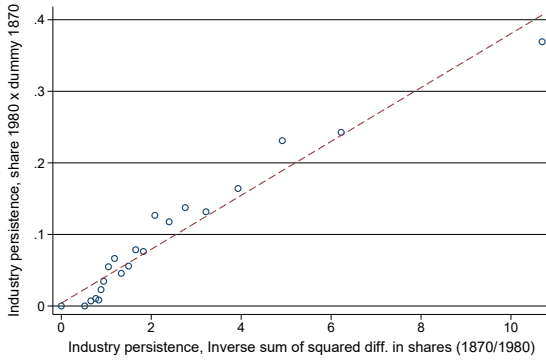
<sup>5</sup>Alternatively, we could have computed industry persistence at the location-industry level using dummies for employment in either 1870 or 1980, or both, and then aggregated appropriately at the location level. All our results are robust to either definition, but we prefer the one introduced in the main text.

of industry persistence.

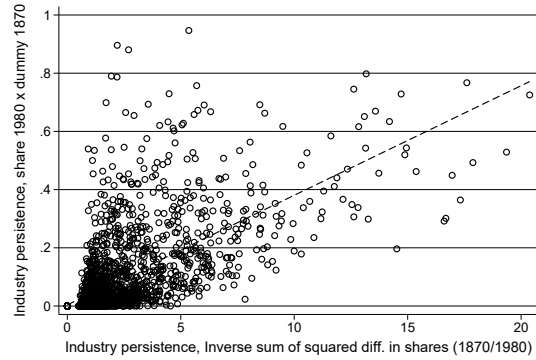
Our first measure assigns higher values of persistence to locations in which surviving industries capture a large employment share in 1980. Our second measure instead assigns higher values to counties in which more industries have similar employment shares in both years. As evident from Figure 4, both measures are highly correlated.

The maps in Figure 5 illustrate the spatial variation in industry persistence for both measures at the county level. Darker shades of blue stand for higher quintiles of our measures. As many counties in the Great Plains region were not settled by 1870, these areas have zero persistence. High persistence is common in the manufacturing belt extending from the Great Lakes to New England, along the Pacific Northwest coast, and scattered across the South. Even within these regions, however, there is sizable variation in our measure. Appendix Figure A.1 shows the variation in industry persistence for both measures in absolute values.<sup>6</sup>

Figure 4: Comparison of Industry Persistence Measures  
Panel A



Panel B



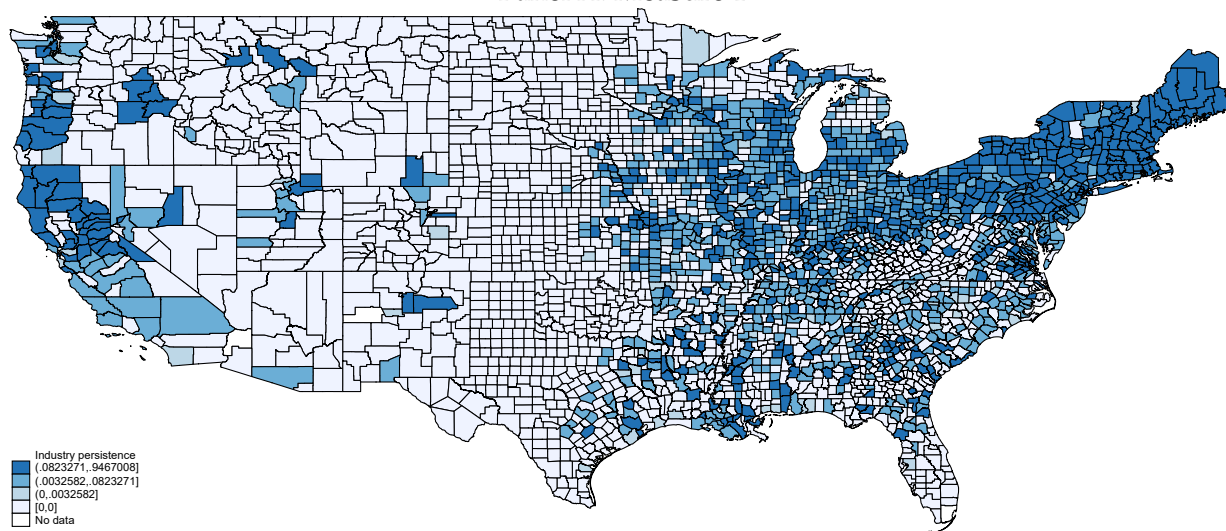
Notes: Panel A is a binscatter, or a binned scatter plot. Panel B is a scatter plot, in which each observation is a county. The measure on the x-axis is computed using Equation (1), while the measure on the y-axis is computed using Equation (2).

### 3 Effects of Industry Persistence on Mobility

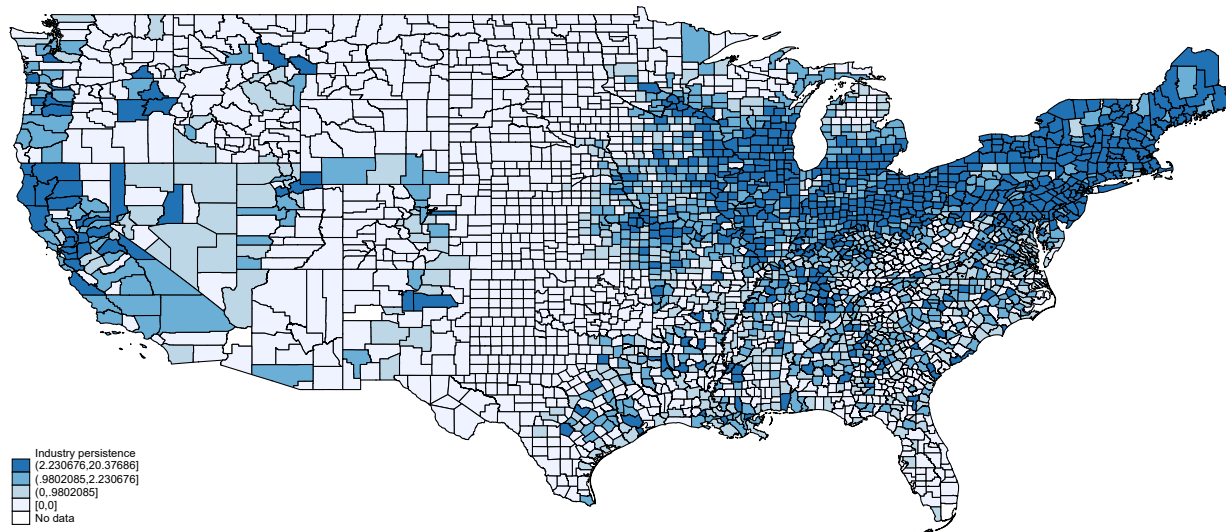
In this section, we first show that locations with sizable employment persistence in the same broad industries from 1870 to 1980 exhibit lower out-migration in each decade from 1960 to 2000. We then show that the differential mobility of individuals in these places is especially pronounced when facing external shocks, for which we employ the “China

<sup>6</sup>Appendix Figures A.2 and A.3 contain similar graphs but for the CZ and SEA levels.

Figure 5: Industry Persistence by County (1870–1980): Geographical Variation  
Panel A: Measure 1



Panel B: Measure 2



Notes: Panel A is computed using Equation (1). Panel B is computed using Equation (2).

shock” of [Autor, Dorn and Hanson, 2013](#). We delay until the next section the discussion of why locations with higher industry persistence adjust differently.

### 3.1 Lower Out-Migration Where Industries Are Persistent

We test whether locations with a higher share of employment in persistent industries have lower out-migration by estimating the following cross-sectional specification at the SEA level:

$$\ln \left( \frac{\text{out-migrants}}{\text{in-migrants}} \right)_{ct} = \alpha + \beta IP_c + \mathbb{X}_{ct}\Gamma + \varepsilon_{ct}, \quad (3)$$

where  $\ln \left( \frac{\text{out-migrants}}{\text{in-migrants}} \right)_{ct}$  is the logarithm of the number of out-migrants relative to in-migrants. Migration data is available for decades between  $t \in \{1960; 2000\}$  and collected from decennial census volumes by [Song \(2019\)](#).  $\mathbb{X}_{ct}$  is a vector of controls, including the logarithm of population, manufacturing employment share, geographical controls, and historical controls. Standard errors are clustered at the state level.

Panel A of Table 1 presents our OLS results for the first measure. In columns I to V, we report results for 1980, the year in which we measure industry persistence. We always include state fixed effects, effectively comparing relative out-migration rates between SEAs within states, and we compare 1980 population counts to account for differences in mobility by city size. We include the 1980 manufacturing share in column II to reassure ourselves that our measure is not simply capturing variation across SEAs in economic structure. Column III adds geographic controls, including a cubic polynomial of longitude and latitude and the area of SEAs. Column IV adds controls for 1870, when our measure of industry persistence first records employment. This is particularly relevant, as later we will introduce a historical instrumental variable that starts shortly thereafter. We include total population in 1870, the share of population residing in urban settlements, and the SEAs’ market access based on [Donaldson and Hornbeck \(2016\)](#). Column V includes all the controls at once and is our preferred specification. In all columns, we document a significantly negative association between relative out-migration and industry persistence. Columns VI and VII use all available migration data (from 1960 to 2000) and include state-decade fixed effects as controls. Panel B repeats this analysis using our second measure. Again, the estimates of  $\beta$  are negative and precisely estimated.

Table 1: Fewer People Leave When Industries Are Persistent

Panel A	I	II	III	IV	V	VI	VII
	Dependent variable: Log (out-migration/in-migration)						
Industry Persistence, 1870/1980	-0.077***	-0.073***	-0.066***	-0.110***	-0.107***	-0.036**	-0.082***
1(Emp. 1870) x manuf. emp. share 1980	(0.017)	(0.015)	(0.019)	(0.020)	(0.019)	(0.014)	(0.019)
Population 1980	X	X	X		X	X	X
Manuf. Emp. share 1980		X			X		X
Area + lat&lon (cubic pol.)			X		X		X
1870 controls (pop., urban sh., MA)				X	X		X
Year	1980	1980	1980	1980	1980	1960-2000	1960-2000
State f.e.	X	X	X	X	X		
State x Year f.e.						X	X
R-squared	0.384	0.397	0.390	0.446	0.487	0.357	0.375
Observations	507	507	507	507	507	2,535	2,535
Panel B	I	II	III	IV	V	VI	VII
	Dependent variable: Log (out-migration/in-migration)						
Industry Persistence, 1870/1980	-0.004***	-0.004***	-0.003***	-0.007***	-0.008***	-0.003***	-0.008***
$\Sigma(\text{emp.sh.1870} - \text{emp.sh.1980})^2$	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Population 1980	X	X	X		X	X	X
Manuf. Emp. share 1980		X			X		X
Area + lat&lon (cubic pol.)			X		X		X
1870 controls (pop., urban sh., MA)				X	X		X
Year	1980	1980	1980	1980	1980	1960-2000	1960-2000
State f.e.	X	X	X	X	X		
State x Year f.e.						X	X
R-squared	0.381	0.394	0.389	0.447	0.490	0.360	0.387
Observations	507	507	507	507	507	2,535	2,535

Notes: Standard errors in brackets are clustered at the state level. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.10.

Table 2, below, presents results of estimating column V, including the most stringent set of controls, for every decade for which we have migration data. It establishes that out-migration to in-migration ratio is significantly negatively associated with industry persistence. The effect is especially pronounced after the start of the decline in manufacturing employment after 1980. Nevertheless the effect is already sizable and highly significant in 1960.

The OLS results presented above may suffer from endogeneity. First, we may have reverse causality: locations with lower out-migration today might have had lower out-migration earlier, precisely when these industries set up shop in the late nineteenth century, and exactly for that reason. Alternatively, whatever attracts and keeps both industries and individuals in a location could be an omitted variable in our framework. These could include rivers or other natural amenities that prove useful for industry.

We address this endogeneity concern by using an instrumental variable. Poyker (2018) argues that the introduction of convict labor in the late nineteenth century and the re-

sulting production of low-skill intensive goods in prisons all across the country — immediately following our initial measurement for persistence in 1870 — forced firms in affected industries and locations to innovate and create separation from their competition with prison-made goods. Thereafter, these locations and industries exposed to convict labor were more likely to survive to the 1980s. There are good reasons to think of the instrument as exogenous to either out-migration rates or other omitted variables in our main specification above: First, there is the historical practice of locating prisons solely based on demographic determinants. Second, as shown in [Poyker \(2018\)](#), the exposure to pre-convict-labor prison capacity is uncorrelated with pre-1870 trends in manufacturing wages, either overall or in specific industries.

Table 2: Every Decade, Fewer People Leave When Industries Are Persistent

Panel A	I	II	III	IV	V
	Dependent variable: Log (out-migration/in-migration)				
Outcome-Year	1960	1970	1980	1990	2000
Industry Persistence, 1870/1980	-0.059**	-0.057**	-0.107***	-0.105***	-0.085***
1(Emp. 1870) x manuf. emp. share 1980	(0.027)	(0.026)	(0.019)	(0.022)	(0.021)
R-squared	0.422	0.311	0.487	0.473	0.431
Observations	507	507	507	507	507
Panel B	I	II	III	IV	V
	Dependent variable: Log (out-migration/in-migration)				
Industry Persistence, 1870/1980	-0.007***	-0.008***	-0.008***	-0.010***	-0.008***
$1/\sum_i(\text{emp.sh. 1870} - \text{emp.sh. 1980})^2$	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
R-squared	0.431	0.330	0.490	0.488	0.445
Observations	507	507	507	507	507

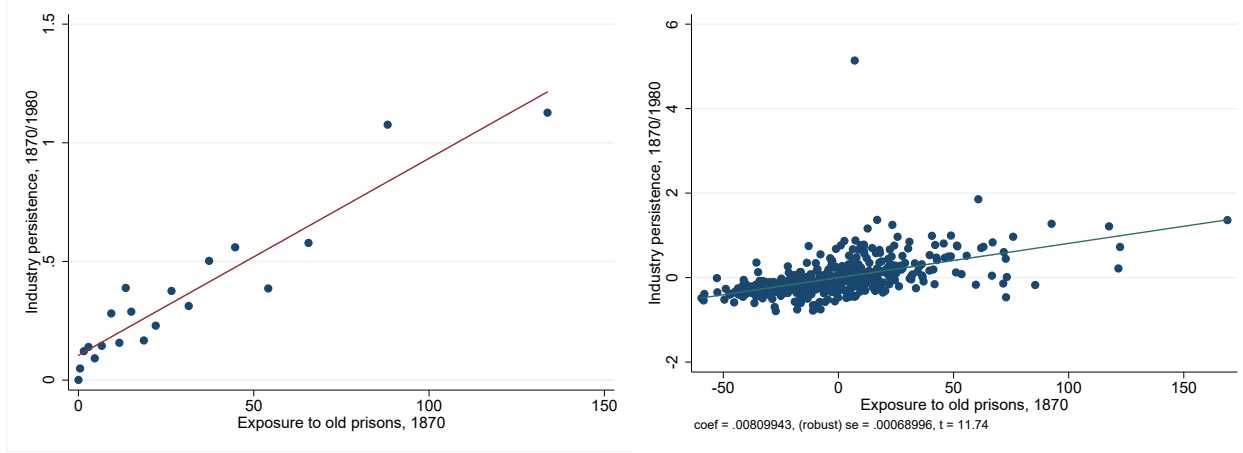
Notes: Standard errors in brackets are clustered at the state level. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.10.

We construct the instrument — exposure to old prisons — as follows:  $OP_{c,1870} = \sum_{k \in K} \left( \frac{\ln(\text{Old prison capacity}_k)}{(\text{Trade Cost}_{c,k})^\sigma} \right)$ , where  $c$  is a county,  $k$  is a county with a prison, and  $K$  is the set of all counties with old prisons in 1870. We assume linear decay of the exposure to prison capacities; i.e.,  $\sigma = 1$ . Trade costs $_{c,k}$  are from [Donaldson and Hornbeck \(2016\)](#) and are measured using the calculated county-to-county lowest-cost freight transportation routes in 1870, and old prison capacity $_k$  comes from [Poyker \(2018\)](#). For the SEA- and CZ-level specifications, we aggregate it to the corresponding levels.

Panels A and B of Figure 6 show the correlation between exposure to pre-convict-labor-era prison capacities and industry persistence, and the residual plot of the first stage. From



Figure 6: Residual Plot: First Stage  
Panel A Panel B



Notes: Panel A shows the first-stage relation between exposure to pre-convict-labor-era prison capacities and industry persistence. Panel B shows the residual plot of the first stage

the latter, the linear relationship is evident.

Formally, our first stage is

$$IP_c = \tilde{\alpha} + \gamma OP_c + \mathbb{X}_{ct} \tilde{\Gamma} + \varepsilon_{ct}, \quad (4)$$

and our second stage is

$$y_{ct} = \alpha + \beta \widehat{IP}_c + \mathbb{X}_{ct} \Gamma + \epsilon_{ct}. \quad (5)$$

Table 3 presents 2SLS of our preferred specification of 1, where out-migration relative to in-migration is measured in 1980 and all controls are included. Columns I to III present the reduced form, OLS and our second stage for our first measure. Column IV and V present the OLS and second-stage results using our second measure. As Columns III and V indicate, the instrument is highly relevant. In the second stage, the coefficient for the effect on migration increases, which we interpret as a large local average treatment effect for these locations affected by the instrument.

Table 3: Fewer People Leave When Industries Are Persistent

	I	II	III	IV	V
	Dependent variable: Log (out-migration/in-migration)				
	Reduced Form	OLS	Second Stage	OLS	Second Stage
Industry Persistence, 1870/1980 1(Emp. 1870) x manuf. emp. share 1980		-0.107*** (0.019)	-0.286*** (0.069)		
Industry Persistence, 1870/1980 $\Sigma(\text{emp.sh.1870} - \text{emp.sh.1980})^2$				-0.008*** (0.002)	-0.014*** (0.004)
Exposure to pre-convict-labor prisons capacities	-0.0002*** (0.000)				
First-stage coefficient			0.001*** (0.000)		0.017*** (0.003)
F-stat. of excluded instrument			39.7		39.2
R-squared	0.48	0.49	0.15	0.49	0.19
Observations	507	507	507	507	507

Notes: Standard errors in brackets are clustered at the state level. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.10.

### 3.2 Industry Employment Persistence and Mobility during the China Shock

Above, we have shown that locations with high industry employment persistence have seen lower out-migration throughout the second half of the twentieth century. One concern with such an approach is that unobserved cross-location variation correlated with high industry persistence is responsible for lower out-migration. In this subsection, we employ a well-defined and widely used external shock to labor demand across U.S. commuting zones to show that labor supply in CZs with higher industry employment persistence adjusts differently to similar shocks.

We closely follow [Autor, Dorn and Hanson \(2013\)](#) and estimate the following specification in stacked first differences at the CZ level:

$$\Delta y_{c,t} = \gamma_t + \beta_1 \Delta IPW_{ct} + \beta_2 IP_c + \beta_3 \Delta IPW_{ct} \times IP_c + X'_{ct} \beta_4 + \varepsilon_{ct}, \quad (6)$$

where observation  $c$  is a CZ and  $t = \{1990 - 2000, 2000 - 2007\}$ .

Our outcomes,  $\Delta y_{c,t}$ , are changes in the logarithm of total population, in unemployment and the number of people not in the labor force as a share of total population for each of the periods.  $\Delta IPW_{ct}$  is the change in exposure of local labor market to imports

from China as constructed in [Autor, Dorn and Hanson \(2013\)](#). The main difference is that we include our industry persistence measure  $IP_c$  and its interaction with the measure of competition with Chinese-made goods,  $\Delta IPW_{ct} \times IP_c$ .  $X$  is a full matrix of controls in [Autor, Dorn and Hanson \(2013\)](#) and includes the manufacturing-to-total-employment ratio, college education, female, foreign born, share of routine workers, and outsourcing. We use [Autor, Dorn and Hanson](#)'s instrument for  $\Delta IPW_{ct}$  and interaction of  $IP_c$ , and [Autor, Dorn and Hanson](#)'s instrument as the instrument for the interaction  $\Delta IPW_{ct} \times IP_c$ . Standard errors are clustered at the state level.

Table 4: Higher Unemployment, Yet Smaller Population Declines When Industries Are Persistent

Dep. Var.:	$\Delta \text{MfgEmp}/\text{Emp}$		$\Delta \text{NonMfgEmp}/\text{Emp}$	
	I	II	III	IV
$\Delta \text{IPW}$	-0.61*** (0.10)	-0.55*** (0.09)	-0.17 (0.14)	-0.04 (0.18)
IP 1980	-0.64* (0.36)	0.19 (0.74)	0.25 (0.48)	2.27* (1.17)
$\Delta \text{IPW} \times \text{IP 1980}$		-0.55 (0.39)		-1.33* (0.76)
Int.-qtl. persistence cond. mean China shock (1.9)	-0.09	-0.12	0.04	-0.04
R-squared	0.34	0.34	0.37	0.37

Notes:  $N = 1,444$ . Dependent variables are 10-Year Equivalent Log Changes in Headcounts (in log pts, column 1) and 10-Year Equivalent Changes in Population Shares and Employment Status (in % pts, all other columns). All regressions include a time dummy, region fixed effects, and the full set of controls of [Autor, Dorn and Hanson \(2013\)](#): lagged percentage of employment in manufacturing, of college-educated population, foreign-born population, of employment among women, employment in routine occupations, and an average offshorability index of occupations. Standard errors in brackets are clustered at the state level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

Panel A of Figure 1 in the introduction demonstrates the main insights of our results by comparing the density of outcomes for counties above the median of the industry persistence measure with those below it. Commuting zones with a higher share of persistent industries than the median experienced larger increases in unemployment compared to CZs with a smaller-than-median share of persistent industries. However, while these locations faced larger increases in unemployment, Panel B documents that the labor-market adjustment channel of out-migration does not seem to have taken place in such locations: CZs with persistent industries also had smaller out-migration.

Table 4 shows that the regression result reports the corresponding results from regression analysis, confirming the headline takeaways already evident in the graphs. Table 5 provides evidence on the heterogeneity of the baseline effect. Columns I and II report the change in population of the college educated and the non-college educated. For both, baseline out-migration is higher in locations with persistent industries, reflective of a general downward trend in population for these. However, facing external shocks, the non-college educated population declines more slowly. Columns III to V present results, with the change in population for three broad age groups (16–34 years, 35–49 years, and 50–64 years) as the respective outcomes. The latter two are particularly responsible for the slower decline of population when facing labor demand shocks, but for all three, the effect is evident and sizable. Column VI includes an interaction of "exposure to Chinese competition" with "share of college-educated population," to ensure that this differential is not primarily driven by differences in the local skill structure.

Table 5: Fewer People Leave When Industries Are Persistent: Heterogeneity

Dep. Var.:	$\Delta \text{Log(PopC)}$	$\Delta \text{Log(PopNC)}$	$\Delta \text{Log(Pop1634)}$	$\Delta \text{Log(Pop3549)}$	$\Delta \text{Log(Pop5064)}$	$\Delta \text{Log(Pop)}$
	I	II	III	IV	V	VI
$\Delta \text{IPW}$	-0.47 (0.55)	-0.94 (0.74)	-0.82 (1.03)	-0.24 (0.55)	-0.91 (0.61)	0.08 (2.31)
IP 1980	-13.84** (6.51)	-26.05*** (5.59)	-21.12*** (6.36)	-20.25*** (5.20)	-21.02*** (5.08)	-20.04*** (4.95)
$\Delta \text{IPW} \times \text{IP 1980}$	2.43 (2.15)	5.41*** (1.56)	3.77 (2.44)	2.91* (1.58)	5.11** (2.06)	3.91*** (1.39)
$\Delta \text{IPW} \times \text{ShareCollege}$						-0.02 (0.05)
R-squared	0.37	0.56	0.46	0.76	0.62	0.46

Notes:  $N = 1,444$ . Dependent variables are 10-Year Equivalent Log Changes in Headcounts (in log pts) of demographic subgroups. All regressions include a time dummy, region fixed effects, and the full set of controls of Autor, Dorn and Hanson (2013): lagged percentage of employment in manufacturing, of college-educated population, of foreign-born population, of employment among women, of employment in routine occupations, and an average offshorability index of occupations. Standard errors in brackets are clustered at the state level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

Concerned about potential confounders, we use exposure to pre-convict-labor-era prison capacities,  $OP_{c,1870}$ , as the instrument for the industry persistence,  $IP_c$ . Table 6 presents the results.

Table 6: Fewer People Leave When Industries Are Persistent: IV with Convict Labor

Dep. Var.:	$\Delta \text{Log(Pop)}$	$\Delta \text{Unemp/Pop}$	$\Delta \text{NILF/Pop}$
	I	II	III
IPW	-1.52 (1.13)	1.09 (2.24)	-0.70 (2.09)
IP 1980	-41.58*** (8.68)	-69.88** (31.53)	-56.36*** (18.16)
$\Delta \text{IPW} \times \text{IP 1980}$	9.20** (4.44)	35.10** (17.53)	23.03* (12.56)
Int.-qtl. persistence cond. mean China shock (1.9)	-1.77	0.085	0.0712
<i>F</i> -stat. interaction	12.7	12.7	12.7
<i>R</i> -squared	0.41	0.41	0.42

Notes:  $N = 1,444$ . Dependent variables are 10-Year Equivalent Log Changes in Headcounts (in log pts, Column I) and 10-Year Equivalent Changes in Population Shares by Employment Status (in % pts, all other columns). All regressions include a time dummy, region fixed effects, and the full set of controls of Autor, Dorn and Hanson (2013): lagged percentage of employment in manufacturing, of college-educated population, of foreign-born population, of employment among women, of employment in routine occupations, and an average offshorability index of occupations. Standard errors in brackets are clustered at the state level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

## 4 Local Ties Are Stronger When Industry Employment Is Persistent

The evidence presented in the section just above begs the question, "Why should locations that have had sizable employment shares in the same industries over more than a century have lower out-migration, and particularly so when facing a shock to their labor demand?" In what follows, we draw on an existing literature, spanning the fields of economics and sociology, which argues that the strength of local ties negatively affects migration opportunities. We first lay out our reasoning, then provide evidence from two separate sources to show that the population in locations with higher industry employment persistence has (i) fewer connections to other locations, as well as (ii) a lower willingness to switch occupations, a lower reported geographic mobility, and smaller but denser social networks.

## 4.1 Mechanism

The literature in sociology and economics on migration has already established a connection between the strength of local social networks and migration. On the one hand, stronger local ties are associated with a higher amenity for people living in that location. Neighbors and relatives can rely on one another for economic and social support, such as having grandparents take care of children instead of paying for day care. On the other hand, [Granovetter \(1977\)](#) suggests that “weak ties” to people we know less well can be particularly valuable for accessing information not locally available. Therefore, individuals in communities that are more broadly connected may be more likely to hear about a wider range of business, job, or educational opportunities. This theory is in line with the migrant-network literature, and is seminally employed as an instrumental variable by [Card \(2001\)](#). It suggests that migrants are more likely to choose a destination because of an already established network of people from their place of origin that can aid them in job search and local integration. Where such links are missing, migration costs are invariably higher, and realized out-migration will be lower, even if the location where they have settled faces the decline of its major industries.

We hypothesize that once an industry sets up shop in a location, it provides (directly or indirectly) various employment opportunities for new local entrants into the labor markets. These entrants are unlikely to be college educated, since the college educated often move away for college and return at lower rates. In such locations, high school graduates can more easily find employment and remain within the social network they established during primary and secondary education and through family links. Repeated over generations (which is arguably the time horizon of our measure), this recurring opportunity for locals to “stay in town” limits their cross-locational social network compared to locations where such employment opportunities are more dire. There is a second imaginable result of such a local opportunity—namely an emerging consumption value of these local networks, once established. In either case, cities where there are plenty of employment opportunities likely allow for the creation of local social networks for individuals raised there. These networks in turn act as an individual location-specific amenity and make it more costly to move out.

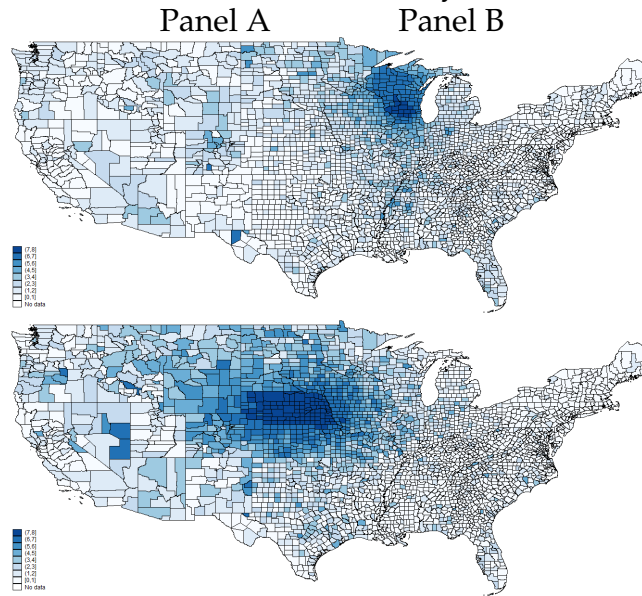
## 4.2 Evidence from Social Connectedness on Facebook

[Bailey et al. \(2018\)](#) constructed a data set of the connectedness of individuals across the U.S. based on Facebook friendships from a snapshot of the platform in April 2014.<sup>7</sup> We use

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<sup>7</sup>The *New York Times* provides a web-based application illustrating the social connected-

Figure 7: Social Connectedness of Rock County, WI, and Seward County, NE



*Notes:* Because counties with more people invariably have links to more places, this map rescales the index to account for differences in population.

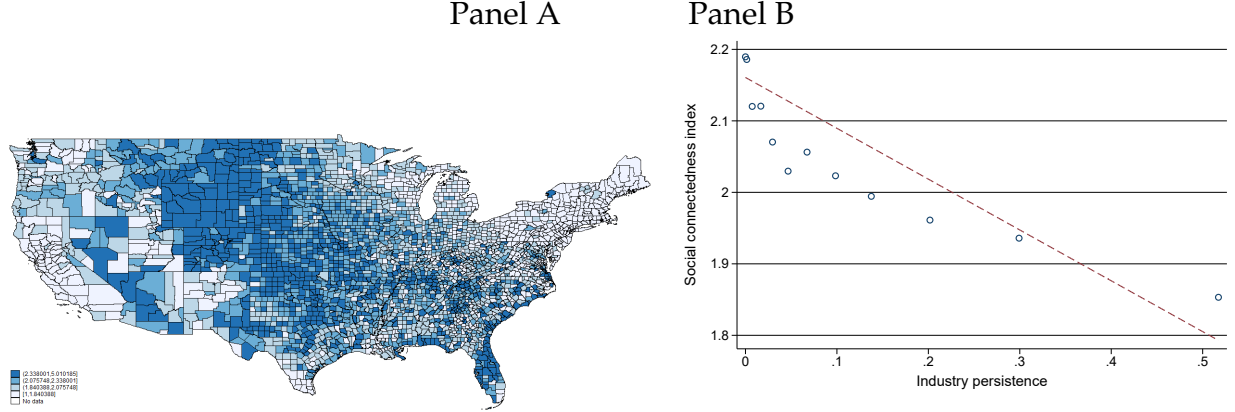
this measure of social connectedness for each county, comparing it to every other county as a proxy for the weakness of local ties. As an example, consider Panel A of Figure 7, which shows the connectedness of Rock County, Wisconsin, where the city of Janesville is located. Counties with darker colors have stronger friendship links on Facebook to Rock County. By comparison, Panel B contains the connectedness map for Seward County, Nebraska, which does not have persistent industries.

As a departure point from these illustrating examples, we are ultimately interested in cross-county variation. In this vein, Panel A of Figure 8 shows the average social connectedness index across U.S. counties. We document a negative correlation between the average social connectedness index and the industry persistence measure from Figure 5. To show this fact empirically, Panel B presents a binscatter plot, depicting the strong negative correlation between a county's industry persistence and its average social connectedness.

ness for every U.S. county accessible on [www.nytimes.com/interactive/2018/09/19/upshot/facebook-county-friendships.html](http://www.nytimes.com/interactive/2018/09/19/upshot/facebook-county-friendships.html). We received a version of the underlying data set directly from Facebook.



Figure 8: Counties with Persistent Industries Are Less Connected



Notes: Because counties with more people invariably have links to more places, this map rescales the index to account for differences in population.

To shed light on this relation econometrically, we employ regressions similar to those we used before for the out-migration to in-migration ratio:

$$SCI_{ct} = \alpha + \beta IP_c + \mathbb{X}_{ct}\Gamma + \varepsilon_{ct}, \quad (7)$$

where  $SCI_{ct}$  is the social connectedness index, which is measured at  $t = 2016$ . Standard errors are clustered at the state level. Table 7 presents results of this regression. Columns I and II present OLS estimates using both of our measures of industry persistence. The effect is sizable and highly significant. In columns III to V, we again rely on exposure to pre-convict-labor era prison capacities to isolate exogenous variation in the industry persistence. Column III presents the reduced form, while columns IV and V show the second stages. Appendix Table A.1 reports the same results as in Table 7 but uses the alternative weighting of the social connectedness index; it gives higher weights for connections farther away.

Table 7: Social Connectedness to Other Counties Is Lower When Industries Are Persistent

	I	II	III	IV	V
Dependent variable: Social connectedness index					
	OLS		Reduced Form	Second Stage	
Industry Persistence, 1870/1980	-0.082**			-0.391***	
1(Emp. 1870) x manuf. emp. share 1980	(0.034)			(0.089)	
Industry Persistence, 1870/1980		-0.006***			-0.020***
$\Sigma(\text{emp.sh.1870} - \text{emp.sh.1980})^2$		(0.002)			(0.005)
Exposure to pre-convict-labor prisons capacities			-0.0004*** (0.000)		
F-stat. of excluded instrument				39.1	39.6
Observations	507	507	507	507	507

Notes: Standard errors in brackets are clustered at the state level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

If our hypothesis stated above (i.e., that persistent industries lowered both the willingness to out-migrate and actual out-migration from lower accumulated levels of connectedness) is true, then a natural question that arises is whether the effect of persistent industries on out-migration works through lower cross-location social connectedness. The social connectedness index, measured in April 2016, proxies for how many friends people living in a particular county have outside of that county. This index does not only depend on friends and relatives who migrated out from that county previously but includes other friends who never lived there, friends of friends, and so on. Thus we assume that the social connectedness index is a proxy for the “weak ties” in the sense used by [Granovetter \(1977\)](#) and that it determines how easy it is for people to migrate out from their counties in case local economic shocks require them to. Following [Dippel et al. \(2017\)](#), we estimate the effect of industry persistence on out-migration both directly and indirectly (through the social connectedness index), again using a county’s exposure to pre-convict-labor-era prison capacities as an instrument. As is evident from Table 8, two-thirds of the effect of industry persistence works indirectly through the social connectedness index. This is the first evidence that persistent industry employment hinders locals from establishing “weak ties” outside their counties and ultimately makes it more difficult for them to leave when employment prospects dim.

Table 8: Mediation Analysis: Industry Persistence Affects Out-Migration Exclusively through Weak Connectedness

	I	II
	Dependent variable: Log (out-migration/in-migration)	
	Measure of IP 1(Emp. 1870) x manuf. emp. share 1980	$\sum_i(\text{emp.sh.1870} - \text{emp.sh.1980})^2$
IP, 1870/1980 total effect	-0.284*** (0.071)	-0.014*** (0.003)
IP, 1870/1980 direct effect	-0.097*** (0.029)	-0.005*** (0.002)
IP, 1870/1980 indirect effect through SCI	-0.187** (0.085)	-0.009** (0.004)
Mediator explains of the total effect	66.0%	62.9%
First stage (IP on Old prison exposure)	65.2	149.1
First stage (SCI on Old prison exposure   IP)	38.6	40.4
Observations	507	507

Notes: Computed using package ivmediate in Stata [Dippel, Ferrara and Heblich, 2020](#). Standard errors in brackets are clustered at the state level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

### 4.3 Evidence from the General Social Survey

All of the evidence presented thus far was spatially aggregated. In what follows we show, based on responses to questions in the General Social Survey (GSS),<sup>8</sup> that individuals in counties with persistent industries have significant differences in their labor market behavior, social networks, and past migration behavior. Specifically, we estimate regressions for individuals  $i$  residing in county  $c$ :

$$y_{ci} = \alpha + \beta IP_c + \mathbb{X}_{ci}\Gamma + \varepsilon_{ci}, \quad (8)$$

where controls include a gender dummy, age and age squared, a dummy for a college degree female age, and marriage. We include fixed effects for broad census region, as well as one-digit occupation and industry codes.

In Table 9, we present results. Generally, industry persistence is correlated with individual values related to social connectedness. Respondents living in counties with higher industry persistence show a consistent pattern in their labor market behavior; they are less likely to learn new skills, accept a lower-paid job, accept a temporary job to avoid unemployment, and are more willing to become self-employed. In addition, their social environment is more localized. They are less likely have ever moved during their life, less likely to have more than 10 contacts/interactions per working day, and are more likely to

<sup>8</sup>The GSS is publicly available on <https://gss.norc.oregon.edu/>. We use all available data at almost yearly frequency from 1972 to 2010.

Table 9: People Are Less Mobile and Have Stronger Kinship Ties When Industries Are Persistent

	Labor market behavior: Willingness to				Social environment		
	learn new skill	accept low pay	accept temp work	self emp	never moved	>10 contacts/wkday	evening w friends
IP	-0.26** (0.11)	-0.19* (0.11)	-0.18* (0.11)	0.14** (0.06)	0.16*** (0.05)	-0.22** (0.09)	0.07** (0.03)
Observations	965	964	965	2,704	24,541	1,373	14,635
R-squared	0.12	0.09	0.06	0.06	0.07	0.11	0.08

Notes: All regressions include region fixed effects, occupation and industry one-digit fixed effects, and control for gender, age, age squared, college degree, and marital status. This is a pooled cross-section, and we include survey-year fixed effects. Standard errors in brackets are clustered at the county level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

spend evenings with friends.

## 5 Discussion and Concluding Remarks

This paper shows three main results. First, locations that have employment persistence in old industries have lower levels of out-migration relative to in-migration. Second, such areas start to have weaker outward connectedness to other locations and stronger local ties. Third, in time of local labor market shocks, such locations are worse at adjusting their labor supply; people in affected areas do not migrate out, and the wage does not adjust. This result suggests that differences in adjustment are predetermined, and it provides insights on how to design and focus place-based policies aimed at mitigating adverse effects of labor demand shocks.

Our results emphasize the social consequences of industrial structure and its persistence, and they show its direct effects on migration and local labor market outcomes. In particular, we demonstrate how local ties can result from local industrial structure, and how they affect economic and social behavior. We also document the importance of persistent local industrial structure for low migration rates.

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**Online Appendix**

**to**

**Why Aren't People Leaving Janesville?**

**Industry Persistence, Trade Shocks, and Mobility**

## A Additional Results

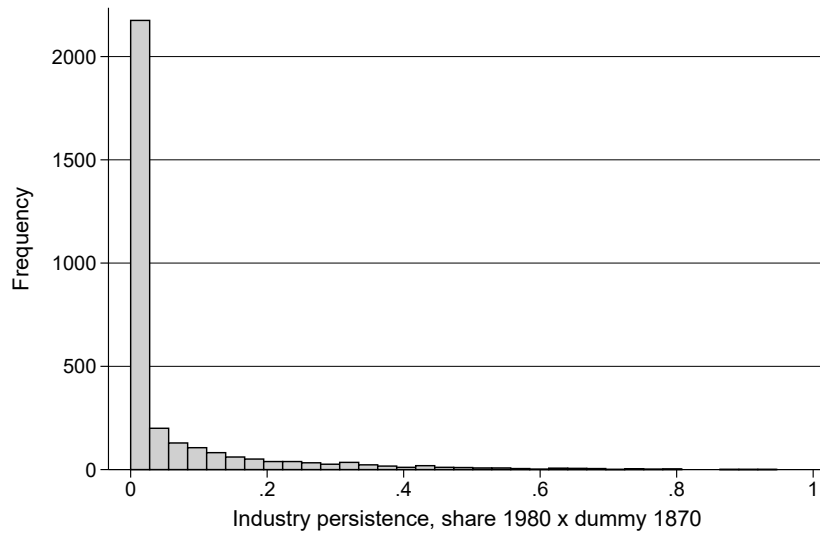
Table A.1: Social Connectedness to Other Counties Is Lower When Industries Are Persistent (alternative weighting of SCI)

	I	II	III	IV	V
	Dependent variable: Social connectedness index (weighted)				
	OLS		Reduced Form	Second Stage	
Industry Persistence, 1870/1980 1(Emp. 1870) x manuf. emp. share 1980	-0.435 (0.282)			-2.473*** (0.557)	
Industry Persistence, 1870/1980 $\Sigma(\text{emp.sh.1870} - \text{emp.sh.1980})^2$		-0.038*** (0.010)			-0.124*** (0.032)
Exposure to pre-convict-labor prisons capacities			-0.0024*** (0.000)		
F-stat. of excluded instrument				39.1	39.6
Observations	507	507	507	507	507

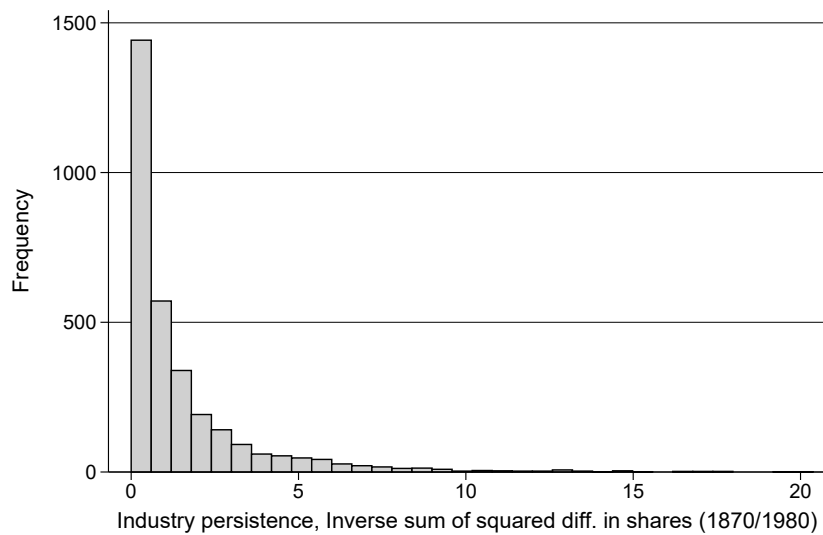
Notes: Standard errors in brackets are clustered at the state level. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.10.



Figure A.1: Industry Persistence by County (1870–1980): Histogram  
Panel A: Measure 1

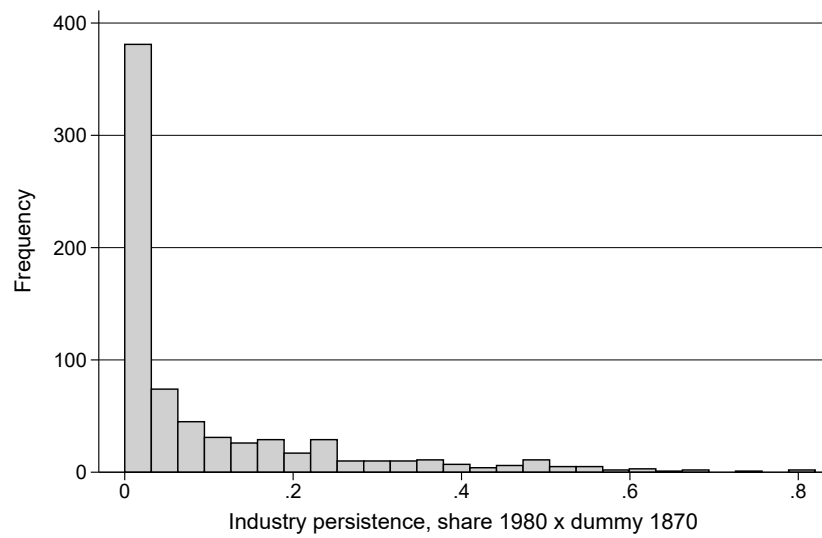


Panel B: Measure 2

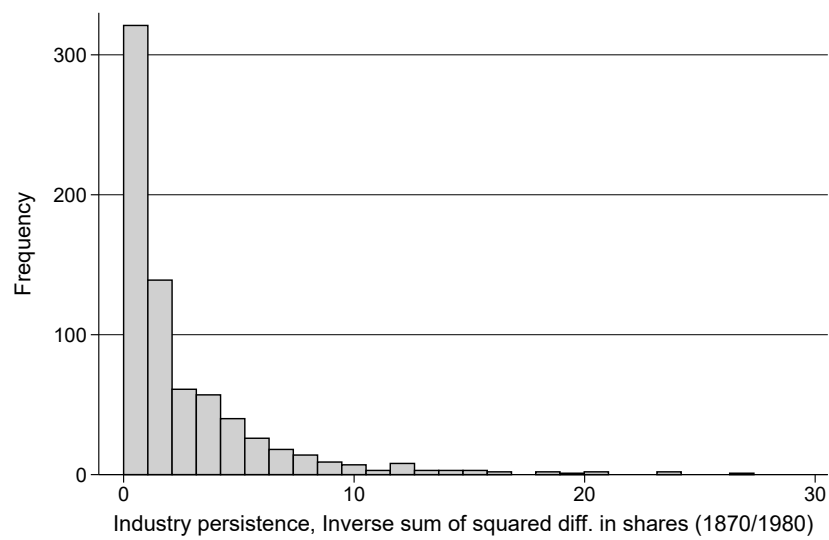


Notes: Panel A is computed using Equation (1). Panel B is computed using Equation (2). Figure A.2 contains histograms for industry persistence measure on the CZ level. Figure A.3 contains histograms for industry persistence measure on the SEA level.

Figure A.2: Industry Persistence by CZ (1870–1980): Histogram  
Panel A: Measure 1



Panel B: Measure 2

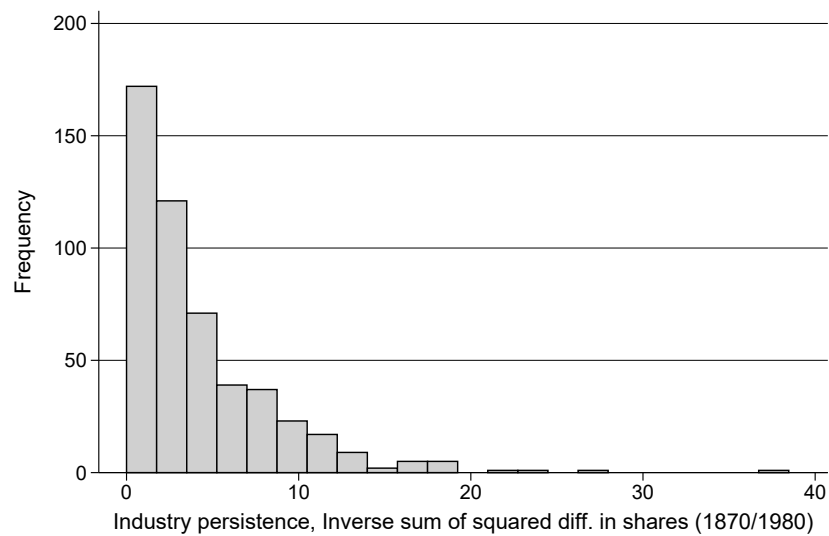


Notes: Panel A is computed using Equation (1). Panel B is computed using Equation (2).

Figure A.3: Industry Persistence by SEA (1870–1980): Histogram  
Panel A: Measure 1



Panel B: Measure 2



Notes: Panel A is computed using Equation (1). Panel B is computed using Equation (2).