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# Did the Rust Belt Become Shiny? A Study of Cities and Counties That Lost Steel and Auto Jobs in the 1980s

How DO COUNTIES, CITIES, or regions respond to adverse economic shocks? How quickly does an area recover and through which adjustment mechanisms? These questions touch on many different areas of social science and economics and are relevant to our understanding of economic growth, income gaps across regions (for example, North and South in the United States or Italy), and the plight of individual laid-off workers and their families.

In this paper we undertake a study of one of the biggest negative shocks to affect the U.S. economy in the past fifty years, namely, the massive loss of steel- and auto-related jobs in the early 1980s, which we refer to collectively as the Rust Belt shock. In the decade between 1977 and 1987 the United States shed about 500,000 jobs in the auto industry and 350,000 jobs in the steel industry, far outstripping any other job losses in recent U.S. history. These job losses were concentrated in roughly 140 of the 3,000 counties in the United States. Kahn as well as Black, McKinnish, and Sanders discuss the size of the manufacturing shocks and accompanying job losses.<sup>1</sup>

For the first section of our paper, we assemble total employment, industry-level employment, population, labor force participation, and income data at the level of the county and the metropolitan statistical area (MSA). Our basic approach is to regress short- and long-run changes in outcomes on the size of

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1. Kahn (1999); Black, McKinnish, and Sanders (2003).

the Rust Belt shock. Consistent with the state-level analysis in Blanchard and Katz, we find very rapid recovery in the unemployment rate in Rust Belt cities and counties.<sup>2</sup> Within five years, unemployment rates in the Rust Belt areas returned to the U.S. average.<sup>3</sup> The adjustment took place entirely through outmigration of people rather than in-migration of jobs or a change in labor force participation. Each steel or auto job lost in a county led to a net decrease in population of 1.8 persons. In the long run, population in Rust Belt counties tended to stay flat or slightly below 1977 levels, likely due to the Glaeser and Gyourko effect of durable housing.<sup>4</sup>

After establishing the basic facts of shock and recovery, we attempt to distinguish among successful and unsuccessful shock places based on the long-run growth of population in these counties. The most successful post-shock counties tend to be those that are located in warm sunny climates such as Jefferson County (Alabama) or near a major city, for example, Carbon County (Pennsylvania). The Glaeser and Saiz relationship between city growth and human capital holds within our general sample of all counties, but we do not have enough statistical power to identify the effect within our sample of shock counties.

Like Kahn as well as Glaeser, Kolko, and Saiz, we believe that city- or region-level amenities are a key input to an area's desirability and growth. We find that, while Rust Belt counties and MSAs recovered quickly on certain dimensions like unemployment and income per capita, amenities in these places experienced a negative shock that did not diminish over time and, if anything, worsened. This effect may be a simple result of declining population. However, it is also possible that our Rust Belt counties (which are disproportionately in the North) have underutilized infrastructure and abandoned capital that are particularly ugly, even though deindustrialization has made the air and water cleaner and safer. We hypothesize that the lack of ameni-

- 2. Blanchard and Katz (1992).
- 3. This statement is true for the average Rust Belt county or city. Unemployment rates in Michigan, for example, remain 1–2 percentage points above the U.S. average.
  - 4. Glaeser and Gyourko (2005).
- 5. Jefferson County is part of the Birmingham MSA. Carbon County (Pennsylvania) is part of the Allentown-Bethlehem-Easton MSA (top fifty in 1977) and is 90 miles from both New York City and Philadelphia. The fact about weather is consistent with Pack (2005), Glaeser, Kolko, and Saiz (2001), and Glaeser and others (1992).
  - 6. Glaeser and Saiz (2004).
  - 7. Kahn (1999); Glaeser, Kolko, and Saiz (2001).
  - 8. Kahn (1999).

ties, more than crime or unemployment per se, is what contributes to Detroit's and Cleveland's relatively low current rankings in lists of the best places to live.<sup>9</sup>

As noted by our discussants, our findings may help to distinguish between various models of urbanization and agglomeration externalities. We find that adjustment to the shock takes place through net population outflow, which indicates that locational economies may be very important for Rust Belt cities. These cities specialized in a few industries and, when those industries were hit by a large negative shock, populations began to decline. If urbanization economies (the advantages of mere size) were important for the growth of these cities, then other industries would have moved in to take advantage of these economies. There appears to be flexibility in the labor market at the national level, but inflexibility at the local level. At the same time, we also find evidence of agglomeration externalities in amenities, as modeled by Helsley and Strange. We find that as the Rust Belt cities shrank (in relative and in absolute terms), the relative attractiveness of their restaurants, culture, and overall appearance declined as well.

We also examine adjustment to the Rust Belt shock in the United Kingdom. Comparing across U.K. regions, we find that adjustment to the regional employment shifts was considerably slower, taking more than ten years for unemployment rates to converge to pre-shock levels, versus the five-year convergence window observed in the United States. Furthermore, only half of the adjustment in the United Kingdom occurred through population movement, while the other half occurred through a relative decrease in labor force participation.

The remainder of the paper is structured as follows. The first section describes the data sets employed and our basic definitions. The second describes our empirical approach (which is straightforward). The following four sections present the results, while a final section concludes.

<sup>9.</sup> See, for example, *Places Rated* or *Cities Ranked and Rated* (Boyer and Savageau 1981; Sperling and Sander 2004). Venkatu (2006) confirms this but offers a different interpretation, suggesting that Cleveland's poor amenities partially caused its job and population loss. With regard to the low rankings of Rust Belt places, Pittsburgh is potentially one of the exceptions. However, as Pack (2005) notes, Pittsburgh has poor job growth, and it gets only a middling rank in the Forbes-Milken Rank for "best places to advance a career." We discuss the successful Rust Belt areas in a section that follows.

<sup>10.</sup> Henderson (1974).

<sup>11.</sup> Helsley and Strange (1994).

#### **Data Sources and Definitions**

We start with employment data by industry from County Business Patterns (CBP). <sup>12</sup> Our fundamental unit of analysis is the county. We wish to measure steel and auto jobs lost relative to total jobs in a region. CBP provides county-level measures of employment by industry. For some of our analyses, we then aggregate up to the MSA level using a crosswalk file published by the census. <sup>13</sup>

We define steel and auto jobs as all employment in two standard industrial code (SIC) classifications: primary metals (33) and transportation (37), respectively. The bulk of the employment in these SICs falls within the steel and auto industries, as seen by looking at the four-digit industries within SICs 33 and 37, which are summarized in appendix A. Within SIC 33, as late as 1993, 70 percent of total employment was within steel and iron foundries, steel rolling mills, and steel and iron pipe factories. The remaining employment was within occupationally related (and also dirty, high-paying, highly unionized) industries like aluminum smelting and copper ore smelting. Within SIC 37, the bulk of employment was directly in the production of cars, trucks, buses, and motor homes.

We define the shock period as the years 1977–82 and the recovery period as 1982–87. The initial year of the shock period, 1977, modestly predates the steepest decline in steel and auto jobs in the United States. The end of the shock period is timed to include the 1980 recession. We also pick years that correspond with the quinquennial economic census in order to maximize the reliability of the employment counts.

We calculate the size of the shock for each county as the change in steel and auto jobs during 1977–82 as a fraction of total initial jobs in the county. In the remainder of the paper, we refer to this as the Rust Belt shock. In most of our analysis, we use the full range of variation across counties and regress outcomes on size of the shock, that is, the fraction of total jobs lost. We limit the counties in the analysis to those with 10,000 people or more in 1977. This is intended to eliminate small rural counties, almost none of which experienced the Rust Belt shock according to our data.

- 12. Data are available at www.census.gov/epcd/cbp/view/cbpview.html [March 2007]; earlier years are on CD-ROM.
  - 13. County names and codes are at www.census.gov/datamap/fipslist/AllSt.txt [March 2007].
- 14. The shock change is defined such that job losses generate a negative number. A positive coefficient on the shock change variable indicates that job losses are associated with a decrease in the dependent variable.

Job losses in autos and steel amounted to more than 0.1 percent of total jobs in 226 counties. Of these counties, 138 experienced auto and steel job losses of 0.5 percent or more. Sixty-seven counties lost 2 percent or more of their total jobs due to steel and auto losses, and we refer to these specifically as "shock counties." There may, of course, have been additional job losses in these counties that are correlated or not correlated with the Rust Belt shock. In portions of our analysis, we define a shock county dummy to designate these sixty-seven counties and regress changes in outcomes on it. Table 1 lists the shock counties and the associated job losses. Saginaw County (Michigan) lost 18 percent of its jobs in the shock. Genesee County (Michigan), which contains the city of Flint, lost 8.5 percent of jobs. Wayne County (Michigan), which contains Detroit, lost 6.8 percent of jobs. For comparison purposes, table 2 presents summary statistics for the shock counties and the entire data set.

Figure 1 presents a map of the United States with counties shaded by severity of the shock experienced. The Rust Belt counties are concentrated in Pennsylvania, Ohio, Michigan, Indiana, and Illinois. However, affected counties are also located in upstate New York, near Birmingham (Alabama), where steel was produced, and in the Central Valley of California. There are also several shock counties in Florida, Georgia, and Tennessee. New London (Connecticut) was among the hardest hit counties.

As defined by total jobs lost in a five- or ten-year period, the steel and auto shocks were among the largest seen in the United States in the last fifty years. Figures 2 and 3 show total jobs lost in the United States by two-digit SIC during 1977–87 and 1987–97. With nearly a million jobs lost, steel and auto losses were significantly larger than even the large loss of coal and textile jobs. Furthermore, the 1980 recession was a watershed event in which several of the largest industries in the United States (autos, steel, and textiles) saw their employment peak and their world market share begin a permanent decline.

The population data by county are from the Census Bureau. <sup>15</sup> They include total population as well as population by age; intercensal years are estimated by the Census Bureau. Unemployment rates and labor force participation rates by county are from the Bureau of Labor Statistics. <sup>16</sup> These labor force estimates are compiled using data from the Current Population Survey, the Current

<sup>15.</sup> Data for most of the years used are available from the Census Bureau (www.census. gov/popest/datasets.html [March 2007]), and data for the remaining earlier years were e-mailed to us by the Census Bureau.

<sup>16.</sup> Most years are available from the Bureau of Labor Statistics (www.bls.gov/lau/home.htm [March 2007]). Earlier years were obtained directly from the Bureau of Labor Statistics.

Table 1. Shock Counties and Descriptive Statistics for the Shock Period<sup>a</sup>

Percent unless otherwise noted

		Steel and auto industries		Steel industry		Auto industry	
County and state	City or MSA (if applicable)	Number of jobs lost	Change in jobs due to steel and auto job loss	Number of jobs lost	Change in jobs due to steel jobs lost	Number of jobs lost	Change in jobs due to auto jobs lost
Jefferson, Alabama	Birmingham	-13,300	-0.046	-9,105	-0.031	-4,195	-0.014
Shelby, Alabama	Birmingham	-401	-0.025	-401	-0.025		
Boone, Arkansas		-246	-0.024	-246	-0.024	0	0.000
Faulkner, Arkansas	Little Rock	-795	-0.047			-795	-0.047
New London, Connecticut	New London-Norwich	-4,205	-0.041	159	0.002	-4,364	-0.043
Chatham, Georgia	Savannah	-2,657	-0.035	403	0.005	-3,060	-0.040
Floyd, Georgia		-731	-0.022	-731	-0.022		
Jersey, Illinois	St. Louis	-308	-0.046			-308	-0.046
Macon, Illinois	Decatur	-1,716	-0.031	-1,716	-0.031	0	0.000
Madison, Illinois	St. Louis	-2,679	-0.027	-2,679	-0.027	0	0.000
Adams, Indiana	Fort Wayne	-703	-0.056	0	0.000	-703	-0.056
Allen, Indiana	Fort Wayne	-12,784	-0.097	-170	-0.001	-12,614	-0.096
De Kalb, Indiana	Fort Wayne	-485	-0.033	-485	-0.033	0	0.000
Elkhart, Indiana	Elkhart-Goshen	-6,336	-0.095	-435	-0.007	-5,901	-0.088
Lake, Indiana	Gary	-9,318	-0.041	-6,566	-0.029	-2,752	-0.012
Vigo, Indiana	Terre Haute	-1,489	-0.032	-1,489	-0.032	0	0.000
Wayne, Indiana		-1,230	-0.039	0	0.000	-1,230	-0.039
Scott, Iowa	Davenport-Moline- Rock Island	-4,157	-0.061	-4157	-0.061	0	0.000
Labette, Kansas		-185	-0.021	0	0.000	-185	-0.021
Sumner, Kansas		-294	-0.029	0	0.000	-294	-0.029
Wilson, Kansas		-276	-0.055	0	0.000	-276	-0.055
Henderson, Kentucky	Evansville-Henderson	-1,530	-0.097	-1,530	-0.097	0	0.000

McCracken, Kentucky		-683	-0.022	0	0.000	-683	-0.022
Baltimore, Maryland	Washington-Baltimore	-8,343	-0.028	-3,515	-0.012	-4,828	-0.016
Berrien, Michigan	Benton Harbor	-4,697	-0.068	-2,833	-0.041	-1,864	-0.027
Branch, Michigan		-1,222	-0.059	-327	-0.016	-895	-0.043
Genesee, Michigan	Flint	-14,190	-0.085	34	0.000	-14,224	-0.085
Gratiot, Michigan		-604	-0.040			-604	-0.040
Lapeer, Michigan	Detroit	-577	-0.022	-235	-0.009	-342	-0.013
Macomb, Michigan	Detroit	-13,522	-0.043	-1,428	-0.005	-12,094	-0.039
Menominee, Michigan		-214	-0.022	0	0.000	-214	-0.022
Muskegon, Michigan	Grand Rapids-Muskegon-	-1,988	-0.033	-1,929	-0.032	-59	-0.001
	Holland						
Saginaw, Michigan	Saginaw-Bay City-Midland	-16,263	-0.180	0	0.000	-16,263	-0.180
Sanilac, Michigan	Detroit-Ann Arbor-Flint	-549	-0.039			-549	-0.039
Washtenaw, Michigan	Detroit-Ann Arbor-Flint	-2,903	-0.024	-63	-0.001	-2,840	-0.023
Wayne, Michigan	Detroit-Ann Arbor-Flint	-61,290	-0.068	-18,495	-0.020	-42,795	-0.047
Rock, Minnesota		-209	-0.039			-209	-0.039
Chemung, New York	Elmira	-1,550	-0.043	813	0.023	-2,363	-0.066
Cortland, New York		-380	-0.020	0	0.000	-380	-0.020
Allen, Ohio	Lima	-2,340	-0.048	0	0.000	-2,340	-0.048
Cuyahoga, Ohio	Cleveland-Akron	-18,945	-0.026	-6,714	-0.009	-12,231	-0.017
Darke, Ohio		-1,445	-0.057	0	0.000	-1,445	-0.057
Fulton, Ohio	Toledo	-1,038	-0.073	-347	-0.024	-691	-0.048
Huron, Ohio		-638	-0.028	-103	-0.004	-535	-0.023
Lawrence, Ohio	Huntington-Ashland	-1,437	-0.068	-1,437	-0.068	0	0.000
Lucas, Ohio	Toledo	-4,976	-0.023	-2,276	-0.011	-2,700	-0.013
Madison, Ohio	Columbus	-335	-0.027	-335	-0.027	0	0.000
Mahoning, Ohio	Youngstown-Warren	-11,144	-0.093	-11,635	-0.097	491	0.004
Scioto, Ohio		-819	-0.035	-819	-0.035		
Seneca, Ohio		-1,102	-0.043	-1,102	-0.043	0	0.000
Trumbull, Ohio	Youngstown-Warren	-8,264	-0.087	-2,792	-0.029	-5,472	-0.057
Williams, Ohio		-383	-0.024	0	0.000	-383	-0.024
						_	

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Table 1. Shock Counties and Descriptive Statistics for the Shock Period<sup>a</sup> (continued)

Percent unless otherwise noted

		Steel and auto industries		Steel industry		Auto industry	
County and state	City or MSA (if applicable)	Number of jobs lost	Change in jobs due to steel and auto job loss	Number of jobs lost	Change in jobs due to steel jobs lost	Number of jobs lost	Change in jobs due to auto jobs lost
Allegheny, Pennsylvania	Pittsburgh	-15,799	-0.027	-15,799	-0.027	0	0.000
Beaver, Pennsylvania	Pittsburgh	-4,999	-0.061	-4,999	-0.061	0	0.000
Carbon, Pennsylvania	Allentown-Bethlehem- Easton	-977	-0.042	-977	-0.042		
Dauphin, Pennsylvania	Harrisburg-Lebanon-Carlisle	-2,139	-0.020	0	0.000	-2,139	-0.020
Elk, Pennsylvania	_	-1,431	-0.094	-1,431	-0.094		
Erie, Pennsylvania	Erie	-9,337	-0.084	-605	-0.005	-8,732	-0.079
Lawrence, Pennsylvania		-766	-0.020	353	0.009	-1,119	-0.030
Mercer, Pennsylvania	Sharon	-1,509	-0.031	-1,509	-0.031	0	0.000
Snyder, Pennsylvania		-331	-0.026			-331	-0.026
Washington, Pennsylvania	Pittsburgh	-1,838	-0.021	-1,896	-0.022	58	0.001
Dickson, Tennessee	Nashville	-1,296	-0.099	0	0.000	-1,296	-0.099
Harrison, Texas	Longview-Marshall	-745	-0.036	-745	-0.036	0	0.000
Newport News City, Virginia	Norfolk-Virginia Beach- Newport News	-2,061	-0.034	0	0.000	-2,061	-0.034
Marion, West Virginia		-537	-0.023	-530	-0.023	-7	0.000

Source: Authors' calculations.

a. A "shock county" is defined as any U.S. county with a population of 10,000 or more in 1970 that lost more than 2 percent of its total employment in the steel and automotive industries alone between 1977 and 1982. These sixty-six counties are defined as our set of "shock counties" (that is, "shock dummy" is 1). This definition applies to this and all further tables.

Table 2. Variable Means and Descriptive Statistics

	Number of		Standard		
Variable	observations	Mean	deviation	Minimum	Maximum
Non-shock counties					
Shock size	1,373	0.001	0.008	-0.020	0.096
Steel shock size	1,373	0.000	0.004	-0.026	0.096
Auto shock size	1,373	0.001	0.007	-0.024	0.082
Change in steel or auto jobs	1,373	45.73	1,143.11	-16,836.00	16,044.00
Shock employment rate change	1,373	-0.039	0.033	-0.219	0.073
Employment rate, 1977	1,373	0.932	0.026	0.786	0.982
Employment rate, 1982	1,373	0.894	0.040	0.711	0.969
Employment rate, 1987	1,373	0.928	0.032	0.710	0.982
Employment rate, 2004	1,373	0.943	0.016	0.844	0.975
Initial college education	1,373	0.127	0.057	0.039	0.425
Initial population	1,253	131,336.60	334,726.60	10,000.00	7,044,886.00
Initial per capita income	1,373	6,454.91	1,241.47	3,213.00	14,144.00
Initial crime rate (per 100,000)	1,252	7,264.19	23,358.36	43.00	523,772.00
Final crime rate (per 100,000)	1,373	6,963.95	19,656.89	0.00	398,758.00
Shock counties					
Shock size	66	-0.047	0.029	-0.180	-0.020
Steel shock size	66	-0.018	0.025	-0.097	0.023
Auto shock size	66	-0.029	0.033	-0.180	0.004
Change in steel or auto jobs	66	-4,415.88	8,528.17	-61,290.00	-185.00
Shock employment rate change	66	-0.059	0.034	-0.130	0.007
Employment rate, 1977	66	0.929	0.021	0.848	0.965
Employment rate, 1982	66	0.871	0.039	0.789	0.954
Employment rate, 1987	66	0.925	0.021	0.878	0.966
Employment rate, 2004	66	0.939	0.013	0.909	0.971
Initial college education	66	0.117	0.043	0.065	0.361
Initial population	62	231,789.10	421,107.20	10,789.00	2,474,662.00
Initial per capita income	66	7,010.42	873.31	5,313.00	9,152.00
Initial crime rate (per 100,000)	62	12,557.31	28,087.62	129.00	194,635.00
Final crime rate (per 100,000)	66	8,845.56	18,266.63	0.00	127,240.00

Source: Authors' calculations.

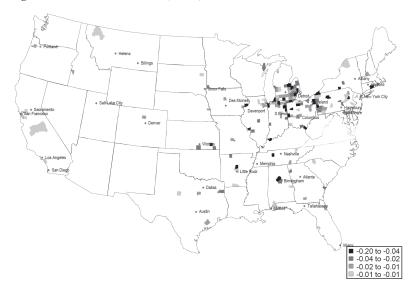


Figure 1. Location of Rust Belt (Shock) Countiesa

a. Depicts counties that lost 2 percent or more of total initial jobs during 1977–82 due to losses in steel and auto jobs. Shading indicates the fraction of total jobs lost.

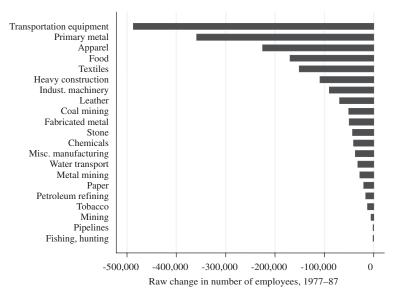


Figure 2. Two-Digit SICs with Decreases in Number of Employees, 1977-87<sup>a</sup>

a. Number of jobs lost by two-digit SIC for those that had decreases. Calculated from 1977 and 1987 County Business Patterns

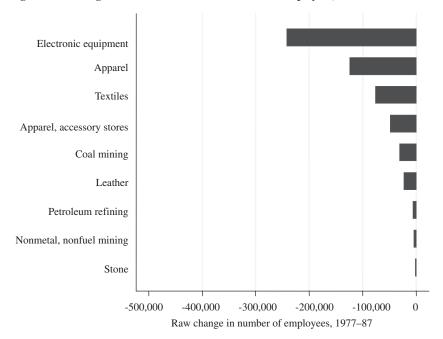


Figure 3. Two-Digit SICs with Decreases in Number of Employees, 1987-97a

Source: Authors' calculations from the 1987 and 1997 County Business Patterns data. a. Number of jobs lost by two-digit SIC for those that had decreases.

Employment Statistics program, unemployment insurance claims, and several other sources. Data on income per capita at the county level are from the Bureau of Economic Analysis and are based on administrative data, including social security tax information. Crime data are from the Federal Bureau of Investigation's Uniform Crime Reports.

Our measures of amenities at the county and city level are from two sources. First, using the County Business Patterns data, we have the number of bars and restaurants (SIC 58), food stores (SIC 54), and department and variety stores (SIC 53) for each county for each year. Again we limit ourselves to the economic census years (1977, 1982, 1987, 1992, 1997, and 2002) to minimize noise in the data. This allows us to examine the change in number of bars and restaurants per capita in response to the shock, relative to all the other counties over the same time period.

Second, we have the most recent year of data for *Cities Ranked and Rated* by Sperling and Sander, who provide detailed data on amenities at the city

level for 331 U.S. cities.<sup>17</sup> Detail on the construction of these amenities rankings is provided in appendix B. Each ranking is based on the sum of the scores for ten to twelve criteria within that category. Many of these criteria are objective and verifiable, such as the number of Starbucks or the number of public libraries. The leisure and recreation ranking includes a restaurant rating, the number of Starbucks, the number of warehouse clubs, a rating for college sports, and several other factors.<sup>18</sup>

From these data, we use the arts and culture ranking, the leisure and recreation ranking, and the quality of life ranking. A rank of 1 is the best for a city, and 331 is the worst. We use this rank as our dependent variable. Covariates that are negatively correlated with the city's rank are associated with higher amenities. We also have the arts and recreation rankings from the same source for 1981 and so are able to ask whether the shock is associated with a change in these rankings.

# **Empirical Framework**

We use ordinary least squares regressions in which we regress the change in the dependent variable on the size of the Rust Belt shock or on a dummy for the county's being one that lost 2 percent or more of total jobs in the shock. A typical regression is of the following form:

(1) 
$$\Delta Y_i = \alpha + \beta$$
 shock size<sub>i</sub> +  $\gamma$  region dummies +  $\delta$  msa status<sub>i</sub> +  $\varepsilon_i$ ,

where  $Y_i$  represents an outcome such as the employment rate for county i, and shock size $_i$  refers to the fraction of total jobs lost during 1977–82 for county i. We calculate  $\Delta Y_i$  for several different intervals, including 1977–82, which we call the shock period, 1982–87, which we call the recovery period, and 1977–87, which we call the total period. We also take the long difference of 1987–2004, where possible, to examine the very long-run effects of the shock.

- 17. Sperling and Sander (2004).
- 18. One conference participant noted that the choice of these metrics is itself subjective and weighted to the tastes of higher-income people. This is certainly true, although the ultimate rankings of cities produced does seem to accord with commonly accepted notions of where is a good place to live (and with housing prices!). The rankings also correlate with more objective measures like the number of restaurants or stores per capita. We also note that the attractiveness of the city to high-income or high-human-capital people is surely important for growth.

First differencing in this manner removes any level effect that is specific to the county. For example, if some county has inherently higher unemployment rates throughout the twenty-seven-year period, that effect would be removed. We control for initial MSA status and include dummies for the nine census divisions. We control for census division since it is well established that the Sunbelt has a long-term trend distinct from that of the Northeast and Midwest, and our Rust Belt counties are disproportionately in the North. <sup>19</sup> We do not put other controls in the regression simply because we want to look at the complete "reduced-form" effect of the shock. The one exception to this rule is that we interact the shock size variable with initial human capital to ask whether human capital mitigates the effect of the shock.

Perhaps more interesting is our decomposition of the shock's effect on employment rates into its constituent parts. We refer to our key dependent variable as the employment rate, but we define this term as 1 minus the unemployment rate.<sup>20</sup> This departure from convention is quite useful algebraically since we want to decompose the change in the unemployment rate into the change in the number of jobs, the change in the working-age population, and the change in the labor force participation rate.

We define the employment rate as follows:

where LFPR $_i$  is the labor force participation rate in county i. Taking logs of both sides yields:

(3) 
$$\log(\text{employment rate}) = \log(\text{number employed}) - \log(\text{LFPR}) - \log(\text{working-age population}).$$

And first differencing equation 3 yields:

(4) 
$$\Delta \log(\text{employment rate}) = \Delta \log(\text{number employed}) - \Delta \log(\text{LFPR}) - \Delta \log(\text{working-age population}).$$

<sup>19.</sup> Pack (2005).

<sup>20.</sup> In other words, when we discuss employment rates, we mean simply the inverse of the unemployment rate, not the more traditional *E*/pop.

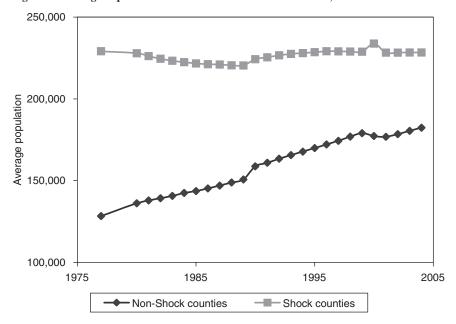


Figure 4. Average Population for Shock and Non-Shock Counties, 1975–2005<sup>a</sup>

Source: Population numbers are from the Census Bureau. Intercensal years are Census Bureau estimates.

a. The sample of counties is limited to those that had 10,000 or more people in 1977. The figures are simple averages across counties in each year.

In other words, the change in the log employment rate is the linear combination of the change in log jobs, the change in log labor force participation, and the change in log working-age population. We make use of this identity by regressing each of the four terms in equation 4 on the size of the shock (ratio of jobs lost to initial jobs). This enables us to decompose the effect of the shock on the employment rate into its effect on the three constituent parts.

### **Basic Empirical Results**

Figures 4 to 7 illustrate the evolution of population, unemployment rates, and jobs between 1975 and 2005 for the sixty-seven shock counties and all other counties. Figure 4 shows that population grew steadily from 1977 to 2004 for the non-shock counties, while the shock counties experienced a drop in

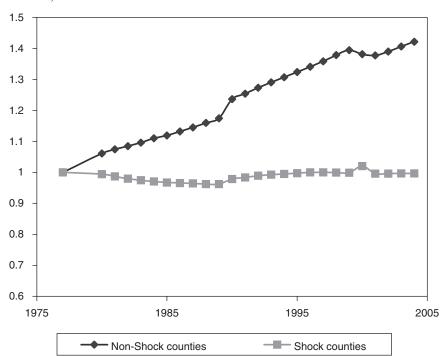


Figure 5. Population as a Fraction of 1977 Population in Shock and Non-Shock Counties,  $1975-2005^{\circ}$ 

Source: Population numbers are from the Census Bureau. Intercensal years are Census Bureau estimates.

a. The sample of counties is limited to those that had 10,000 or more people in 1977. The percentages are simple averages across counties in each year.

population followed by a slight recovery and zero growth thereafter.<sup>21</sup> Figure 5 elucidates this trend by plotting the average county population as a fraction of county initial (1977) population for the two groups. It is clear from the graph that the Rust Belt (shock) counties experienced some outflow of population followed by essentially zero population growth. This result is predicted by Glaeser and Gyourko and by Gyourko and Saiz.<sup>22</sup>

Figure 6 graphs unemployment rates over time for Rust Belt counties and all other counties. This figure is particularly interesting because it shows the huge

<sup>21.</sup> The minor blips in the two series occur in census years when the data move from a census projection to a number based on decennial census.

<sup>22.</sup> Glaeser and Gyourko (2005); Gyourko and Saiz (2003).

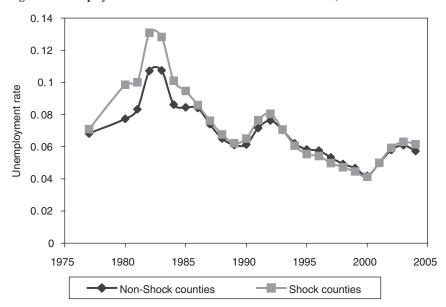


Figure 6. Unemployment Rates for Shock and Non-Shock Counties, 1975-2005a

Source: Unemployment rates by county are from the Bureau of Labor Statistics and based on the Current Population Survey.

a. The sample of counties is limited to those that had 10,000 or more people in 1977, based on the simple averages across counties in each year.

increase in unemployment for the Rust Belt starting in 1980. By 1982, unemployment had risen sharply for all counties in the United States. The average county had unemployment of more than 10 percent, but the Rust Belt counties had average unemployment rates significantly above this, at 13 percent. However, the Rust Belt counties fully converged back to the U.S. average by 1987. Relative to our prior beliefs, this was a very rapid recovery for a shock this large.

The baseline results have several possible implications. First, consistent with the state-level analysis of Blanchard and Katz, adjustment in the U.S. labor market was quite rapid.<sup>23</sup> Second, for all the negative factors associated with declining Rust Belt cities, on average these counties do not have chronically high long-term unemployment rates.

Figure 7 plots the number of jobs in Rust Belt counties and all other counties relative to initial (1977) jobs. The Rust Belt counties experienced a larger dip in jobs in 1982 relative to other counties and then very little growth in jobs relative to all other counties from 1987 to 2004. Note that figures 5 and 7

#### 23. Blanchard and Katz (1992).

1.8 1.7 1.6 obs as fraction of initial 1.5 1.4 1.3 1.2 1.1 1 0.9 8.0 1975 1980 1985 1990 2000 2005 1995 Non-Shock counties Shock counties

Figure 7. Number of Jobs as a Fraction of Initial (1977) Jobs for Shock and Non-Shock Counties, 1975–2005<sup>a</sup>

Source: Employment counts are from County Business Patterns.

a. The sample of counties is limited to those that had 10,000 or more people in 1977, based on the simple averages across counties in each year.

combined imply increasing labor force participation over time, which we presume is a result of women's entering the labor force.

# Effects of the Shock on the Change in the Employment Rate

Table 3 shows a county-level regression of the change in the employment rate on a dummy for being a shock county, that is, one that lost 2 percent or more of jobs. Column 1 indicates that during the shock period of 1977–82 these counties, on average, experienced a 1.3 percent drop in the employment rate, that is, a 1.3 percent increase in the unemployment rate. However, during 1982–87, this effect was almost completely reversed, and the shock counties gained 1.1 percent more in their employment rates relative to all other counties. Pack also finds this faster growth and convergence for manufacturing cities that were hit in the early 1980s.<sup>24</sup> Thus for the total period of 1977–87

Variable	Shock period, 1977–82 (1)	Recovery period, 1982–87 (2)	Total period, 1977–87 (3)	Subsequent period, 1987–2004 (4)
Shock dummy	-0.013***	0.011***	-0.002	0.000
-	(0.003)	(0.003)	(0.003)	(0.003)
Constant	-0.045***	0.053***	0.008***	0.011***
	(0.003)	(0.003)	(0.003)	(0.002)
Number of observations	1,439	1,439	1,439	1,439
$R^2$	0.37	0.40	0.47	0.31

Table 3. Simple Regression of Change in County-Level Employment Rate on a Shock Dummy  $^{\rm a}$ 

(column 3), we see no significant effect of the shock on the change in employment rate. We also see no effect of the shock on the change in employment rate during the subsequent period from 1987 to 2004.

In table 4 the dependent variable is again the change in employment rate, but we switch the right-hand-side variable to the fraction of initial jobs lost due to steel and autos. This gives us a broader range of variation for identifying the effects of the shock, although it does assume linearity of the effect. For the shock period, the coefficient on the shock size is 0.163. This means that a loss of 10 percent of jobs due to steel and autos increased the unemployment rate by 1.63 percent. During the recovery period of 1982–87, that same loss in the shock period is associated with a *decrease* in the unemployment rate of 1.44 percent. Thus in column 3 for the 1977–87 period overall, there is no relationship between the shock size and the change in unemployment rate. This is the same point made in table 3 and in figure 6 about faster growth in employment rate during the recovery period and convergence.

In table 5 we examine whether initial human capital helped Rust Belt counties to mitigate the effects of the shock or to reinvent themselves.<sup>25</sup> We use a dummy for being a shock county, the initial fraction of people in the county with four years of college, and the interaction of these two variables. Across U.S. counties in general, higher human capital is strongly associated with positive changes in the employment rate during the shock period. However, we do not find any evidence that human capital interacted with the shock

<sup>\*\*\*</sup>p < 0.01.

a. For this and all further regressions, the sample is limited to only those counties with an ex ante population of 10,000 and the shock period is defined as 1977–1982, the recovery period as 1982–87, and the total period as 1977–87.

	Shock period, 1977–82	Recovery period, 1982–87	Total period, 1977–87	Subsequent period, 1987–04
Variable	(1)	(2)	(3)	(4)
Shock size <sup>a</sup>	0.163***	-0.144***	0.019	0.020
	(0.051)	(0.052)	(0.047)	(0.039)
Constant	-0.045***	0.053***	0.008***	0.011***
	(0.003)	(0.003)	(0.003)	(0.002)
Number of observations	1,439	1,439	1,439	1,439
$R^2$	0.37	0.40	0.47	0.31

Table 4. Simple Regression of Change in County-Level Employment Rate on Shock Size

Table 5. Regression of Change in Employment on Shock Size and Education with Interaction Effects<sup>a</sup>

Variable	Shock period, 1977–82 (1)	Recovery period, 1982–87 (2)	Total period, 1977–87 (3)	Subsequent period, 1987–04 (4)
Shock dummy	-0.005	0.005	0.000	-0.007
	(0.009)	(0.010)	(0.009)	(0.007)
Initial college educated	0.197***	-0.099***	0.098***	-0.114***
	(0.014)	(0.015)	(0.014)	(0.011)
Initial education *	-0.042	0.037	-0.005	0.044
shock dummy	(0.072)	(0.078)	(0.070)	(0.058)
Constant	-0.072***	0.067***	-0.006	0.027***
	(0.003)	(0.004)	(0.003)	(0.003)
Number of observations	1,439	1,439	1,439	1,439
$R^2$	0.45	0.41	0.49	0.35

<sup>\*\*\*</sup>p < 0.01.

in a way that mitigated the employment effect of the shock. The point estimate on the interaction term moves in the other direction, indicating that Rust Belt counties with higher human capital experienced larger rises in unemployment than did Rust Belt counties with lower human capital.

Both of our discussants correctly point out that human capital levels across counties were endogenous to the shock and that individuals with high human capital may have moved away in anticipation of the shock. Or firms may have

<sup>\*\*\*</sup>p < 0.01.

a. For this and all further regressions, "shock size" is defined as the percentage change in total county-level employment expressed as a decimal.

a. Average education is defined as the average number of years of schooling per individual among individuals over the age of twenty-five (Census Bureau). The 1970 levels of average education are used as an ex ante measure of pre-shock education.

chosen to close plants in counties with high or low human capital.<sup>26</sup> Furthermore, education has a direct effect on county and city growth.<sup>27</sup> This is an important caveat to the interpretation of the results in table 5. One certainly cannot say that human capital caused shock counties to have larger employment losses during 1977–82. But, as purely a matter of descriptive statistics, it is not the case that counties with high human capital experienced less severe shocks or shorter adjustment times.

#### Implementing the Decomposition at the County and MSA Level

Tables 6 and 7 show our decompositions at the county and city level, respectively. The four panels are for the shock period, the recovery period, the sum of those two, and the subsequent (1987–2004) period. We regress the change in the log of the employment rate and each of its components on the size of the shock. In the shock period, a 10 percent loss of initial jobs is associated with a 1.9 percent change in the employment rate.<sup>28</sup> This effect can be decomposed into an 8.8 percent decrease in the number of jobs, a statistically insignificant 0.75 percent increase in labor force participation, and a 7.7 percent decrease in the number of working-age individuals.

To put this more concretely, when a county lost 1,000 steel or auto jobs, there was a net job loss to the county of 884: 771 working-age individuals left the county, but seventy-five new ones entered the workforce. This left 188 people unemployed. During the recovery period, the log employment rate moved in an equal and opposite direction. The number of jobs and labor force participation rate did not change. However, an additional 283 people moved out for every 1,000 steel or auto jobs lost. This additional population outflow fully explains the relative increase in the employment rate experienced by shock counties during the recovery period.

Thus when we look at the overall picture in panel C, we see no long-run effect of the shock on the employment rate. A 10 percent loss of jobs due to the shock is associated with an 11 percent loss of jobs overall and an 18 percent loss of jobs in the working-age population to balance out the jobs lost, while 5 percent more of the population is in the labor force. Due to the imprecision of our estimates, we cannot reject that labor force participation did not move

<sup>26.</sup> In results not reported, we find that education is not a statistically significant predictor of the shock, but we do not infer from this fact that education is exogenous.

<sup>27.</sup> Pack (2002); Glaeser and Saiz (2004).

<sup>28.</sup> Columns 1 and 3 require taking the log of a percentage or rate. A 3 percent change in the employment rate is not quite equal to a 3 percentage point change in the employment rate.

Table 6. Simple Decomposition at the County Level

A. Shock period

Variable	Shock	Shock	Shock	Shock
	log(emp)	log(jobs)	log(LFPR)	log(WA pop)
	change	change	change	change
	(1)	(2)	(3)	(4)
Shock size	0.188***	0.884***	-0.075	0.771
Constant  Number of observations	(0.059)	(0.237)	(0.766)	(0.766)
	-0.052***	0.078***	-0.040	0.170***
	(0.003)	(0.013)	(0.043)	(0.043)
	1,439	1,439	1,439	1,439
$R^2$	0.36	0.20	0.03	0.03
B. Recovery period				
Variable	Recovery log(emp) change	Recovery log(jobs) change	Recovery log(LFPR) change	Recovery log(WA pop) change
	(1)	(2)	(3)	(4)
Shock size Constant	-0.172***	0.192	0.081	0.283**
	(0.060)	(0.288)	(0.215)	(0.127)
	0.060***	0.094***	0.006	0.028***
Number of observations $R^2$	(0.003)	(0.016)	(0.012)	(0.007)
	1,439	1,439	1,439	1,439
	0.38	0.14	0.03	0.28
C. Total period				
Variable	Total	Total	Total	Total
	log(emp)	log(jobs)	log(LFPR)	log(WA pop)
	change	change	change	change
	(1)	(2)	(3)	(4)
Shock size	0.017	1.076***	-0.504	1.808**
Constant	(0.052)	(0.384)	(0.777)	(0.795)
	0.008***	0.172***	-0.044***	0.208***
Number of observations $R^2$	(0.003)	(0.021)	(0.011)	(0.011)
	1,439	1,439	1,439	1,439
	0.45	0.22	0.00	0.00
D. Subsequent period				
	Subsequent	Subsequent	Subsequent	Subsequent
	log(emp)	log(jobs)	log(LFPR)	log(WA pop)
	change	change	change	change
Variable	(1)	(2)	(3)	(4)
Shock size	0.026	0.965**	-0.044	0.945***
	(0.044)	(0.396)	(0.240)	(0.357)
Constant	0.013*** (0.002)	0.225*** (0.006)	0.060*** (0.003)	0.148*** (0.005)
Number of observations	1,439	1,439	1,439	1,439
Shock size	0.026	0.965	-0.044	0.945

Source: Authors' calculations. \*\*\*p < 0.01. \*\*p < 0.05.

Table 7. Simple Decomposition at the MSA Level<sup>a</sup>

### A. Shock period

Variable         change (I)         change (2)         change (3)         change (4)           Shock size         0.149         0.981*** (0.092)         0.331)         (0.796)         (0.812)           Constant         -0.048** (0.024)         0.093         -0.090         0.232           Number of observations         260         260         260         260         260           Recovery period         Recovery log(emp) log(jobs) change chang					
Variable         change (I)         change (2)         change (3)         change (4)           Shock size         0.149         0.981*** (0.092)         0.331)         0.796)         0.812)           Constant         -0.048** (0.024)         0.093         -0.090         0.232           Number of observations         260         260         260         260         260           Recovery period         Recovery log(emp) log(jobs) change					
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$			log(jobs)	log(LFPR)	log(WA pop)
Shock size		change	change	change	change
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Variable	(1)	(2)	(3)	(4)
Constant $-0.048^{**}$ $0.093$ $-0.090$ $0.232$ Number of observations $R^2$ $260$ </td <td>Shock size</td> <td>0.149</td> <td>0.981***</td> <td>0.642</td> <td>0.192</td>	Shock size	0.149	0.981***	0.642	0.192
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.092)	(0.331)	(0.796)	(0.812)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Constant	-0.048**	0.093	-0.090	0.232
R² $0.45$ $0.41$ $0.04$ $0.10$ B. Recovery log(emp)         Recovery log(jobs) change         Recovery log(jobs) log(LFPR) log(WA pop) change         Recovery log(WA pop) log(DA pop) change         Recovery log(WA pop) change         Recovery log(WA pop) log(DA pop) change         Recovery log(WA pop) log(DA pop) change         Recovery log(WA pop) log(DA pop) change         Recovery log(WA pop) change         Recovery log(WA pop) change         Recovery log(WA pop) change         Recovery log(WA pop) log(WA pop) change         Recovery log(WA pop) log(WA pop) log(WA pop) change         Recovery log(WA pop) log(WA pop) log(WA pop) change         Recovery log(		(0.024)	(0.087)	(0.209)	(0.214)
Recovery   Recovery   Recovery   Recovery   Recovery   log(emp)   log(jobs)   log(LFPR)   log(WA pop)   change   chang	Number of observations	260	260	260	260
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$R^2$	0.45	0.41	0.04	0.10
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	B. Recovery period				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		Recovery	Recovery	Recovery	Recovery
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$					
Variable         (1)         (2)         (3)         (4)           Shock size         -0.176         -0.070         -0.195         0.301           Constant         (0.091)         (0.415)         (0.290)         (0.230)           Constant         0.052**         0.068         -0.032         0.049           (0.024)         (0.109)         (0.076)         (0.061)           Number of observations         260         260         260         260           R2         0.51         0.16         0.07         0.32           C. Total period         Total Total log(emp) change         Total log(EFPR) log(WA pop) change         Subsequent log(ions) log(EFPR) log(WA pop)         Change         Change         Change         Change         Change         Change         Change         Change         Change				change	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Variable			0	0
Constant $0.052^{***}$ $0.068$ $-0.032$ $0.049$ Number of observations $260$ $260$ $260$ $260$ $260$ $260$ $R^2$ $0.51$ $0.16$ $0.07$ $0.32$ C. Total period           Total log(emp) log(jobs) log(LFPR) log(WA pop) change change change change change           Shock size $-0.027$ $0.911$ $0.446$ $0.492$ Constant $0.005$ $0.162$ $-0.123$ $0.281$ Constant $0.005$ $0.162$ $-0.123$ $0.281$ Number of observations $260$ $260$ $260$ $260$ $260$ $260$ $260$ D. Subsequent period           Subsequent log(jobs) log(LFPR) log(WA pop) change           Change change         Change         Change         Change           Subsequent log(jobs) log(LFPR) log(WA pop) change           Change         Change         Change         Change           Subsequent log(jobs) log(LFPR) log(WA pop) change         Change         Change         <	Shock size	-0.176	-0.070	-0.195	0.301
Constant $0.052^{***}$ $0.068$ $-0.032$ $0.049$ Number of observations $260$ $260$ $260$ $260$ $260$ $260$ $R^2$ $0.51$ $0.16$ $0.07$ $0.32$ C. Total period           Total log(emp) log(jobs) log(LFPR) log(WA pop) change change change change change           Shock size $-0.027$ $0.911$ $0.446$ $0.492$ Constant $0.005$ $0.162$ $-0.123$ $0.281$ Constant $0.005$ $0.162$ $-0.123$ $0.281$ Number of observations $260$ $260$ $260$ $260$ $260$ $260$ $260$ D. Subsequent period           Subsequent log(jobs) log(LFPR) log(WA pop) change           Change change         Change         Change         Change           Subsequent log(jobs) log(LFPR) log(WA pop) change           Change         Change         Change         Change           Subsequent log(jobs) log(LFPR) log(WA pop) change         Change         Change         <		(0.091)	(0.415)	(0.290)	(0.230)
Number of observations $R^2$ $260$ $0.51$ $260$ $0.16$ $260$ $0.07$ $260$ $0.32$ C. Total period         Total $log(emp)$ $log(jobs)$ $log(LFPR)$ $log(WA pop)$ Variable         Total $log(emp)$ $log(jobs)$ $log(LFPR)$ $log(WA pop)$ Shock size $-0.027$ $0.911$ $0.446$ $0.492$ Constant $0.005$ $0.162$ $-0.123$ $0.281$ Number of observations $R^2$ $260$	Constant	0.052**		-0.032	0.049
Number of observations $R^2$ $260$ $0.51$ $260$ $0.16$ $260$ $0.07$ $260$ $0.32$ C. Total period         Total $log(emp)$ $log(jobs)$ $log(LFPR)$ $log(WA pop)$ Variable         Total $log(emp)$ $log(jobs)$ $log(LFPR)$ $log(WA pop)$ Shock size $-0.027$ $0.911$ $0.446$ $0.492$ Constant $0.005$ $0.162$ $-0.123$ $0.281$ Number of observations $R^2$ $260$		(0.024)	(0.109)	(0.076)	(0.061)
$R^2$ $0.51$ $0.16$ $0.07$ $0.32$ C. Total period         Total log(emp) change         Total log(jobs) log(LFPR) log(WA pop) log(WA pop) log(LFPR)         Total log(WA pop) log(WA pop) log(WA pop) change           Variable $Change$ <td>Number of observations</td> <td></td> <td>· /</td> <td>\ /</td> <td>\ /</td>	Number of observations		· /	\ /	\ /
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$R^2$				
Variable   log(emp)   log(jobs)   log(LFPR)   log(WA pop)	C. Total period				
Variable         change         change         change         change           Shock size         -0.027         0.911         0.446         0.492           (0.076)         (0.570)         (0.808)         (0.902)           Constant         0.005         0.162         -0.123         0.281           (0.020)         (0.150)         (0.213)         (0.237)           Number of observations         260         260         260         260           R²         0.55         0.32         0.04         0.17           D. Subsequent period         log(jobs)         log(LFPR)         log(WA pop)           Variable         change         change         change         change           Shock size         0.031         0.656         0.046         0.579           (0.068)         (0.538)         (0.466)         (0.603)           Constant         0.017         0.309**         0.074         0.218           (0.018)         (0.142)         (0.123)         (0.159)           Number of observations         260         260         260         260		Total	Total	Total	Total
Variable         change         change         change         change           Shock size         -0.027         0.911         0.446         0.492           (0.076)         (0.570)         (0.808)         (0.902)           Constant         0.005         0.162         -0.123         0.281           (0.020)         (0.150)         (0.213)         (0.237)           Number of observations         260         260         260         260           R²         0.55         0.32         0.04         0.17           D. Subsequent period         log(jobs)         log(LFPR)         log(WA pop)           Variable         change         change         change         change           Shock size         0.031         0.656         0.046         0.579           (0.068)         (0.538)         (0.466)         (0.603)           Constant         0.017         0.309**         0.074         0.218           (0.018)         (0.142)         (0.123)         (0.159)           Number of observations         260         260         260         260		log(emp)	log(jobs)	log(LFPR)	log(WA pop)
Constant $(0.076)$ $(0.570)$ $(0.808)$ $(0.902)$ Constant $0.005$ $0.162$ $-0.123$ $0.281$ $(0.020)$ $(0.150)$ $(0.213)$ $(0.237)$ Number of observations $260$ $260$ $260$ $260$ $260$ D. Subsequent period  Subsequent $log(emp)$ $log(jobs)$ $log(LFPR)$ $log(WA pop)$ $change$ $change$ $change$ $change$ $change$ Shock size $0.031$ $0.656$ $0.046$ $0.579$ $0.008$ Constant $0.017$ $0.309**$ $0.074$ $0.218$ $0.018$ 0 $0.0142$ 0 $0.0123$ 0 $0.0159$ 0 Number of observations $0.018$ 0 $0.0162$ 0 $0.0162$ 0 $0.0163$ 0	Variable	0. 1,	0.0	0,	0. 11,
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Shock size	-0.027	0.911	0.446	0.492
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.076)	(0.570)	(0.808)	(0.902)
Number of observations $R^2$ $260$ $0.55$ $260$ $0.32$ $260$ $0.04$ $260$ $0.17$ D. Subsequent period         Subsequent $log(jobs)$ $log(LFPR)$ $log(WA pop)$	Constant	0.005	0.162	-0.123	0.281
R2         0.55         0.32         0.04         0.17           D. Subsequent period         Subsequent log(emp) log(jobs) log(LFPR) log(WA pop) log(LFPR) log(WA pop) log(LFPR) log(WA pop) log(LFPR) log(WA pop) log(EFPR) log(WA pop) change         Subsequent log(jobs) log(LFPR) log(WA pop) log(WA pop) log(EFPR) log(EFFR) log(EFFRR) log(EFFRR) log(EFFRR) log(EFFR		(0.020)	(0.150)	(0.213)	(0.237)
D. Subsequent period $ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Number of observations	260	260	260	260
Subsequent log(emp)         Subsequent log(jobs)         Subsequent log(LFPR) log(WA pop)         Subsequent log(WA pop)           Variable         change         change         change         change         change           Shock size         0.031         0.656         0.046         0.579           (0.068)         (0.538)         (0.466)         (0.603)           Constant         0.017         0.309**         0.074         0.218           (0.018)         (0.142)         (0.123)         (0.159)           Number of observations         260         260         260         260	$R^2$	0.55	0.32	0.04	0.17
Variable         log(emp) change         log(jobs) change         log(LFPR) change         log(WA pop) change           Shock size         0.031 (0.068) (0.538) (0.466) (0.603)         0.046 (0.603)         0.579 (0.068)           Constant         0.017 (0.309** 0.074 (0.123) (0.159)         0.218 (0.018) (0.142) (0.123) (0.159)           Number of observations         260 (260 (260 (260 (260 (260 (260 (260 (	D. Subsequent period				
Variable         change         change         change         change           Shock size         0.031         0.656         0.046         0.579           (0.068)         (0.538)         (0.466)         (0.603)           Constant         0.017         0.309**         0.074         0.218           (0.018)         (0.142)         (0.123)         (0.159)           Number of observations         260         260         260         260		Subsequent	Subsequent	Subsequent	Subsequent
Variable         change         change         change         change           Shock size         0.031         0.656         0.046         0.579           (0.068)         (0.538)         (0.466)         (0.603)           Constant         0.017         0.309**         0.074         0.218           (0.018)         (0.142)         (0.123)         (0.159)           Number of observations         260         260         260         260					log(WA pop)
(0.068) (0.538) (0.466) (0.603)  Constant 0.017 0.309** 0.074 0.218 (0.018) (0.142) (0.123) (0.159)  Number of observations 260 260 260 260	Variable	change	change	change	change
Constant         0.017         0.309**         0.074         0.218           (0.018)         (0.142)         (0.123)         (0.159)           Number of observations         260         260         260         260	Shock size	0.031	0.656	0.046	0.579
(0.018) (0.142) (0.123) (0.159) Number of observations 260 260 260 260		(0.068)		(0.466)	(0.603)
Number of observations 260 260 260 260	Constant	0.017	0.309**	0.074	0.218
		(0.018)	(0.142)	(0.123)	(0.159)
$R^2$ 0.39 0.36 0.04 0.26	Number of observations	260	260	260	260
	$R^2$	0.39	0.36	0.04	0.26

Source: Authors' calculations.

<sup>\*\*\*</sup>p < 0.01. \*\*p < 0.05.

a. Here and in table 8, the expression "Log(x)" represents the log of variable "x" over the specified period, where "emp" is countya. There and made s, the expression Log(x) represents the log of variable X over the spectual period, where emply the level employment rate as defined by the Bureau of Labor Statistics, "jobs" is equal to the total number of jobs per county as defined by the County Business Patterns, "LFPR" is equal to the imputed labor force participation rate, and "WA pop" is the size of the workingage population. Dummies are included for MSA status and the nine census divisions.

and that the population outflow was exactly equal to the job loss. In fact, when we trim the smaller counties from our sample, our point estimates say exactly this. We take two messages from this decomposition. First, labor market adjustment was quite rapid, and, second, it occurred largely through population change as opposed to net job inflow.

In the final panel, we ask what happened to the Rust Belt counties after 1987 and run the decomposition for the period 1987–2004. We see that *relative* to the rest of the country, the Rust Belt counties lost one additional working-age person and one additional job for each Rust Belt job lost during the shock. We know from figures 5 and 7 that this stems from the fact that employment and population in the Rust Belt counties remained flat, while the rest of the country grew.

We then aggregate the county-level data up to the MSA level and run the same decomposition. We find very similar results at the MSA level. This makes sense in light of Glendon and Vigdor, who show that neighboring counties have similar industrial composition and labor market conditions.<sup>29</sup> Results for MSAs are shown in table 7. During the shock period, for each job lost in steel and autos, 0.98 job was lost overall and 0.19 people moved out. Since labor force participation fell by 0.64 people, this left 0.15 people unemployed.

During the recovery period, more people moved out than additional jobs were lost. This reversed the increase in unemployment. For the total 1977–87 period at the MSA level, we see a loss of 0.9 job and 0.49 working-age resident for every steel and auto job lost. During the 1987–2004 period, the Rust Belt MSAs fell behind the rest of the country by another 0.66 job and 0.58 people for every steel and auto job lost. Again, this is due to a lack of growth in the Rust Belt MSAs as opposed to absolute population and job decline.

Is the Shock a Break in the Growth Trend, and Are the Estimated Effects of the Shock Causal?

Thus far we have proceeded as if the shock were a purely exogenous phenomenon that occurred strictly during 1977–82. This assumption is necessary for a comparison between shock and non-shock counties to yield causal estimates of the impact of the shock. Our discussants and editors asked whether preexisting trends in the shock places differed from the non-shock places and also whether the shock were a true break in trend. Saiz asked whether there

was a discrete jump followed by mean reversion to the old trend, a discrete jump followed by reversion to a new trend, or a discrete jump immediately to a new trend.

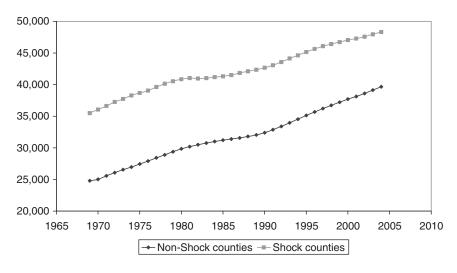
Having reexamined this issue, we find that the shock period of 1977–82 was indeed a discrete and large change in trend for the shock counties. But at the same time, the larger shock counties were already on a different and flatter growth path than the counties in our comparison (non-shock) group. In figure 8 we divide the sample of counties into those above and below median population in 1970. We examine population growth in these counties from 1970 to 2004 and separate out the shock and non-shock counties. The first panel is for the smaller counties. Visually, the evidence for a trend break around 1980 is compelling. Both the shock and non-shock counties were growing at about the same rates up until 1980. The shock counties then experienced zero population growth for about a six-year period starting in 1980. This figure presents weak evidence validating a comparison between the shock and non-shock counties for the smaller counties—that is, those that started out below the median level of population.

The larger counties are a different story in that the relative decline in these places began around 1973 as opposed to 1977. This is shown in the second panel of figure 8. It is clear from the figure that the large counties experiencing the shock were on a different growth path than the comparison large counties even before the shock; population was flat or slightly decreasing in the shock counties between 1973 and 1977. The trend did worsen around 1980. Like the smaller counties, the large shock counties also show a break in trend followed by mean reversion to the earlier trend. This is evidenced by the modest dip in the line during 1980 to 1992, followed by recovery in population to the 1980 level and zero growth thereafter. As Saiz suggested to us, there is an interesting analogy between our break plus mean reversion and the more striking pattern found by Davis and Weinstein in their analysis of population growth in Hiroshima and Nagasaki following the World War II atomic bombings.<sup>30</sup> As Glaeser pointed out, though, we are looking at cities and counties that have lost their comparative advantage and are in a long slow decline, as opposed to the Japanese case, where the shock was massive and the growth preceding the shock was very robust.

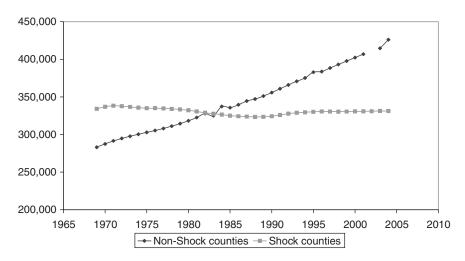
Overall there is some evidence that the shock represented a change in the growth path of these counties, followed by reversion to the earlier trend. In the case of the large-shock counties, this earlier trend is quite different from

Figure 8. Population Growth in Shock and Non-Shock Counties in Bottom and Top Fifty Counties, by Size, 1970–2005

# Population in bottom 50th percentile of counties (by size)



# Population in top 50th percentile of counties (by size)



Variable	$\Delta$ log population (1)	Log(population) (2)
Log(pop[t-1])		1.002***
		(0.000)
Post-1982 dummy	0.008***	0.008***
•	(0.000)	(0.000)
Post-1982 * shock dummy	-0.003***	-0.003***
-	(0.001)	(0.001)
Shock dummy	-0.005***	-0.007***
•	(0.001)	(0.001)
Constant	0.007***	-0.018***
	(0.000)	(0.002)
Number of observations	75,631	75,631
$R^2$	0.0343	0.9997

Table 8. Growth Regressions on Annual County-Level Data<sup>a</sup>

that of the large non-shock counties, so one must be cautious in interpreting our estimates as being strictly a causal effect of the 1977–82 shock.

In table 8, we test explicitly for a break in trend in 1982. We use annual data for county population from 1970 to 2004. We allow for separate trends for shock and non-shock counties both before and after 1982. In column 1 we regress the annual change in log of population on dummies for shock county, post-1982, and post-1982 interacted with our shock county. The coefficient on post-1982 \* shock dummy is -0.003 and is statistically significant. This indicates 0.3 percent slower population growth per year for the shock places following the shock and shows that the shock places were on a different trajectory after 1982. Unfortunately for our story, the shock dummy itself also has a statistically significant coefficient of -0.005, meaning that the shock places were on a different growth path from the non-shock places even before 1982. This can also be seen in the second panel of figure 8. Column 2 is essentially the same regression, but instead of explicitly using the change in log population, we use the log of population as the dependent variable and include the one-year lagged dependent variable on the right-hand side. This specification allows for the possibility that changes in county-level growth rates were temporary, with all counties converging to a common growth rate in the long run. Since the lagged dependent variable is estimated to have a coefficient of roughly 1, this regression is algebraically similar to that in column 1, suggesting that the trend difference is permanent (or at least extremely long-lived).

Source: Authors' calculations.

<sup>\*\*\*</sup>p < 0.01.

a. See the note to table 7. These regressions are intended to test for a change in the trend of population growth after 1982 for the shock and the non-shock counties. Annual data on population are at the county level from 1970 to 2004. Column 1 uses the year-to-year change as the dependent variable. Column 2 uses the level of log population as the dependent variable and controls for the one-year lag of log population on the right-hand side.

What can we do to control for the fact that the larger shock and non-shock counties looked different from one another prior to the 1977–82 period and that the shock contained some element of endogeneity? One sensible strategy is to limit our analysis to the smaller half of counties. This produces results that are qualitatively quite similar to those shown in tables 3 through 7. We again find that the shock had a sharp effect on unemployment that was quickly mitigated through relative loss of population. A second strategy might be to use propensity scores or other matching to find better control counties for the larger counties. One disadvantage to this strategy is that we might simply choose control counties that were experiencing other manufacturing shocks in the 1980 recession, just not steel and auto shocks. We did not have time to pursue this matching strategy but acknowledge that it could be a useful analysis.

Endogeneity of the shock is surely an important issue. In particular, firms might choose to close plants in areas that are already in decline, have undesirable amenities, undesirable weather, or high tax burdens, or have workers with low human capital. One interesting strategy for dealing with this might be to use the initial level of steel and auto jobs as an instrument for the size of the shock. Unfortunately in trying to implement this instrumental variables strategy, we could not get enough statistical power in the first stage to obtain reasonable standard errors in the second stage of the estimation.

Is the Relative Population Loss from People's Moving out or Failing to Move in?

In discussing tables 6 and 7 (decomposition tables), we said that the shock was absorbed by population loss in the counties that experienced the shock. Our editors asked us to clarify whether this came from a change in births, deaths, immigration, or out-migration. Since the adjustment happened so rapidly and happened among the working-age population, we decided to put aside for the moment the question of the effects on births and deaths.<sup>31</sup> We chose to focus on the differences for in-migration and out-migration between the shock and non-shock counties.

We start with the micro census data for 1980, 1990, and 2000.<sup>32</sup> These censuses collected individual-level data on both the current MSA and the MSA

<sup>31.</sup> Black, McKinnish, and Sanders (2003) investigate the effects of industry decline on mortality.

<sup>32.</sup> These data are from Integrated Public Use Microdata Series (http://ipums.org [March 2007]).

Table 9.	Population	Growth and	Movement in	and out	of Shock	and Non-Shock	MSAs,
1980-20	$00^{\mathrm{a}}$						

Census year and moving status		
over past five years	Non-Shock MSAs	Shock MSAs
1980		
Percent in same MSA	0.715	0.801
Percent moved in	0.285	0.199
Percent moved out	0.260	0.222
Number of MSAs	171	24
1990		
Percent in same MSA	0.738	0.806
Percent moved in	0.262	0.194
Percent moved out	0.257	0.220
Number of MSAs	168	22
2000		
Percent in same MSA	0.734	0.785
Percent moved in	0.266	0.215
Percent moved out	0.260	0.208
Number of MSAs	189	23

Source: Authors' calculations.

a. Census data are used to calculate the percentage of in-migrants, out-migrants, and stayers by MSA, based on the census questions that record current MSA and MSA five years ago. The analysis is imperfect in that the latter question is missing in a high percentage of cases, and the data make it impossible to distinguish between "missing" and "not living in an MSA." The shock MSAs are those that lost 1 percent or more of initial (1977) jobs to steel and auto reductions.

where an individual lived five years ago. We limit the sample to individuals for whom we know both the current and previous (five years ago) MSA.<sup>33</sup> For every MSA, we calculate the percentage of current residents who lived in the same MSA five years ago. One minus this figure is an estimate of the percentage who moved in during the past five years. We also calculate the percentage of the previous residents who moved to a different MSA. We collapse our county-level shock variables to the MSA level and merge this into the data on movers in and out by MSA. We define shock MSAs as those twenty-four MSAs that lost 1 percent or more of initial jobs to job reductions in steel and autos. We compare in- and out-migration rates for shock and non-shock places.

The results are shown in table 9. Interestingly, residents of shock MSAs were much less mobile than Americans in general. In 1980, 80 percent of the

<sup>33.</sup> This sample selection introduces two sources of bias. First, we lose people who did not live in an MSA in both years, and we lose people for whom the previous location is missing. Dropping the non-MSA and missing people is fairly unavoidable since we cannot distinguish between "missing" and "non-MSA" for previous location. We do eliminate births and deaths since our sample only includes people alive in both time periods (now and five years ago.)

Table 10. Movement of College-Educated Persons in and out of Shock and Non-Shock MSAs,  $1980-2000^{\rm a}$ 

Census year and moving status of college-educated over past five years	Non-Shock MSAs	Shock MSAs	
1980			
Percent moving in	0.297	0.300	
Percent moving out	0.306	0.282	
1990			
Percent moving in	0.315	0.306	
Percent moving out	0.344	0.322	
2000			
Percent moving in	0.338	0.330	
Percent moving out	0.369	0.350	

Source: Authors' calculations.

a. See note to table 9.

residents of shock MSAs lived in the same MSA five years earlier versus 72 percent for all other MSAs. In the shock MSAs, 22 percent of the 1975 residents moved out by 1980 versus 26 percent for all other MSAs. How did shock places adjust via population loss given that the shock places had *lower*, not higher, out-migration? Migration into shock places was vastly lower for shock places than for other MSAs. Twenty percent of residents of shock MSAs migrated in during the previous five years versus 29 percent for all other MSAs. Thus the population adjustment observed in our decomposition and figure 4 is largely about the shock places' having low in-migration.

A related question is whether migration patterns serve to reduce the average human capital level of the Rust Belt (shock) MSAs. We do not see evidence of this in the data. In table 10, we limit the migration analysis to persons with four years of college (roughly 12 percent of the sample in 1980). We also limit the sample to persons older than twenty-two years of age. In 1980 for the shock MSAs, 30 percent of the current college-educated residents were new migrants to the MSA. Of the 1975 college-educated residents, 28.2 percent moved out by 1980, so these two figures suggest a similar percentage gain and loss of college-educated individuals. The figures for the non-shock MSAs look similarly balanced. In general (looking over all three sample years), about 30–35 percent of college-educated individuals changed MSAs within a five-year period, and this migration was not particularly biased away from the shock MSAs. Naturally, college education is only one measure of human capital, and it is, of course, possible (or even likely) that shock MSAs were losing high-tech or high-productivity or highly entrepreneurial workers to other MSAs.

### Other Effects of Shocks to Steel and Auto Jobs

The previous section established that the recovery from steel and auto job losses was relatively rapid and occurred mainly through adjustments to the working-age population. The most striking finding is that, by the mid-1980s, unemployment rates were no higher in our shock counties than in other U.S. counties. Since the employment situation in these counties appears to be healthy, why then do people think of "Rust Belt" counties as depressed areas? This section examines other outcomes that may play a role in the negative perception of the Rust Belt such as incomes, housing prices, crime, demographics, and quality of life.

#### Income per Capita

It would not be surprising to find that per capita income suffered after the loss of steel and auto jobs in the shock counties. In 1977 the shock counties had per capita incomes that were 8.5 percent higher than those of all other counties, and this advantage eroded to 3.7 percent in 1982. However, the subsequent long-run effects on income per capita were economically modest in that the shock counties remained 1.2 percent above the other counties in 2004. Figure 9 graphs income per capita over time, showing that it was comparable in shock and non-shock counties throughout the period. Table 11 shows exactly this. The effect of the shock on change in per capita income from 1977 to 1982 was -8 percent in shock counties relative to the rest of the country.

We infer two things from these numbers. First, the loss of thousands of high-paying manufacturing (union) jobs removed the Rust Belt's income advantage. However, the Rust Belt counties are not inherently poor today, as judged by income per capita.

# Housing Prices

Another way in which residents of the Rust Belt may have suffered economically from the loss of auto and steel jobs is through loss of wealth in the form of housing. To test this conjecture, table 12 shows the effect of the shock dummy on MSA-level housing prices. We use the Office of Federal Housing Oversight's repeat sales index by MSA for 1987–2002. We do not find a statistically significant fall in housing prices in the shock MSAs, at least for the decades following the shock period. (The index is not widely available before the mid-1980s). It may be that house prices in the Rust Belt cities had a discrete jump downward in response to the shock and then followed a trend

30,000 25,000 20,000 15,000 10,000 5,000 0 1975 1980 1985 1990 1995 2000 2005 2010 Non-Shock counties Shock counties

Figure 9. Income Per Capita in Shock and Non-Shock Counties, 1975-2005

Source: Income data are from the Bureau of Economic Analysis.

Table 11. Changes in Per Capita Income Regressed on Shock Dummy<sup>a</sup>

Change in shock income, 1977–82 (1)	Change in recovery income, 1982–87 (2)	Change in total income, 1977–87 (3)	Change in subsequent income, 1987–2004 (4)
-0.045***	-0.011	-0.082***	-0.047**
(0.012)	(0.011)	(0.022)	(0.021)
0.501***	0.308***	0.960***	0.954***
(0.010)	(0.009)	(0.018)	(0.017)
1,476	1,476	1,476	1,476
0.359	0.399	0.426	0.084
	shock income, 1977–82 (1) -0.045*** (0.012) 0.501*** (0.010) 1,476	Change in shock income, 1977–82         recovery income, 1982–87           (1)         (2)           -0.045***         -0.011           (0.012)         (0.011)           0.501***         0.308***           (0.010)         (0.009)           1,476         1,476	Change in shock income, 1977–82         recovery income, 1982–87         Change in total income, 1977–87           (1)         (2)         (3)           -0.045***         -0.011         -0.082***           (0.012)         (0.011)         (0.022)           0.501***         0.308***         0.960***           (0.010)         (0.009)         (0.018)           1,476         1,476         1,476

Source: Authors' calculations.

<sup>\*\*\*</sup>p < 0.01.

<sup>\*\*</sup>p < 0.05.

a. Income data are from the Bureau of Economic Analysis, which defines per capita personal income as the personal income of the residents of a given area divided by the resident population of the area, where personal income is the income received by persons from all sources. Dummies are included for MSA status and the nine census divisions.

Variable	Change in housing index, 1987–2004
Shock dummy	-0.023
•	(0.072)
Constant	0.523***
	(0.065)
Number of observations	158
$R^2$	0.377
Shock size	0.479
	(0.660)
Constant	0.522***
	(0.065)
Number of observations	158
$R^2$	0.379

Table 12. Subsequent Changes in MSA-Level Housing Prices<sup>a</sup>

Source: Authors' calculations.

similar to the rest of the MSAs. This evidence is also consistent with the fact that housing prices largely follow construction costs for most of the country.<sup>34</sup>

## Effects on Age Structure of the Population

A commonly held belief is that Rust Belt counties consist disproportionately of older and retired people. This is also related to the notion that declining cities have lower amenities since younger people are often seen as crucial to the quality of an area's bar, music, restaurant, and recreational amenities. We find only modest evidence that the population who remained in Rust Belt counties became older relative to the population of other counties after the shock. In table 13, the dependent variable is the change in the percentage of the population in various age categories over the period 1980–96. The right-hand-side variable is the size of the shock. The data are for our standard cross section of counties.

All of the estimated coefficients in table 13 are economically modest. For example, losing 10 percent of initial jobs in the shock led to a decrease in the percentage of the population under fifteen of 0.2 percentage point over a twenty-four-year period. The increase in the percentage of individuals over sixty-five is 0.2 percentage point. The predicted decrease in the percentage

<sup>\*\*\*</sup>p < 0.01.

a. House price data are from Office of Federal Housing Enterprise Oversight's index of repeat sales. Controls are included for the nine census regions.

<sup>34.</sup> Gyourko and Saiz (2003); Glaeser and Gyourko (2005).

Table 13. Changes in County-Level Population Demographics<sup>a</sup>

Variable	Change in population age 14 or younger (1)	Change in population age 15–44	Change in population age 45–64	Change in population age 65 and older (4)
Shock size	0.018	-0.119**	0.116**	-0.015
	(0.036)	(0.048)	(0.051)	(0.041)
Constant	-0.040***	-0.043***	0.073***	0.010***
	(0.002)	(0.003)	(0.003)	(0.003)
Number of observations	1,284	1,284	1,284	1,284
$R^2$	0.085	0.225	0.131	0.094

Source: Authors' calculations.

Table 14. Changes in the Crime Rate<sup>a</sup>

Variable	Shock period, 1977–82	Recovery period, 1982–87	Total period, 1977–87	Subsequent period, 1987–04
Shock dummy	-0.243***	-0.001	-0.245	-0.145
	(0.092)	(0.134)	(0.176)	(0.157)
Constant	0.209***	0.087***	0.296***	-0.098***
	(0.020)	(0.030)	(0.039)	(0.035)
Number of observations	103	103	103	103
$R^2$	0.06	0.00	0.02	0.01

Source: Authors' calculations.

of individuals between the ages of forty-five and sixty-four is 1 percent. These effects are in the expected direction, but are small relative to the variation in age structure observed across the United States in general.

#### Crime

Another potential contributor to the negative perception of Rust Belt cities may be an increase in crime rates. Table 14 shows the changes in crime for the shock counties. During the shock period, the shock counties experienced a 24 percent fall in the number of crimes per capita relative to non-shock counties. During the recovery period, the crime rates in the shock counties moved in tandem with the non-shock counties. Overall, crime fell in the shock

<sup>\*\*\*</sup>p < 0.01.

<sup>\*\*</sup>p < 0.05.

a. Population statistics are from the Census Bureau. The shock size is regressed on the change in the size of each age cohort over the period 1980-2004. The change in population demographics is tracked over the 1980-96 period. Dummies are included for MSA status and the nine census divisions.

<sup>\*\*\*</sup>p < 0.01.

a. Data are from the Federal Bureau of Investigation's Universal Crime Reports (UCR) database. Crimes are reported per 100,000 persons. Dummies are included for MSA status and the nine census divisions.

counties relative to the non-shock counties from 1977 until 1987, and this trend continued between 1987 and 2004.

Since crime fell dramatically in the Rust Belt (on an absolute and relative basis), it would be hard to conclude that crime rates explain any of the negative perception of Rust Belt cities. However, we are not claiming that the shock had a negative causal impact on crime.

#### Restaurants and Other Amenities

Given that unemployment quickly converged back to U.S. levels and crime actually fell more in Rust Belt counties and cities, why do these places have such a poor reputation in the press and in city and area rankings such as Forbes Best Places and Sperling's Best Places? Rust Belt cities appear to have experienced a permanent negative shock to their amenities. Part of this reduction in amenities may be common to all areas with declining population. As areas decline, agglomeration externalities diminish, as implied by Helsley and Strange. For example, the absolute number of restaurants or sports teams that an area can support is reduced. The aging infrastructure (for example, roads, highways, and bridges) in declining areas is less attractive and useful even if it is less congested than the infrastructure in growing regions. There may also be a loss of aesthetics that is specific to these counties. Thirty acres of abandoned steel mill is inherently uglier than an underutilized office building or an abandoned farm.

In table 15 we examine the effect of the Rust Belt shock on the number of bars and restaurants. The dependent variable is the percentage change in the number of establishments for three time periods, 1977–82, 1982–87, and 1977–97. We also show results for the change in bars and restaurants per capita. The right-hand-side variable is a dummy for being a shock county. Each cell reports the coefficient on this dummy from a separate regression.

The pattern over time is quite different from the pattern for employment rates in table 3. Instead of recovering from the shock after 1982, the loss of bars and restaurants actually accelerated. This makes sense if it takes several years for restaurant owners to give up on an area or to go broke. During the shock period, the Rust Belt counties lost 5 percent of their bars and restaurants. However, by 1997, 28 percent of the bars and restaurants had disappeared! This is significantly greater than the loss of population. Thus in the second row of the table, we see that bars and restaurants per capita had fallen 13 percent

Indicator	Shock period, 1977–82 (1)	Recovery period, 1982–87 (2)	Full period, 1977–97 (3)
Percent change in number	-0.049**	-0.029	-0.280***
of restaurants and bars	(0.022)	(0.032)	(0.100)
Percent change in number of	-0.020	-0.029	-0.134*
restaurants and bars per capita	(0.056)	(0.032)	(0.079)
Number of observations	1,396	1,394	1,207

Table 15. Effect of Shock on Number of Bars and Restaurants in the County<sup>a</sup>

by 1997. It is not clear whether one should focus on the total number of establishments or on the number of establishments per capita. Our view is that the former matters for the sake of variety, while the latter matters for the sake of congestion and perhaps proximity.

It is also likely that vintage effects are working against the quality or appeal of the restaurants in the Rust Belt cities. Assuming that fewer new restaurants get started in these places, Rust Belt cities may be less likely to offer recently imported (to the U.S.) types of ethnic food or the latest bistros or clubs. If people have a taste for variety and for new types of restaurants and food, this demand is less likely to be met in a declining city.

In table 16 we further explore the effect of the Rust Belt shock on amenities using the data from *Cities Ranked and Rated*. Recall from the previous section that these rankings range from 1 to 331, where a ranking of 1 indicates the most attractive place. We run a county-level cross-sectional regression. We have a cross section of the most recent data for the 331 cities, and we match these to any county that contains all or part of the central city being rated. Results for the quality of life ranking are shown in column 1. The quality of life ranking is the combination of separate scores for the city's physical attractiveness, the quality of the public buildings, the degree to which historical and cultural heritage is well preserved, and the ease of shopping and commuting. Being a Rust Belt city decreases this ranking by a full thirty-nine cities. In results not shown, we find that controlling for weather has no effect on this

<sup>\*\*\*</sup>p < 0.01.

<sup>\*\*</sup>p < 0.05.

<sup>\*</sup>p < 0.10.

a. Dependent variables are the change (in decimals) in the number of bars and restaurants and the change in the number of bars and restaurants per thousand residents. We report the coefficient from regressing the change in bars and restaurants on the "shock dummy," The shock dummy equals 1 for counties losing 2 percent or more of total initial jobs due to steel and autos during 1977–82. Each cell is from a separate regression. In other regressions not shown, the shock is found to have no effect on the number of food stores or the number of retail stores. Standard errors are in parentheses. In results not reported, similar results are found when controlling for MSA status and four region dummies. Controlling for MSA status and nine census division dummies eliminates the statistical significance for the per capita results for the full period.

able 16. I	able 16. Effect of Steel and Auto Shock on Measures of City Quality of Life $^{\scriptscriptstyle a}$	hock on Measur	es of City Quality of I	"ife"	
			Change in ranking	Change in ranking Change in ranking	
			on recreation	on recreation	Change in rankin
	Ranking on	Ranking on Ranking on	and leisure,	and leisure,	on arts and cultur

Table 16. Effect of	Steel and Auto S	hock on Measur	Table 16. Effect of Steel and Auto Shock on Measures of City Quality of Life <sup>a</sup>	Life <sup>a</sup>		
: :	Ranking on quality of life	Ranking on quality of life	Change in ranking on recreation and leisure, 1981–2004	Change in ranking on recreation and leisure, 1981–2004	Change in ranking on arts and culture, 1981–2004	Change in ranking on arts and culture, 1981–2004
Variable	(1)	(2)	(3)	(4)	(5)	(0)
Shock dummy	39.209* (20.130)		5.039 (20.321)		9.892 (13.668)	
Population growth,		-31.872***		-17.038*		-1.210
1977–2000		(8.857)		(9.443)		(6.513)
Constant	130.747***	136.269***	-57.271	-57.797	-36.263	-63.488*
	(37.083)	(34.330)	(63.369)	(54.152)	(42.622)	(37.351)
Number of	298	310	245	249	245	249
observations						
$R^2$	0.159	0.180	0.232	0.231	0.079	0.082
**** $p < 0.01$ .  * $p < 0.10$ a. Data are from Cities Ranked and Rated, which ranks 33 assigned 3.11. The rankings are described in the text. The cranking. The ranking is regressed on the shock dummy. Pos	ked and Rated, which range te described in the text. Tessed on the shock dumm.	nks 331 cities on various The criteria and method 1 y. Positive coefficients in	categories, including arts and re behind each ranking are describ ndicate that the shock dummy h	***p < 0.01. *p < 0.01	st or most attractive city is assign at contains (partially or complet 's number of cities. Dummies ar	ned 1, and the least attractive is ely) a ranked city is assigned a e included for MSA status and

assigned 331. The rankings are described in the text. The crite ranking. The ranking is regressed on the shock dummy. Positi the nine census divisions. Standard errors are in parentheses.

result. Even controlling for the change in population across counties, the Rust Belt scores thirty-eight cities worse in the rankings relative to other places.

In the point estimates, the Rust Belt cities also are meaningfully worse on arts, recreation, and leisure. However, these effects are not statistically significant. See appendix B for the full list of attributes that are added together to derive these rankings. In columns 3 and 5 we regress the change in ranking from 1981 to 2004 on a dummy for being a Rust Belt city. For the Rust Belt cities, the rankings worsen by five cities for arts and by ten cities for recreation, controlling for census division. In columns 2 and 4, we show that each 10 percent of additional growth in population from 1977 to 2000 is associated with a three-city improvement in the ranking for quality of life and a 1.7 city improvement in the ranking for recreational opportunities.

Given that the quality of life regression in table 16, column 1, is cross-sectional, one can question whether the Rust Belt cities were worse on certain amenities even prior to the shock. However, the panel evidence on restaurants and bars from the previous table points to a loss in amenities that follows the shock. Certainly, Pittsburgh and Cleveland were not always undesirable places, and in the early and mid-twentieth century Cleveland was one of the most affluent and culturally rich cities in America. In the early twentieth century, Euclid Avenue in Cleveland was known as millionaire's row and was described in Baedecker's Travel Guide as "the most beautiful street in America."

# Distinguishing between Successful and Unsuccessful Rust Belt Counties

Another interesting take on the data is to ask what factors differentiate the subsequently successful Rust Belt counties from the unsuccessful. We take long-run population growth as our measure of growth and ask whether the factors identified in the literature on growth in cities predict long-run growth among Rust Belt counties.<sup>36</sup>

In table 17 we again list the counties that experienced a shock to jobs of 2 percent or more and show population growth from 1977 to 2004. In general these counties grew far less than the United States as a whole. Median growth across these shock counties was 5 percent versus 26 percent for the United States over the twenty-seven-year time period. Mean growth was 14 percent for the Rust Belt counties versus 40 percent for U.S. counties. However,

<sup>36.</sup> Glaeser and others (1992); Pack (2002); Glaeser and Saiz (2004); Shapiro (2006).

Table 17. Population Growth in Shock (Rust Belt) Counties, 1977–2004<sup>a</sup>

FIPS	County and state	MSA	Percentage of jobs lost in shock	Population growth, 1977–2004	Population, 1977
1073	Jefferson, Alabama	Birmingham	-0.046	0.015	652,583
1117	Shelby, Alabama	Birmingham	-0.025	1.628	55,000
5045	Faulkner, Arkansas	Little Rock-North Little Rock	-0.047	n.a.	38,021
5009	Boone, Arkansas		-0.024	n.a.	22,000
9011	New London, Connecticut		-0.041	1.038	127,326
13051	Chatham, Georgia	Savannah	-0.035	0.244	186,753
13115	Floyd, Georgia		-0.022	0.131	80,298
17115	Macon, Illinois	Decatur	-0.031	-0.067	122,735
17083	Jersey, Illinois	St. Louis	-0.046	0.192	18,177
17119	Madison, Illinois	St. Louis	-0.027	0.050	246,802
18089	Lake, Indiana	Chicago-Gary-Kenosha	-0.041	-0.099	537,976
18039	Elkhart, Indiana	Elkhart-Goshen	-0.095	0.393	131,730
18001	Adams, Indiana	Fort Wayne	-0.056	0.121	30,000
18003	Allen, Indiana	Fort Wayne	-0.097	0.097	303,230
18033	De Kalb, Indiana	Fort Wayne	-0.033	0.292	31,263
18167	Vigo, Indiana	Terre Haute	-0.032	-0.112	119,050
18177	Wayne, Indiana		-0.039	-0.112	80,000
19163	Scott, Iowa	Davenport-Moline-Rock Island	-0.061	0.008	157,500
20099	Labette, Kansas		-0.021	-0.087	24,928
20191	Sumner, Kansas		-0.029	0.139	22,817
20205	Wilson, Kansas		-0.055	-0.162	12,299
21101	Henderson, Kentucky	Evansville-Henderson	-0.097	0.121	40,000
21145	McCracken, Kentucky		-0.022	0.059	61,800
24005	Baltimore, Maryland	Washington-Baltimore	-0.028	0.175	643,363
26021	Berrien, Michigan	Benton Harbor	-0.068	-0.052	171,477
26049	Genesee, Michigan	Detroit-Ann Arbor-Flint	-0.085	-0.026	448,697
26087	Lapeer, Michigan	Detroit-Ann Arbor-Flint	-0.022	0.430	61,758
26099	Macomb, Michigan	Detroit-Ann Arbor-Flint	-0.043	0.135	820,069
26161	Washtenaw, Michigan	Detroit-Ann Arbor-Flint	-0.024	0.318	246,096
26163	Wayne, Michigan	Detroit-Ann Arbor-Flint	-0.068	-0.168	2,474,662
26121	Muskegon, Michigan	Grand Rapids-Muskegon-Holland	-0.033	0.099	155,181

Saginaw, Michigan Branch, Michigan	Saginaw-Bay City-Midland	-0.180 -0.059	0.026	204,602 36,800
Gratiot, Michigan Menominee, Michigan		-0.040 -0.022	0.081	39,149 25.918
Sanilac, Michigan		-0.039	0.348	33,049
Rock, Minnesota		-0.039	-0.100	10,789
Chemung, New York	Elmira	-0.043	-0.064	97,307
Cortland, New York		-0.020	0.013	47,968
Cuyahoga, Ohio	Cleveland-Akron	-0.026	-0.156	1,649,293
Madison, Ohio	Columbus	-0.027	1.047	19,652
Lawrence, Ohio	Huntington-Ashland	-0.068	0.161	53,638
Allen, Ohio	Lima	-0.048	0.103	98,394
Fulton, Ohio	Toledo	-0.073	0.214	34,715
Lucas, Ohio	Toledo	-0.023	0.035	439,530
Mahoning, Ohio	Youngstown-Warren	-0.093	0.042	246,598
Trumbull, Ohio	Youngstown-Warren	-0.087	0.040	216,361
Darke, Ohio		-0.057	0.007	52,958
Huron, Ohio		-0.028	0.206	49,410
Scioto, Ohio		-0.035	0.011	78,240
Seneca, Ohio		-0.043	-0.034	60,700
Williams, Ohio		-0.024	0.269	30,898
Carbon, Pennsylvania	Allentown-Bethlehem-Easton	-0.042	0.202	48,961
Erie, Pennsylvania	Erie	-0.084	0.050	267,465
Dauphin, Pennsylvania	Harrisburg-Lebanon-Carlisle	-0.020	0.134	221,994
Allegheny, Pennsylvania	Pittsburgh	-0.027	-0.180	1,561,123
Beaver, Pennsylvania	Pittsburgh	-0.061	-0.119	205,509
Washington, Pennsylvania	Pittsburgh	-0.021	-0.011	205,339
Mercer, Pennsylvania	Sharon	-0.031	-0.040	125,238
Elk, Pennsylvania		-0.094	-0.063	37,407
Lawrence, Pennsylvania		-0.020	-0.091	104,081
Snyder, Pennsylvania		-0.026	0.237	30,346
Dickson, Tennessee	Nashville	-0.099	1.140	20,258
Harrison, Texas	Longview-Marshall	-0.036	0.397	44,444
uliable; FIPS = Federal information processing standards. If counties that lost 2 percent or more of jobs in the steel year period. The counties are grouped by MSA to show the	ilable; FIPS = Federal information processing standards.  f counties that lost 2 percent or more of jobs in the steel and auto industries during 1977–82 and experienced long-run population growth. Median population growth was 5 percent over the year period. The counties are grouped by MSA to show that, in most cases, long-run growth was negative or positive for all counties in the MSA. Detroit was an exception.	experienced long-run population gative or positive for all countie	α growth. Median population gr s in the MSA. Detroit was an e>	rowth was 5 percent over the xception.

n.a. Not availab a. The set of co twenty-seven-yea



Figure 10. Subsequent Population Growth in Shock Counties, 1977-2004<sup>a</sup>

a. The set of counties that lost 2 percent or more in the shock 1977–82, divided into two groups: those that gained 10 percent or more in population between 1977 and 2004 and those that did not.

there are some positive outliers among the shock counties. Shelby County (Alabama) more than doubled in size, as did New London (Connecticut) and Chatham County (Georgia).

One clear pattern in the data is that Rust Belt counties in warm, sunny places were more likely to rebound, a fact that is consistent with the existing literature. This result can be seen in figure 10, which maps the shock

counties and divides the group by those that grew more or less than 10 percent from 1977 to 2004. The southern counties were more likely to be in the former category, although certain northern Rust Belt counties also did well.

Proximity to a very large metropolitan area appears to have a positive effect on growth. For example, Carbon County (Pennsylvania), part of the Allentown-Bethlehem MSA, may benefit from its short distance (ninety miles) to New York City and Philadelphia. Baltimore County is central to the entire Washington-Baltimore MSA. Several other successful Rust Belt counties such as Dauphin County (Pennsylvania) and Madison County (Ohio) are home to or near state capitals. A couple of the counties in Michigan appear to have benefited from the exodus from the area's central city. In the Detroit area, Lapeer and Washtenaw gained population at the same time that Wayne lost significant population. But this negative correlation of population growth within an MSA is atypical.

Table 18 shows cross-sectional population growth regressions for the shock counties and all counties in our sample. Table 19 contains summary statistics for the variables used in the regression. The dependent variable is population growth from 1977 to 2000. For the set of shock counties, the two significant predictors of growth are mean temperature and minutes of sunshine. In the point estimates, being close to a major city adds 9.2 percentage points to a Rust Belt county's population growth over the twenty-three years. However, this effect is not statistically significant. Raising the average January low temperature for the county by 30 degrees Fahrenheit adds 7.8 percent to the county's growth. Interestingly, human capital is not a significant predictor, but this may simply be a lack of statistical power, since we only have sixty-two shock counties in the regression. In the regression for all counties (column 2), the 1980 percent of the population with four years of college is a very strong predictor of county growth. An additional 5 percent of the population with college degrees in 1980 adds almost 6 percent to county population in 2000.

Since the successful Rust Belt counties are adding jobs, we also asked (in results not reported) which industries are growing or moving into the successful counties. Much of what we found is not surprising, since many of the industries that grew in the successful counties are the ones such as building construction and auto repair that we would naturally associate with growing population. However, the successful counties also added additional manufacturing jobs, having positive growth in rubber and fabricated metal. They also added jobs in health and business services.

Table 18. Determinants of Long-Run Growth in Shock and Non-Shock Counties<sup>a</sup>

Determinant	Population growth, 1977–2000 (1)	Population growth, 1977–2000 (2)
Percent with 16 years of education, 1980	0.305	1.255***
•	(0.994)	(0.370)
Percent black, 1980	-1.695***	-1.616***
	(0.516)	(0.157)
County has a doctoral-granting university	-0.052	-0.037
	(0.141)	(0.053)
County is within 75 miles of a top-fifty city by size	0.092	
	(0.080)	
Average low temperature in January for state	0.026**	0.007**
	(0.011)	(0.003)
Minutes of sunshine as a percent of possible	-0.026*	0.010**
• •	(0.014)	(0.004)
Industry concentration, 1977 (Herfindahl)	0.543	-0.272
	(0.888)	(0.335)
Steel and auto job change/initial employment	1.455	0.580
	(1.304)	(1.033)
Constant	1.416*	-0.464*
	(0.792)	(0.243)
Number of observations	62	1,171
$R^2$	0.562	0.279

Source: Authors' calculations.

Table 19. Additional Table of Means

Variable	Number of observations	Mean	Standard deviation	Minimum	Maximum
Population growth, 1977–2000					
All counties	1,732	0.35	0.58	-0.95	8.52
Shock counties	62	0.14	0.33	-0.18	1.63
Percent with four or more years of college in 1980	1,785	0.12	0.05	0.03	0.48
Percent black in 1980	1,785	0.10	0.14	0.00	0.84
County contains a doctoral- granting institution	1,785	0.10	0.30	0.00	1.00
Shock county contains or is near one of the fifty largest cities	64	0.34	0.48	0.00	1.00
Arts ranking	317	164.07	97.77	1.00	331.00
Recreation ranking	317	164.87	97.10	1.00	331.00
Quality-of-life ranking	317	168.90	95.91	2.00	331.00

Source: Authors' calculations.

<sup>\*\*\*</sup>p < 0.01.

p < 0.01\*\*p < 0.05. \*p < 0.10.

a. Long-run growth in population (1977-2000) is regressed on initial human capital, presence of a research university, initial proximity to a top-fifty city by size, and weather. Shock counties are those losing 2 percent or more of jobs via the shock to steel and auto industries during 1977–82. Dummies are included for MSA status and the nine census divisions. Standard errors are in parentheses.

Table 20. Change in Total Employment in the United Kingdom, by Region

	Empl	oyees	Chang	e
Region	1991	1981	Absolute number	Percentage
London	331,439	330,842	597	0.002
North				
North West	252,294	243,489	8,805	0.036
Northern	117,755	112,645	5,110	0.045
Yorkshire and Humberside	199,554	185,290	14,264	0.077
South				
West Midlands	219,103	197,767	21,336	0.108
Wales	106,022	93,269	12,753	0.137
East Midlands	167,408	145,207	22,201	0.153
South East	439,372	355,331	84,041	0.237
East Anglia	89,818	71,169	18,649	0.262
South West	197,339	155,880	41,459	0.266

Source: Data are from U.K. National Statistics (www.nomisweb.co.uk/ [March 2007]) and annual issues of Regional Trends.

### Implementing the Decomposition for the United Kingdom

The United States was not the only developed country to experience significant losses of manufacturing jobs during the 1980s, and a sensible question to ask is whether Rust Belt regions within the United Kingdom, Italy, France, or Germany also experienced rapid adjustment brought about by population mobility. Detailed job counts and unemployment rates at the regional level turn out to be difficult to obtain for the European countries. The country for which we found the most data is the United Kingdom, where basic data items are available at the level of twelve regions, which are listed in table 20. Professor David Blanchflower tells us that these regions correspond roughly to labor markets and that this is the most appropriate level of aggregation for our analysis.

The three northern regions—Northwest, Northern, and Yorkshire—were quite dependent on heavy manufacturing and steel and autos, in particular, up through the 1980s. We designate these three as the Rust Belt regions (the North) and compare their outcomes to those for the six southern regions, excluding London (the South).<sup>37</sup> Figure 11 shows unemployment rates for

<sup>37.</sup> All of the population growth associated with London's economic boom of the last decade is absorbed by the South East, not London itself, due to the fixed amount of housing in London proper.

Unemployment rates

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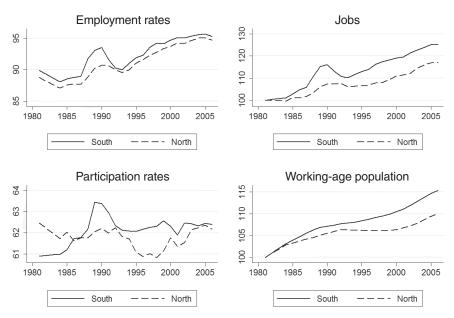
Figure 11. Unemployment Rate in the United Kingdom, by Region, 1980-2005

Source: Data from U.K. National Statistics (www.nomisweb.co.uk/ [March 2007]) and annual issues of *Regional Trends*. Changes in the employment rate are decomposed for select regions in the United Kingdom using equation 4.

the North and the South. In 1984 the North experienced a much bigger jump in unemployment than the South, and full convergence in the unemployment rate was not achieved until 1993. This convergence is a bit different than we expected in that it comes largely from the fact that unemployment in the South was much worse in the 1990s recession.

Figure 12 and table 21 give some indication of how this adjustment can be broken down into movements of people, jobs, and the labor force participation rate. From 1981 to 1992, working-age population grew 1.3 percent more slowly in the North. Labor force participation shrank 0.4 percentage points in the North as compared to the 2.3 percentage points of contemporaneous labor force participation growth in the South. The North closed much of the employment rate gap by having fewer people enter the labor force relative to the South. And population growth was slower. If we add the 1.3 percent slower population growth and the 2.7 percent relative decline in the labor force participation rate and then subtract the 3 percent slower job growth of the North, we get the 1 percent convergence in employment rate experienced by the North relative to the South. Over the period 1992–2002, growth in working-age population in the North was only 0.8 percent, 3 percentage points less than in

Figure 12. Employment Rate, Jobs, Labor Force Participation, and Working-Age Population in the United Kingdom, 1980–2005



Source: Data are from U.K. National Statistics (www.nomisweb.co.uk/ [March 2007]) and annual issues of Regional Trends. Changes in the employment rate are decomposed for select regions in the United Kingdom using equation 4.

Table 21. Change in Employment Rate in the United Kingdom, by Region

Percent change				
Time period and region	Employment rate	Jobs	Size of the working-age population	Labor force participation rate
1981–2002				
South	5.6	19.4	11.3	2.5
North	5.9	11.4	7.0	-1.5
Difference	-0.3	8.0	4.3	4.0
1981–92				
South	0.5	10.3	7.5	2.3
North	1.4	7.3	6.2	-0.4
Difference	-1.0	3.0	1.3	2.7
1992-2002				
South	5.1	9.2	3.8	0.2
North	4.5	4.2	0.8	-1.1
Difference	0.6	5.0	3.0	1.3

Source: Data are from U.K. National Statistics (nomis.uk) and annual issues of Regional Trends. Changes in the employment rate are decomposed for select regions in the United Kingdom, based on equation 4.

the South. Over this period labor force participation fell an additional 1.1 percent in the North.

The picture that emerges is as follows: accommodation of the shock took longer in the United Kingdom (nine years) than in the United States (five years). The northern regions of the United Kingdom experienced a relative decline in labor force participation during those years, compared with no such decline for the United States. The British Rust Belt saw slowed population growth, but no population decline. In the more recent period (1992–2002), the difference in population growth between the two areas (North and South) widened.

These results suggest that there was less labor mobility in the United Kingdom during this time period and that labor market adjustment was therefore slower. But we are cautious in pushing this story, given that the U.K. data are at a very coarse level (the twelve Government Office regions). The advantage of the U.S. county data is that they allow us to identify very specific geographic areas that experienced a sudden and very large loss of jobs. With the U.K. data we are forced to work with broad regions and, while the North had a great deal of steel production and metals-related manufacturing, a wide range of goods and services is produced there.

## **Concluding Remarks**

In this paper we have established several facts. First, the steel and auto shocks were among the largest and most concentrated episodes of job loss in recent U.S. history. Second, in terms of unemployment rates, the counties and MSAs that experienced this shock recovered quite quickly, that is, within five years. However, this recovery took place almost entirely through net population outflow. These facts suggest that even twenty-five years ago the U.S. labor market was characterized by rapid adjustment and that mobility of individuals was the key adjustment mechanism.

One area for further research is to examine more deeply the speed of adjustment to steel and auto shocks in Europe and to see whether Europe's lower mobility meant inherently slower adjustment or whether firms were able to move quickly to the immobile workers. Our results for the United Kingdom suggest that adjustment was indeed slower there and that labor force participation fell (in a relative sense), while population grew more slowly in affected regions. Since the United Kingdom is commonly thought to have one of the

most fluid labor markets in Europe, one would expect continental European countries to exhibit even slower adjustment.

Amenities in the declining counties and cities not only experienced a permanent shock but are still declining relative to the rest of the country. This is the key factor, not crime, unemployment, or income, that has established the Rust Belt's negative reputation. Some Rust Belt counties have been quite successful in recent years, and these tend to be located in the South or near mega cities where there has been substantial job growth.

Part of this loss of amenities is inherent in areas with declining population. It would be interesting to explore whether this negative externality from declining population will affect countries like Japan and Italy that are experiencing zero or negative net population growth.

#### APPENDIX A

This appendix breaks down the two-digit SICs used in the paper to identify steel and auto jobs into several groupings of four-digit SICs. This shows that even by 1993 steel and iron still constituted the vast majority of SIC 33. This percentage would be significantly larger if calculated for 1977.

Table A-1. Disaggregation of Two-Digit SICs, United States, 1993

Industry	Number of establishments	Number of employees	Fraction of total
Disaggregation of SIC 33			
Iron and steel foundries, wire, pipe	13,409	1,368,736	0.701
Copper related	455	32,641	0.017
Aluminum	1,254	122,792	0.063
All other	4,507	427,624	0.219
Total	19,625	1,951,793	
Disaggregation of SIC 37			
Cars, trucks, general	22,375	3,096,996	0.650
Aircraft	3,523	1,014,790	0.213
Ships and boats	6,131	312,557	0.066
Railroads	203	30,076	0.006
Space and missiles related	274	251,172	0.053
All other	1,078	55,889	0.012
Total	33,584	4,761,480	

#### APPENDIX B

The book *Cities Ranked and Rated* is the authoritative source on measuring amenities across cities. Within each category (for example, arts and culture), the book has roughly ten to twelve criteria, which are assigned a score of one to ten for each city. These scores are then added to obtain the city's overall ranking within each category. The highest-scoring city is assigned the best (lowest) rank. Many of the criteria are objective measures such as the number of public libraries.

In our regressions, we simply take the city's rank as the dependent variable, so negative coefficients indicate that the regressor is associated with increasing amenities. We match a city's ranking to any county that contains all or part of that city.

#### **Arts and Culture**

The arts and culture categories and average values are as follows: arts radio, 3; classical music, 4; overall museum, 6; number of public libraries, 28; ballet or dance, 3; art museum, 5; number of library volumes per capita, 2.8; professional theater, 3; science museum, 4; university arts programs, 5; and children's museum, 3.

#### Leisure and Recreation

Leisure and recreation categories and average values are as follows: restaurant, 1; professional sports, 4; golf course, 4; number of outlet malls, 2; college sports, 4; ski area, 4; number of Starbucks, 11; zoo or aquarium, 3; national park, 3; number of warehouse clubs, 4; amusement park, 3; square miles of inland water, 4; botanical garden or arboretum, 3; miles of coastline, 11.

# **Quality of Life**

Coauthors Bert Sperling and Peter Sander determined a combined score for each metropolitan area based on the perceived overall quality of life.<sup>1</sup>

1. Sperling and Sanders (2004). See tables 2.4 and 2.5 in chapter 2 of their work for the quality of life scores for each metropolitan area.

The score is included in scoring and ranking but is not shown in individual city tables. By their very nature, the factors determining this score are difficult to quantify. They are based mainly on perception, personal experience, and anecdotes from others who have spent time in these places. Features considered include physical attractiveness, heritage, and overall ease of living.

- —Physical attractiveness. This includes both the physical setting and overall appearance of the town itself, factors that influence initial impressions and long-term satisfaction in an area. The effects of a pancake-flat, windswept, nondescript landscape with dirty air and little vegetation are far different from those of attractive, well-kept, tree-lined streets with good buildings and a pristine mountain, river valley, or lakeside setting. Cities such as Boulder (Colorado), Corvallis (Oregon), and Burlington (Vermont) do well in this regard, while some larger cities such as Pittsburgh (Pennsylvania) and Chattanooga (Tennessee) are improving.
- —*Heritage*. A city that knows its roots and tries to preserve its physical and cultural heritage is usually more physically attractive as well as genuine in character. These cities are almost invariably better places to live. Metropolitan areas with well-preserved historic districts and public buildings include Charlottesville (Virginia), Boston (Massachusetts), Portland (Maine), and Santa Fe (New Mexico).
- —Overall ease of living. The most subjective element in this subjective category, ease of living incorporates level of congestion, attitude and friend-liness of the people, and simplicity of infrastructure. In essence, it considers the "stress factor." Issues with places like Los Angeles, San Francisco, and New York are obvious, and these cities score poorly, while cities in the South—even the workaholic New South—tend to score high.

# Comments

**Albert Saiz:** The paper examines the aftermath of a major negative economic shock: the massive loss of auto and steel jobs in a number of U.S. counties in the early 1980s. The authors consider three time periods: the shock period (1977–82), the recovery period (1982–87), during which presumably no further major job losses occurred, and the long run in the aftermath of the auto and steel crisis (1987–2004). The authors basically compare the evolution of a number of outcomes in "shock" counties (that is, counties affected by the auto and steel job losses during the 1977–82 period) and all other counties in the United States.

The results in the paper are consistent with three important ideas in urban and regional economics. Confirming previous research by Blanchard and Katz, the economic adjustment to the negative industrial shocks did not entail higher unemployment, even in the short run. In fact, most of the local adjustment to a rapidly shrinking local labor market seems to have occurred through the out-migration of individuals or reduced in-migration of prospective workers. These findings are important, given the relatively large magnitude of the shock under study: U.S. local labor markets respond quickly in a flexible manner, reflecting high mobility and, possibly, relatively low reliance on long-term unemployment insurance schemes.

The study also emphasizes how important "lifestyle" amenities have become to explain population growth. Even in a context where population levels seem to have been driven by production-side locational advantages in the industrial sector, amenities may have been important to retain workers locally. Furthermore, the results are a reminder that amenities are also endogenous to population levels and growth, probably due to agglomeration, scale, and scope economies in the nontradable sectors. This is important because models of city growth that are based on amenities (like some of my previous work

<sup>1.</sup> Blanchard and others (1992).

with Edward Glaeser and Jed Kolko) should take into account the endogeneity of some of the urban amenities.<sup>2</sup>

Finally, the results also point to the importance of regionwide agglomeration economies: proximity to urban areas helped some of these counties to cushion the impact of the shock. Externalities (such as knowledge and educational spillovers) and the advantage of a "diversified" industrial composition may manifest themselves at the broader regional level.

However, we cannot possibly learn about other important issues pertaining to local economic development and urban economics using the methodology that Feyrer, Sacerdote, and Stern propose.

What is the economic shock? The very nature of the economic shock that the authors study is not clear. The counties that experienced substantial losses in employment in the steel and auto industries during the years 1977–82 were probably very different from other counties in the United States. We do not know the "counterfactual" evolution of employment in these counties, and therefore the "shock" dummy variable may simply be capturing the impact of other characteristics of these cities that predict decline more generally. Even if we were confident that the "shock dummy" is not simply capturing the impact of other omitted variables in the relevant period, but stands for a real economic shock, it is not clear that the response of the counties under study is representative. Similar economic shocks that are more general in scope could have very different impacts on more diversified local economies. This is, of course, not a problem if we want to focus on the history of the "shock" counties, as the authors define them, but it is more problematic if we want to learn about how local economies respond to negative economic shocks more generally.

Is the shock exogenous? The way in which the authors define the "shock" counties is problematic due to potential reverse causality: plants that were located in worse environments may have had more of an incentive to shut down. Therefore, selection into the "shock" (as measured by the number of jobs lost) may be a symptom more than a "treatment." Future work in this area should try to deal with this sample selection issue, maybe by specifying a selection model or by deploying an instrumental variables approach. More simply, one could just focus on counties that had initially high levels of steel and auto concentration, rather than measure the shock by using subsequent job losses, which are an *outcome* of the underlying economic situation.

Are controls adequate? Since the shock dummy may simply be capturing the impact of predetermined variables (the initial characteristics of the

2. Glaeser, Kolko, and Saiz (2001).

counties), it is important to control for a number of such variables. The authors are right in arguing that one would not want to control for contemporaneous changes in socioeconomic characteristics that could be affected by the industrial shock. However, one could include a number of lagged variables to control for simple composition effects. For instance, one could control for the initial industrial composition of all counties (say, the share of workers in manufacturing) and see if there was an impact of what the authors qualify as a "shock" beyond and above what would have been predicted by the general trend of deindustrialization of the U.S. economy.

Education matters. The authors propose looking at the interaction between education and the impact of the "shock." When they control for such interaction and also for the initial share of educated individuals (in table 5), the "shock" dummy and its interactions are never significant, even to predict changes in employment during the "shock" period! In table 18, the authors propose looking at the long-run impact of education in the "shock" counties. They consider changes in population between 1977 and 2000 (changes and population and changes in employment levels are very strongly correlated over the long run). Given the fact that there are only sixty-two observations and that the "shock" counties were self-selected into the sample partially on the basis of their education levels, we cannot learn much from the first "education" regression (column 1 in table 18). The second regression (column 2) includes all county observations. An interesting finding is that the "shock" variable (change in steel and auto employment over initial employment) is not a significant predictor of long-run population growth any longer. Education, presence of minorities, and good weather are the only robust correlates of subsequent population growth in this regression, which reinforces the earlier point about omitted variables. As in previous research, education seems to be very important for population growth. The exact channels for this association between regional education levels and growth "success" are a subject of speculation and an important area for research in local economic development.

Going beyond. The results in the paper are quite interesting. The paper is fairly descriptive, which is not a bad thing. But even descriptively we are still far from answering its main question: *How do counties, cities, or regions respond to adverse economic shocks?* In order to learn more about this, it is interesting to follow Davis and Weinstein and make a distinction between changes in trends versus short-term changes in levels.<sup>3</sup> Employment growth is the outcome of interest.

#### 3. Davis and Weinstein (2002).

We can then characterize four scenarios. In two of them, the economic shock changes the growth trend of the region under consideration. Conversely, if we focus on levels, there may or may not have been reversion to the trend after the shock. I use the word "trend" here not to denote exclusively the previous changes in employment in the area, but instead to signify more generally the hypothetical economic evolution of the relevant areas in a counterfactual world without economic shocks. Some regions would have declined anyway without a negative shock, regardless of their previous growth experiences.

The following table summarizes the four possible scenarios regarding the impact of the shock vis-à-vis the counterfactual (trend) in the affected areas in a world without shocks. I briefly discuss the four types of scenarios and depict them. In figures 13–16, the evolution of employment is relative to the average in the United States. I am discussing relative, rather than absolute, decline. The total output in the region is given by the standard production function Y = A \* F(K, L), where A is total factor productivity, K is capital, and L is labor.

In event type I, the economic shock changes the trend line, but employment levels eventually return to the new trend line (see figure 13). This is a situation where the shock affected the growth rate of the local economy (maybe changed the pace of introduction of new innovations: this is the growth in A) but did not affect the capital stock or the level of A per se.

Result	Shock changed trend	Shock did not change trend
Reversion to trend line	I	III
No reversion	II	IV

A type II event has an even more devastating impact on the local economy (see figure 14). The relative growth trend is negatively affected and so is the level of economic activity indefinitely. Not only is the growth rate of A affected, but also the level of A (maybe because of the sudden loss of agglomeration economies), or the capital stock.

The third scenario is the most benign of the four. Here the shock has a short-run impact, but it does not change the growth rate of productivity (growth rate of *A*; see figure 15). The economy reverts to the original trend (maybe because agglomeration economies are less important, and the relative advantages of the location trump other influences in the long run). Alternatively,

Figure 13. Type I Event

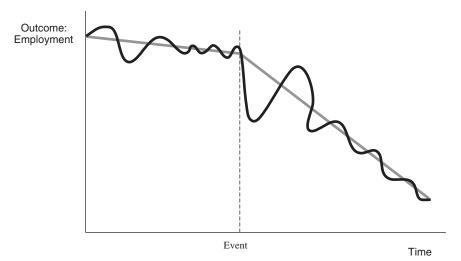
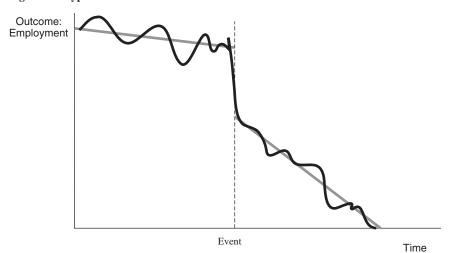


Figure 14. Type II Event



the shock itself may represent the way for the local economy to "catch up" to the trend, if frictions make it costly to adjust gradually.

Finally, scenario IV is such that the growth trend does not change, but the shock has a permanent impact on employment levels (maybe because capital or total factor productivity—and not growth rates—are affected; see figure 16).

Figure 15. Type III Event

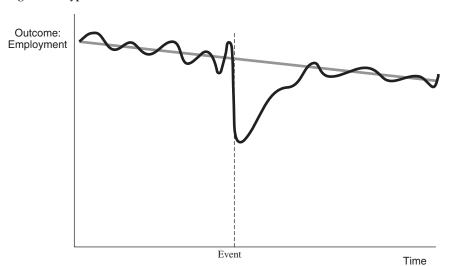
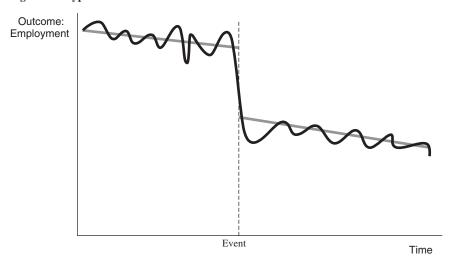


Figure 16. Type IV Event



Distinguishing between these four scenarios is important to learning which likely mechanism determines local economic growth: agglomeration economies, urbanization economies, technological and education spillovers, basic locational advantages, or other. While the authors do present some evidence along these lines in the new version of the paper, future research should elaborate

on these issues. Future research should clearly establish what the counter-factual to the economic shock would have been by studying similar areas that (randomly) were not affected; it also should distinguish between short-run and long-run impacts on both trends and levels; it should carefully validate the assumption of exogeneity of the shocks to previous trends; and, finally, it should establish which current model or urban growth fits the data best. The paper by Feyrer, Sacerdote, and Stern is a valuable first step in this ambitious agenda.

William C. Strange: The very interesting chapter by James Feyrer, Bruce Sacerdote, and Ariel Dora Stern considers the "Rust Belt shock," focusing in particular on how the affected locations adjusted to the loss of jobs in the steel and auto sectors. "Rust" is thus identified with the loss of jobs in these sectors, while "belt" is identified as counties that lost large amounts of employment (more than 2 percent of total county employment). There were sixty-four such counties. 1977–82 is identified as the period of the shock, and 1982–87 is identified as the period of recovery. The chapter considers many dimensions of the shock's impact. These include the effects on county population, employment and unemployment, labor force participation, amenities and quality of life, and demographics. A similar exercise is carried out using U.K. data.

There are several notable results. First, the shock resulted in a permanent loss of population, employment, and amenities or quality of life. Second, the shock did not result in a permanent increase in unemployment or labor force participation. Third, adjustment was rapid, with the county returning to national levels of unemployment within five years. Fourth, adjustment occurred through out-migration from the shocked counties rather than the in-migration of firms. Fifth, the U.K. pattern features slower adjustment than in the United States and an effect on participation that did not appear in the U.S. data. For reasons made clear below, these findings are important contributions to our understanding of what is obviously an important event.

In thinking about the paper's analysis, it is helpful to consider how the dynamics that the paper considers can be incorporated into a simple model of a system of cities. Suppose that there are two sectors: general production and steel. Let  $\psi$  and  $\omega$ , respectively, represent wage for the two sectors. The parameter  $\alpha$  is used to capture shocks to steel production. Agglomeration economies are modeled as a public good K produced at cost c(K) as in Helsley and Strange.<sup>1</sup>

<sup>1.</sup> Helsley and Strange (1994).

Suppose that there is a black box urban congestion cost as a function of city population b(n) and a redistribution of land rent I. In this highly simplified model, if there are localization economies, then cities will specialize.<sup>2</sup> Some will produce only steel, and others will engage only in general production. In this localization case, for a steel city we can specify utility as  $u = \alpha(K + \omega) - c(K) / n - b(n) + I$ . As specified here, a shock is a decrease in  $\alpha$ , resulting directly in a reduction in the utility from local public goods and from employment in steel cities.

The simplest approach to urban development is to suppose that city size and public good maximize utility, as in Henderson's "developers" paradigm.<sup>3</sup> These developers choose levels of local public goods and population, K and n, respectively, in the model's notation. In this case, the first-order conditions characterizing the level of the public good in a city and city population would be  $\partial u / \partial K = \alpha - c'(K) / n = 0$ , a Samuelson condition, and  $\partial u / \partial n =$  $c(K)/n^2 - b'(n) = 0$ , an optimal membership condition. In a more completely fleshed out model with a land market, the second of these conditions would be some sort of Henry George condition. In my basic model, the impact of a shock (decrease in  $\alpha$ ) can be shown to be  $dK/d\alpha > 0$  and  $dn/d\alpha > 0$ . As in the paper, a Rust Belt shock shrinks the size of steel cities and reduces the level of public goods, which proxy here for amenities. This is a consequence of assuming that the shock reduces the value of agglomeration in the steel industry by reducing the contribution to utility from the local public good K. Some assumption like this is necessary in order to obtain a decline of a geographically concentrated "belt" and not just a generalized decline in steel manufacturing ("rust").

This can be contrasted with a model of urbanization economies. The simplest way to capture this is to change the first term of the expression for worker utility:  $K + \alpha \omega$  for steel workers and K + w for general production workers. In this model, cities do not specialize. In this setting, the local infrastructure is not specific to the steel industry, and it does not decline in productivity in response to the steel shock. The sectoral breakdown of a given city's employment can be solved for as a consequence of local or national-international diminishing returns. As in the localization case, Samuelson and optimal membership conditions characterize K and n:  $\partial u / \partial K = 1 - c'(K) / n = 0$  and  $\partial u / \partial n = c(K) / n^2 - b'(n) = 0$ , respectively. In the urbanization case,

<sup>2.</sup> Henderson (1974).

<sup>3.</sup> Henderson (1974).

comparative statics show that the impact of a shock (decrease in  $\alpha$ ) is now  $dK/d\alpha = 0$  and  $dn/d\alpha = 0$ .

This is different from the analysis of the localization case in an important way. It means that, with urbanization economies rather than localization economies, the impact of the Rust Belt shock is entirely sectoral (a switch from steel to general production) and not at all spatial (lost population and amenities in steel cities). This suggests two interpretive points. First, the paper argues that the relatively rapid adjustment suggests that North American labor markets are flexible. This is correct, but the flexibility operates through spatial adjustments that take place at the national level. There seems to be a lack of flexibility at the local level, a consequence of localization. In the systems of cities equilibrium, this lack of flexibility manifests itself in the permanent loss of population and amenities. Second, the paper identifies "shock counties" as those that lose a lot of jobs. Thus it identifies specialized local markets supported by localization economies. Other counties do not lose as many jobs. In these locations, there is intersectoral adaptability.

Marshall, Chinitz, and Jacobs all have noted this sort of dynamic. Chinitz's classic paper on the differences between New York and Pittsburgh is the most relevant here. He argues that the success of New York was a consequence of its greater diversity. This paper's results on diversity in table 18 do not identify a significant effect of diversity (as measured by the industry Herfindahl) on the determinants of long-run growth in shock counties. Although the Herfindahl is a perfectly natural way to capture diversity—indeed, it is something of an industry standard among urban economists—the effects of diversity may not be captured completely. Or the focus on shock counties may mean that the adaptable locations have been excluded from the analysis. Either way, the question of what allowed some counties to weather a substantial shock better than others is definitely worthy of further research.

This sort of dynamic is also related to Glaeser's insightful history of Boston.<sup>5</sup> He presents persuasive evidence that Boston has repeatedly "reinvented" itself. In related work, he demonstrates more generally that a city's ability to reinvent itself is related to its endowment of human capital.<sup>6</sup> In contrast, this paper reaches a different conclusion for Rust Belt counties, finding insignificant effects of both the local level of education and the presence of universities on a Rust Belt county's long-run growth. Taken with the diversity result

<sup>4.</sup> Marshall (1920); Chinitz (1961); Jacobs (1969).

<sup>5.</sup> Glaeser (2005).

<sup>6.</sup> Glaeser and Saiz (2004).

above, this suggests that Rust Belt counties are exceptional in an unfortunate sense. Whether because of their particular pattern of localization or because of some other force, neither local diversity nor local human capital helped them to adapt to the shock that they suffered. Understanding the sources of this exceptionalism is clearly important to any household, business, or policy-maker concerned with the risks facing a particular local economy.

Thus far, I have not had much to say on the role of amenities in the Rust Belt shock and adjustments, a very interesting part of the chapter. As noted, a shock can potentially lead to both sectoral and spatial shifts. In the latter case, there will be lower levels of amenities in shocked locations. The paper looks at this in two ways. First, it takes the particular approach of looking at how the Rust Belt shock has affected a particular sort of local amenity: the number of bars and restaurants. It also takes a general approach to amenities by using ratings of cities' quality of life.

In the basic model, amenities (or other agglomeration-supporting public goods) and population both adjust immediately. One can imagine richer dynamics. For instance, it seems sensible to consider asymmetric adjustment of amenities, parallel to the sort of adjustment considered in models of investment.<sup>7</sup> It also seems sensible to consider vintage effects, with amenities developed at different times entering differently into utility-production functions.

These two approaches to the dynamics of amenities suggest different sorts of adjustment patterns that might be initiated by a shock. With asymmetric adjustment, the shock leads to a period of inactivity when new amenities are not added to the stock. By itself, this might have a multiplier effect. This is the standard sort of effect of a contraction in a region's basic industry on its non-basic industries, as in regional input-output analysis.

With vintage effects, the period of inactivity might have further negative effects. Suppose that there are two sorts of amenities: bistros and diners. A shocked city does not add modern amenities (bistros) and has only the remaining old amenities (diners). If mobile factors are more complementary to new amenities than to old amenities (that is, skilled workers prefer bistros), then the shock may have a second-round multiplier effect. In an earlier volume of this series, Glaeser and Saiz argue that the presence of skilled workers is an important predictor of local growth, especially for cold-weather locations. Thus the effects of an amenity loss would tend to have lasting negative consequences.

<sup>7.</sup> See, for instance Dixit and Pindyck (1994).

<sup>8.</sup> Glaeser and Saiz (2004).

In conclusion, I would like to make two smaller points. The first concerns the degree to which the Rust Belt shock generalizes to other sorts of shocks that can affect local economies. This paper is completely sensible in focusing on the Rust Belt shock, which is notable in its magnitude. This leaves open the question of how the effects of a positive shock would work out dynamically. What adjustments were set in motion by the silicon shock, for example? More systematically, what shocks were set in motion by the defense buildup of the 1990s?

The second point concerns the possibility of there being any "silver linings" associated with the Rust Belt shock. This paper tracks various negative consequences of the Rust Belt shock for amenities. In contrast, Kahn finds some positive environmental consequences of the shock. And historic preservation may be another sort of silver lining associated with other shocks. Savannah, Georgia, became a business backwater after a postwar cotton shock in the last half of the nineteenth century. Its current attractiveness is associated directly with this period of inactivity.

#### References

- Black, Dan A., Terra G. McKinnish, and Seth G. Sanders. 2003. "Does the Availability of High-Wage Jobs for Low-Skilled Men Affect Welfare Expenditures and Family Structure? Evidence from Shocks to the Steel and Coal Industries." *Journal of Public Economics* 87, no. 9–10: 1921–42.
- Blanchard, Olivier Jean, and Lawrence F. Katz. 1992. "Regional Evolutions." *BPEA*, no. 1: 1–61.
- Boyer, Richard, and David Savageau. 1981. *Places Rated Almanac: Your Guide to Finding the Best Places to Live in North America*. Chicago: Rand McNally.
- Chinitz, Benjamin. 1961. "Contrasts in Agglomeration: New York and Pittsburgh." *American Economic Review, Papers and Proceedings* 51, no. 2: 279–89.
- Davis, Donald R., and David E. Weinstein. 2002. "Bones, Bombs, and Break Points: The Geography of Economic Activity." *American Economic Review* 92, no. 5 (December): 1269–89.
- Dixit, Avinash K., and Robert S. Pindyck. 1994. *Investment under Uncertainty*. Princeton University Press.
- Glaeser, Edward L. 2005. "Reinventing Boston: 1630–2003." *Journal of Economic Geography* 5, no. 2: 119–53.
- Glaeser, Edward L., and Joseph Gyourko. 2005. "Urban Decline and Durable Housing." *Journal of Political Economy* 113, no. 2: 345–75.
- Glaeser, Edward L., Hedi D. Kallal, Jose A. Scheinkman, and Andrei Shleifer. 1992. "Growth in Cities." *Journal of Political Economy* 100, no. 6: 1126–52.
- Glaeser, Edward L., Jed Kolko, and Albert Saiz. 2001. "Consumer City." *Journal of Economic Geography* 1, no. 1: 27–50.
- Glaeser, Edward L., and Albert Saiz. 2004. "The Rise of the Skilled City." *Brookings-Wharton Papers on Urban Affairs*, pp. 47–94. Brookings.
- Glendon, Spencer P., and Jacob L. Vigdor. 2003. "Thy Neighbor's Jobs: Geography and Labor Market Dynamics." *Regional Science and Urban Economics* 33, no. 6: 663–93.
- Gyourko, Joseph, and Albert Saiz. 2003. "Urban Decline and Housing Reinvestment: The Role of Construction Costs and the Supply Side." Working Paper 03-9. Federal Reserve Bank of Philadelphia.
- Helsley, Robert W., and William C. Strange. 1994. "City Formation with Commitment." *Regional Science and Urban Economics* 24, no. 3: 373–90.
- Henderson, Vernon J. 1974. "The Sizes and Types of Cities." *American Economic Review* 64, no. 4 (September): 640–56.
- Jacobs, Jane. 1969. The Economy of Cities. New York: Random House.
- Kahn, Matthew E. 1999. "The Silver Lining of Rust Belt Manufacturing Decline." *Journal of Urban Economics* 46, no. 3: 360–76.
- Marshall, Alfred. 1920. Principles of Economics. London: Macmillan.
- Pack, Janet Rothenberg. 2002. *Growth and Convergence in Metropolitan America*. Brookings.

- ——. 2005. "Metropolitan Development: Patterns, Problems, Causes, Policy Proposals." In *Sunbelt/Frostbelt: Public Policies and Market Forces in Metropolitan Development*, pp. 1–25. Brookings.
- Shapiro, Jesse M. 2006. "Smart Cities: Quality of Life, Productivity, and the Growth Effects of Human Capital." *Review of Economics and Statistics* 88, no. 2 (May): 324–35.
- Sperling, Bert, and Peter Sander. 2004. Cities Ranked and Rated: More Than 400 Metropolitan Areas Evaluated in the U.S. and Canada. Hoboken, N.J.: Wiley.
- Venkatu, Guhan. 2006. "Cleveland (on the) Rocks." Federal Reserve Bank of Cleveland.