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CURRENCY AREAS, LABOR MARKETS, AND REGIONAL CYCLICAL SENSITIVITY

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ABSTRACT

In his papers during the lead up to the birth of the European Monetary Union, Obstfeld considered whether the countries forming the EMU were sufficiently similar to survive a single monetary policy—and more importantly, whether they had the capacity to adjust to asymmetric shocks given a single monetary and exchange rate policy. The convention at the time was to take the United States as the baseline for a smoothly functioning currency union. We document the evolution of the literature on regional labor market adjustment within the United States, expanding on stylized facts illustrating how stratification in local labor market outcomes appears far more persistent today than 30 years ago in the context of what Obstfeld and Peri (1998) call non-adjustment in unemployment rates. We then extend the currency union literature by adding an additional consideration: differences in regional cyclical sensitivity. Using measures of cyclicality and Obstfeld-Peri-type non-adjustment, we explore the characteristics of places that can get left behind when local labor markets respond differently to national shocks and discuss implications for policy.

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1 Introduction

Maury Obstfeld's work includes substantial theoretical and conceptual advances in international macroeconomics and finance, but he has also been intensely practical in analyzing real-world problems in real-time. A key example is his collection of work applying the lessons of Optimal Currency Area theory to questions related to the EMU and currency unions (Obstfeld 1997, Obstfeld 1998, Obstfeld and Peri 1998).

While it may seem logical that currency borders overlap with political borders, that was not always the case historically, as coins and specie circulated across different sovereign states (Cipolla, 1967). And, in fact, many early economists argued for a common currency, as Mill did referring to sovereign currencies as a "relic of barbarism" (Mill, 1894). Still, the overlap of currency and nation-state was common, especially into the 20th century (Kocherlakota and Krueger, 1998). Over time, macroeconomics began to debate when different regions or nations should maintain a common currency. Mundell's (1961) foundational contribution uses a simple thought experiment of shocks hitting two regions. If the shock was asymmetric, the question was whether there was some mechanism to smooth the shock across regions (notably labor mobility or interregional fiscal transfers). If the regions were similar and the shock was common, the assumption was that overall macroeconomic policy–broader fiscal or monetary stimulus or contraction–could handle the shock.

In his papers during the lead up to the birth of the EMU, Obstfeld considered whether the countries forming the EMU were sufficiently similar to survive a single monetary policy, and more importantly, whether they had the capacity to adjust to asymmetric shocks given a single monetary and exchange rate policy. He referred to persistent disparities in unemployment rates across regions as *non-adjustment*.

We contribute to the question of currency unions in two directions. First, the papers by Obstfeld, like most other discussions of the EMU often used the United States as a baseline for a well-functioning currency union where regional shocks were smoothed out over time (largely due to labor mobility). We document how the literature of adjustment within the United States has evolved. We summarize and expand stylized facts illustrating how local shocks appear far more persistent today in the United States than they did 30 years ago, and illustrate the characteristics of places that frequently have worse labor market outcomes.

Second, we extend the currency union literature by adding an additional consideration: differences in regional cyclical sensitivity. The currency union literature typically assumes that aggregate shocks to the full currency union can be contained with monetary policy from the single central bank, and that the key consideration for currency unions is whether they have large asymmetric shocks or persistent levels of different unemployment rates. We show that within the United States, there is also wide variation in how *sensitive* different regions are to national shocks.

Third, we use our examination of local cyclical sensitivity to identify two different types of national shocks through factor analysis that makes earlier characterizations of synchronicity (or lack of it) more complicated than earlier characterizations of supply-side or demand-side shocks that affect one region more than another. The first factor tracks closely with the national unemployment gap often used by economists and policymakers to gauge the overall strength of the labor market and is significantly correlated with the presence of manufacturing. The second appears more intricately intertwined with the secular path of technology and spatial variation in worker skill, inviting consideration of what policies and amenities can deepen skill accumulation in local labor markets to fortify communities against this very different set of shocks.

Our study of the dispersion and cyclical sensitivity of local unemployment rates is inspired by Obstfeld and Peri (1998), but is directly rooted in Mundell's own observation. Mundell (1961) states explicitly that when an economic shock hits "in a currency area comprising many regions and a single currency, the pace of inflation is set by the willingness of central authorities to allow unemployment in deficit regions (p.659)." Using the clearest possible example, Mundell considered cases where a shock would affect two regions differently, causing inflation in one and unemployment in the other. However, one need not rely on this extreme case for local preferences toward monetary policy to vary. If one region experiences more severe unemployment than most other regions in response to a common shock, it may have different preferences regarding the depth and duration of the monetary policy response, even if the overall preferences are in the same direction.

This is not to suggest that the US would be better off without a common currency: where regions are highly socially, politically, and economically integrated and interdependent, the many benefits of union would outweigh this pitfall. Rather, we are expanding on Obstfeld and Peri's (1998) work by pointing out—using the US as a benchmark as they did—that in a world with persistent aggregate shocks (e.g. the slow recovery following the global financial crisis) the fact that some regions are hit harder by aggregate shocks can be an important consideration in the policies of any current or prospective currency union.

The rest of the paper is organized as follows. Section 2 notes that the persistence in county-level unemployment is associated with specific characteristics, a launch pad to our more formal exploration in Section 3, measuring the correlation of these characteristics with local average unemployment rates and the degree of cyclicality. Finding considerable heterogeneity in the degree of cyclicality across places, we examine the nature of the national shocks that drive local cyclical fluctuations in our factor analysis in Section 4. These associations open up questions as to underlying mechanisms driving the heterogeneity in cyclical behavior, which we believe are worthy of future research.

2 Changing regional adjustment in the United States

The use of the United States as the baseline case of a smoothly functioning currency union was in many ways consistent with pre-EMU data as seen in influential work by Blanchard and Katz (1992, hereafter BK). Bound and Holzer (1990) further find that mobility is important to understand responses to local labor demand shocks in the 1980s. Importantly, they find that workers with less education are less likely to move in response to a negative labor market shock, a point that will be important later in our analysis.

Slowing or sluggish regional income convergence challenges the idea of smooth regional adjustment prevailing within the United States. Berry and Glaeser (2005) and Moretti (2011) note that regional income convergence had slowed or stopped in the late 20th century, challenging the assumption that the U.S. currency union could easily adjust to regional shocks. Looking across counties, Diamond and Gaubert (2021) show that this appears to be driven by divergence in incomes of residents at the top of the distribution, while local poverty rates are converging. Austin, Glaeser, and Summers (2018) also establish this cessation of economic convergence across regions and highlight the persistence of differences in non-employment rates amongst prime age residents. Nunn, Parsons, and Shambaugh (2018) create a general index of economic prosperity and find surprisingly little mobility across counties from 1980 to 2016. Despite a wide range of shocks and changes in the U.S. economy over that time, by and large, economically successful counties have remained such, and counties with a lower score in the authors' economic vitality index have continued to struggle. Even from a common monetary shock, Herreno and Pedemonte (2020) show very different price and consumption impacts across 28 different metropolitan areas, which they link to imperfect mobility of labor and other frictions.

The mechanisms for this persistent disparity are still a matter for debate, but several recent studies demonstrate that migration is less quantitatively important as a channel for short- or long-term adjustments to local labor market shocks than previously thought. Among those that focus on the US labor market, Beyer and Smets (2015) expand the BK analysis and find much less of a difference between the United States and Europe when looking at later decades, due in part to less interstate migration in the US in response to shocks. Greenaway-McGrevy and Hood (2016) find that shocks to local labor market demand in the US are highly persistent. By controlling for this persistence, they reveal that local job creation, not household out-migration, is the main driver of regional adjustment. They show that this job-creation channel can take more than 20 years.

Dao et al. (2017) also updated the BK approach, enriching it with both actual data on interstate migration and a Bartik instrumental variable (industry employment shares). They find much slower adjustment since 1990, with overall reduced labor mobility and regional adjustment to labor demand shocks. Amior and Manning (2018) document the persistence of local (commuting-zone-level) shocks that can exacerbate inequality across demographic groups and result in dispersion in local unemployment rates. They find that college-educated workers respond more elastically to local shocks through relocation, but that worker characteristics are not sufficient to explain extremely slow observed adjustment in local employment rates. Hershbein and Stuart (2022) also find persistent negative labor market effects at the local level following recessions in those places hit hardest by the recession. As Greenaway-McGrevy and Hood (2016) put it, "the implied levels of labor mobility for the US are much closer to those found in other economies, such as Europe (Decressing and Fatas 1995), Australia (Debelle and Vickery 1999) and New Zealand (Grimes et al 2009) (p.14)." The United States appears to struggle with regional adjustment as well, suggesting that even the baseline used in discussions of EMU had its own issues.

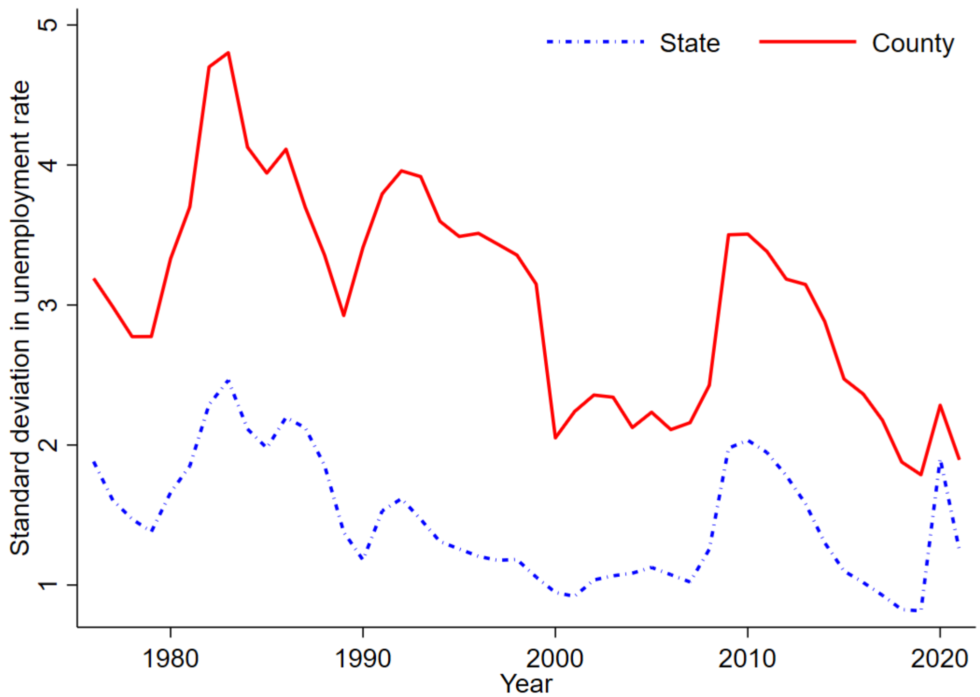
A key focus for policy is joblessness, and in particular unequal incidence of joblessness across places. Amior and Manning (2018, drawing on BK) argue outright that employment rates can serve as a sufficient statistic for local economic wellbeing. As a benchmark, Obstfeld and Peri (1998) examine the dispersion in unemployment rates across US states 1976-1995. We update that series in Figure 1 below and add also the dispersion across counties over the same period.[1] Our standard deviations for the state series closely match their earlier chart through 1995. Two stylized facts stand out. First, dispersion in unemployment rates across counties is (unsurprisingly) considerably higher than dispersion across states. Second, while the dispersion in both series varies dramatically over time, in 2010 reaching a level comparable to the relatively high levels seen in the mid-1980s and early 1990s, it has not changed fundamentally in its level. While state- and county-level dispersion seemed to be trending downward when Obstfeld and Peri (1998) wrote, and dispersion in county rates converging toward dispersion in state rates, dispersion in both spiked again during the great recession and the gap between them widened until the massive disruptions and fiscal stimulus during the pandemic.[2] Our focus is not just on dispersion in outcomes, but in stratification of outcomes across places.

A second key question for policy is how much shocks to labor demand affect the local unemployment rate and how persistent these impacts are. In addition to their detailed mobility analysis, BK had shown that unemployment rates in U.S. states in 1985 were effectively uncorrelated with unemployment rates in 1975. Obstfeld and Peri (1998) recreate this figure for the subsequent decade and find while there is some positive correlation, that correlation is still relatively weak and much weaker than the correlations in Germany. While the rigorous analysis of adjustment in BK has been updated in studies like Greenaway-McGrevy and Hood (2016), Dao et al. (2017), and Amior and Manning (2018), this core stylized fact has not been updated since. In addition, its implications at the sub-state level remain under-explored, leaving many questions about the characteristics of places left behind in the presence of re-

[1] The primary input into estimation of the state-level variables are the Current Population Survey (CPS) and the Current Employment Statistics (CES). The county-level variables are not merely imputed from state-level variables, but involve a great deal of additional information. For these, the BLS uses not only CPS and CES, but also the American Community Survey and Census population estimates which contain more detailed data, the Quarterly Census of Employment and Wages (based on data collected from business), and county-level administrative data on unemployment claims.

[2] While county-level dispersion looks to be lower post-1990 than pre-1990, it is important to note that there is a structural break in the LAUS data in 1990 which make comparisons of these two eras precarious. Still, the gap between state- and county-level dispersion may be narrowing since 1990 and have a cyclical component. This raises the question of whether state-level policies may be at play.

Figure 1: Dispersion in State and County Unemployment Rates 1976-2021



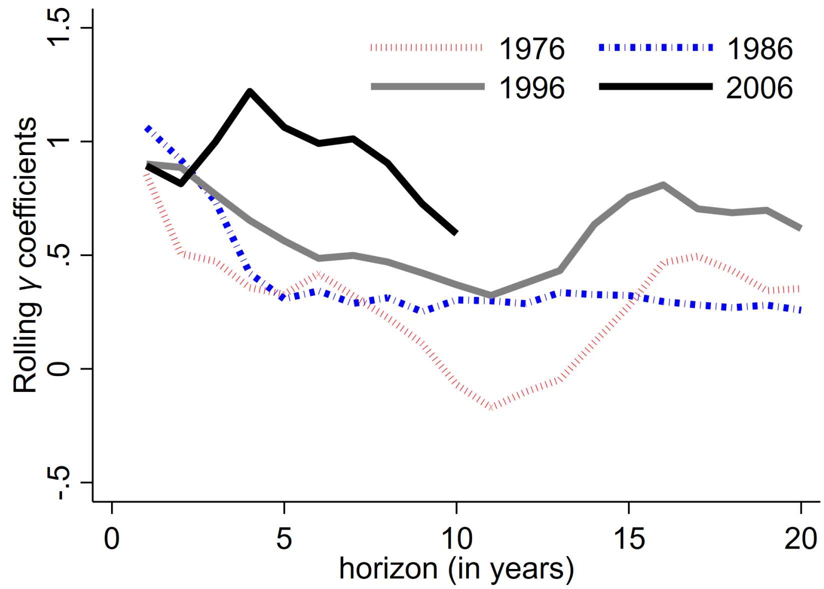
Source: State unemployment rates from U.S. Bureau of Labor Statistics LAUS via FRED, County unemployment rates directly from BLS LAUS, with series prior to 1990 received directly from BLS upon request. Standard deviations are the authors' calculations. Structural break occurs in LAUS data from 1990, so comparisons of levels of dispersion in county unemployment rates before versus after 1990 should be made with caution.

gional non-adjustment within a currency union. Russ and Shambaugh (2019, in unpublished conference proceedings) explored these correlations further and document a steadily strengthening correlation across time.

Figure 2 shows to what degree there is persistence in unemployment at horizons of up to 20 years starting at four different points in time (1976, 1986, 1996, and 2006). The lines report the coefficients estimated from regressing unemployment at horizons $t+h$ on unemployment at time t, $t \in \{1976, 1986, 1996, 2006\}$. Unemployment rates in 1986 do have some predictive power for those in 1996. For every one percentage point above the national average in 1986, a state's unemployment rate was likely to be 0.3 percentage points above the national average in 1996.[3] The relationship is roughly similar over the following decade, though somewhat stronger, and by 2006 to 2016, the outcomes are highly persistent. For every 1 percentage point above the national average in 2006, a state's

[3]The R-squared from a simple regression of state unemployment rates in 1996 on subsequent unemployment rates in 1986 shows that the unemployment rate in 1989 alone could explain 24 percent of the variation in unemployment rates across states in 1996.

Figure 2: Persistence in State Unemployment Rates



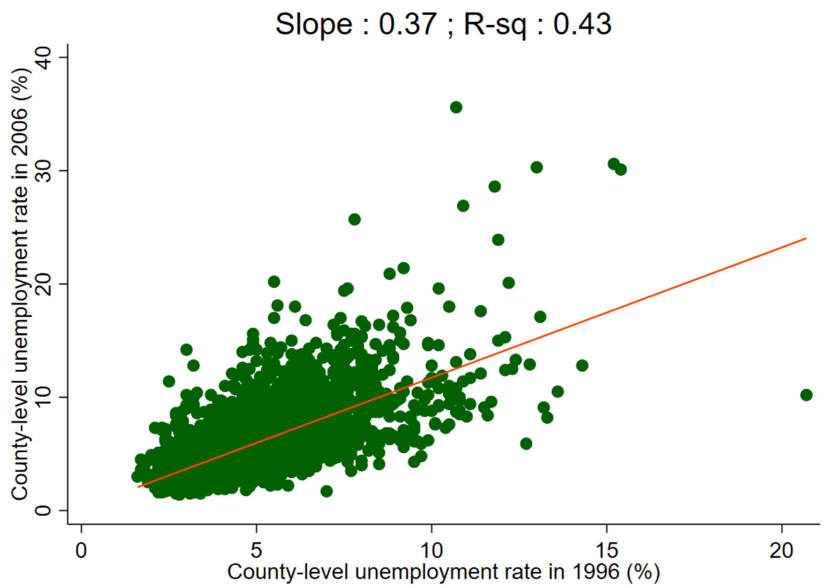
Source: U.S. Bureau of Labor Statistics LAUS. See Data Appendix for more detail. The y axis shows the γ_1^h coefficient from the following regression: $u_{i,t+h} = \gamma_0^{i,h} + \gamma_1^h u_{i,t} + \varepsilon_{i,t+h}$, with ε the error term. The x-axis shows the horizon $h \in [0, 20]$.

unemployment rate is roughly 0.6 percentage points above the national average in 2016. Even looking over three decades, it is still the case that higher unemployment rates in both 1976 and 1986 map to higher unemployment rates in 2016. Levels of unemployment rates at the state level have either become more persistent—a failure of regional adjustment—or waves of shocks are hitting the same states over and over leaving them with consistently higher unemployment rates.

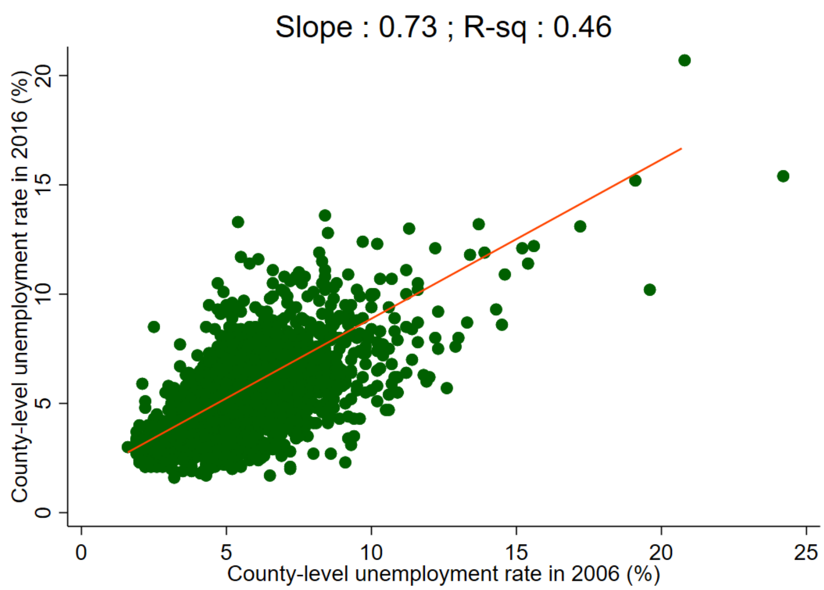
One can instead look at county-level persistence in unemployment rates in Figures 3a and 3b, so far relatively unexplored in the literature on regional adjustment, but important given urban-rural and other variation across places within states. There is a structural break in 1990 in the computational methods for annual county-level unemployment data reported by the Bureau of Labor Statistics, so we use data after that break. Counties with high unemployment rates maintain persistently high unemployment rates over time, and again, the later period (2006-2016) shows a much higher slope and R-squared than the 1996-2006 period, so persistence of unemployment rates across places such as that documented by Amior and Manning (2018) appears to be growing.[4]

[4] Amior and Manning (2018) chart persistence by showing the correlation of employment rates across

Figure 3: County-Level Unemployment Rate 1996 v. 2006 (%)



(a) County-Level Unemployment Rate 1996 v. 2006 (%)



(b) County-level unemployment rate 2006 v. 2016 (%)

Source: U.S. Bureau of Labor Statistics LAUS. See Data Appendix for more detail.

If resilience to regional shocks is a criterion, the functioning of the United States labor market as a currency union no longer seems as successful. In many ways this is an important extension of Obstfeld and Peri (1998). They worried that commentators were too optimistic when they pointed at the United States and regional adjustment. They warned that the pre-EMU adjustment within European countries was a better guide to future EMU performance than successful U.S. adjustment. Over time, though, even that U.S. adjustment appears less successful.

One possible reason for the increasing persistence is declining labor mobility across the United States. Dao et al (2017) find that the migratory response is less important as an adjustment channel now than estimated for earlier decades, leaving a large change in the unemployment rate after a local labor demand shock. There are a number of reasons that have been advanced for the lower mobility. Ganong and Shoag (2017) find that increasing land use restrictions in top counties has limited inflows of people from less prosperous counties. A different explanation—especially for the failure of people to move from weak to strong counties—comes from Autor (2019), who shows that returns for less-educated workers are no longer higher in urban locations than they are in rural locations. This may mean that it is in fact not in the interests of a less-educated worker to move towards a high-wage place, even if the average returns there appear higher.

A big open question is whether persistence grew in a way that led to adverse labor market outcomes accumulating in particular types of places. In this section we look for characteristics of counties that may contribute to the growing persistence in unemployment rates. It could be that increased persistence of unemployment at the local level—the failure of the American labor market to smooth shocks—is tied to lower mobility of less-educated workers. This would fit a number of results. Molloy et al (2016) show that mobility is lower for places with a less-educated population. Autor (2019) found that urban wage premia are lower for less-educated workers. Eriksson et al (2019) find that adverse trade-related shocks to manufacturing industries increasingly have been concentrated in areas with the lowest percentage of high-school-educated workers and that the China Shock left lighter scars on places with the most highly-educated adult populations. Bloom et al (2019) also show that places with more highly-educated workers were better able to pivot to non-manufacturing

commuting zones in 1980 versus 2010.

industries in the face of competition from imported manufactures. All of these results suggest that the increasing persistence may be focused in counties with a lower level of educational attainment in the adult population.

At first glance, though, it does not appear that the increased persistence is only taking place in regions with less-educated workers. Russ and Shambaugh (2019) show that there is little difference in the slope or explanatory power across places with high and low levels of education when comparing 1996 vs. 2016 unemployment rates. A crucial difference, though, is that places with more educated populations had persistently low levels of unemployment while places with a less educated population had persistently high levels of unemployment. That is, the difference was not in the degree of persistence, but in the type of outcome.

One way to see this persistence is to look at the share of counties in the highest and lowest quintile of unemployment rates across the different educational subgroups. In 1970, places with high and low levels of education had a similar likelihood of being in the "good" economic state. They both had a roughly 1 in 5 chance of being in the lowest quintile of unemployment rates. Over time, this shifted, such that by the 21st century, places with high levels of education are far more likely to have the best labor market outcomes relative to places with less education (see Figure A.1 in the Appendix for an illustration). In contrast, a large share of those counties with a high share of adults without a high school degree (or low share of college graduates) are in the high-unemployment quintile throughout the period, and places with high levels of education have become increasingly unlikely to face the worst labor market outcomes. Combined, the growing gap suggests that economic outcomes are far more sorted by education now than they were in 1970 or 1980.

Similarly, since 1980 places with the highest shares of manufacturing in (1970) local employment have been unlikely to have low unemployment rates, very much in contrast with places with the lowest shares of manufacturing in local employment. (See Figure A.2a for an illustration.)[5]

For counties where a large fraction of the population are Black, the likelihood of being in the lowest quintile of unemployment rates has also fallen steadily over time, such that now just 3 percent of counties with the highest concentration of Black residents are in the lowest unemployment rate quintile—as opposed to the expected 20 percent if unemployment rates were distributed

[5] There is no clear relationship between manufacturing employment shares in 1970 and the tendency of some counties to persist within the highest-unemployment quintile.

evenly by race (see Figure A.3 in the Appendix). Yet counties with the highest concentration of Black residents have gone from roughly average odds (20 percent) of being in the highest quintile of unemployment rates in 1970 to now 45 percent being in the high-unemployment rate outcome.[6] Clearly, over the last 50 years, unemployment rate outcomes of counties have increasingly been stratified not only by their educational make-up, but by their racial make-up.[7]

None of this is to suggest the United States is not an optimal currency area. The gains from integration, both trade and financial, almost certainly outweigh any costs, and the impracticality of running independent exchange rates or monetary policy for a region the size of a US county that is integrated into a larger area means these points about regional gaps are not suggesting a different currency arrangement would be optimal. Mundell (1961) himself says, "In the real world, of course, currencies are mainly an expression of national sovereignty, so that actual currency reorganization would be feasible only if it were accompanied by profound political changes. The concept of an optimum currency area therefore has direct practical applicability only in areas where political organization is in a state of flux (p.661)." Yet the literature has long used the United States as an example to explore the functioning of a currency union. This literature and our analysis shows the challenges that even a highly integrated market like the United States can face with persistent gaps in economic outcomes across places. Furthermore, as those gaps have become more persistent, places that have lower levels of education and a higher share of Black residents have increasingly faced worse labor market outcomes. In the next two sections we consider both these level-differences and corresponding local cyclical sensitivity.

[6] When looking at counties by racial make-up, it is important to remember that a large share of counties have very small Black populations, so being in the lowest quintile of percentage Black population is not very different from the second quintile.

[7] The deterioration of unemployment rate outcomes for places with large Black populations in some ways should be a surprise, since the ratio of Black to White unemployment rates nationally is somewhat lower($\sim$1.8-2.0) today than it was in the early 1980s($\sim$2.4). At the same time, the trend is aligned with Derenoncourt, Kim, Kuhn, and Schularick's (2022) evidence that the racial wealth gap has widened in the US since the 1980s.

3 Regional unemployment rates and cyclical sensitivity

Obstfeld and Peri (1998) look at the gap between local unemployment and a national benchmark across areas within countries, using persistence in these gaps over time to illustrate persistent dispersion in unemployment rates rooted in structural factors. If one defines "adjustment" after a positive or negative shock as bouncing back to the national benchmark, then persistent dispersion is an indicator of what they label *fiscal non-adjustment*—a condition that temporary fiscal stimulus after an adverse shock will not remedy. Regressing the gap for any area i at time t on the constant yields a measure of this structural dispersion in mean unemployment rates similar to Obstfeld and Peri's (1998) exercise:

$$UR_{i,t} - UR_{\text{benchmark},t} = \alpha_i + \epsilon_{i,t} \tag{1}$$

We consider heterogeneity in α a measure of structural dispersion. Estimates of this mean unemployment rate by group do not control for business cycles or any characteristics of the local labor market.

From this point, we extend the literature on currency unions to consider not just adjustment (or non-adjustment) to asymmetric shocks, but also asymmetric reactions to symmetric shocks as they hit. Here, we use as a departure point the literature examining the cyclical sensitivity of employment of different groups across the United States and turn those same tools to consider asymmetry in the cyclical sensitivity of regions conditional on the mean gaps. Even when shocks hit the entire monetary union, if some regions experience far more pain, the optimal response from the perspective of different regions may diverge. In addition, in a world where macroeconomic policy is not always able to swiftly combat recessions, lingering simultaneous downturns can generate persistent pain in regions that are more cyclically sensitive.

We draw on a number of insights in the literature to augment the analysis of the average local unemployment rates that were Obstfeld and Peri (1998)'s focus. There is some prior and later work on regional cyclical sensitivity. This work—mostly based on the European experience—is largely focused on questions of time series estimation techniques and stationarity concerns (see Byers (1990), Howland (1984), Beyer and Smets (2015), and Almeida et al (2020)). While documenting heterogeneity in cyclical sensitivity across regions, they leave examination and analysis of this heterogeneity for future research. Here, we focus on the characteristics of local labor markets that exhibit more or less cyclical sensitivity, including demographic and industry mix, inspired by Okun (1973), Freeman (1972), Hoynes (2000), Holzer et al (2006), Modestino et al (2016) and Aaronson et al (2019). Echoing Freeman (1972), Aaronson et al (2019) document clear evidence that Black workers (and to a lesser extent Hispanic workers) experience greater cyclical sensitivity in unemployment rates, in addition to workers with less education.

To gauge the extent of variation in cyclical sensitivity across places in the United States, we augment Obstfeld and Peri's (1998) approach with the specification from Aaronson et al. (2019) to examine the responsiveness of *county* unemployment rates to the national business cycle. We specify our regression to gauge cyclicality by region i instead of by demographic group:

$$UR_{i,t} - UR_{\text{benchmark},t} = \alpha_i + \beta_i(UGAP_t) + \epsilon_{i,t}. \tag{2}$$

Note that the constant in this equation captures the measure of structural dispersion in Obstfeld and Peri's (1998) approach in Eq.(1).

3.1 Data

Rather than look at states and provinces as in Obstfeld and Peri (1998), we note recent lessons in the local nature of labor market shocks from trade and regional studies and instead examine counties. We use BLS LAUS data, rather than CPS microdata, to get county-level detail. Some place-specific information is available in CPS microdata, but the vast majority of CPS observations for individual respondents do not identify the county of the respondent. In addition, counties dropped from the CPS sample when doing county-level regressions are not random, but vary by county characteristics. Therefore, we use the BLS LAUS data to allow for maximum county coverage, since differential employment outcomes across sub-state regions are of central interest in our analysis. The LAUS series are computed with information also from the American Community Survey, Current Employment Statistics, the Quarterly Census of Employment and Wages, and unemployment insurance claims. We begin the sample period in 1990, to avoid confounding a structural break that occurs in the BLS LAUS methodology. We use the median county-level unemployment rate in period t as our benchmark.

To measure cyclicality, we regress the gap between each county's unemployment rate and the median county's unemployment rate on $UGAP$, where $UGAP$ is the gap between the national unemployment rate from the BLS and the CBO measure of the long run unemployment rate.[8] Thus, for counties with unemployment rates that move in step with the median, the coefficient would be zero. For some counties, the unemployment rate may rise less than the median county during a recession, and they would generate a negative β_i. More cyclically sensitive counties would have a β_i above zero.

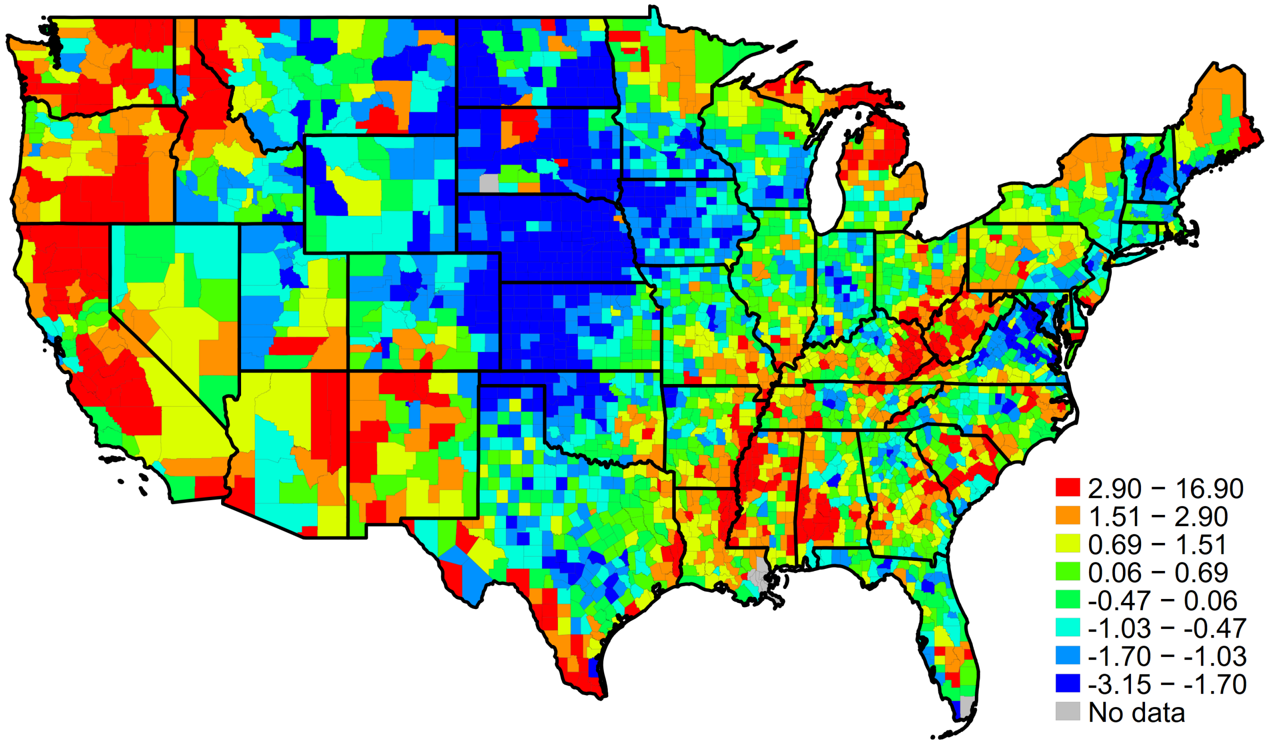
We also regress measures of cyclicality and non-adjustment on county characteristics. County characteristics are from the U.S. Census Bureau County Data Books and described in Appendix C.2. We fix the county characteristics to 1990 values to avoid confounding any demographic shifts generated by economic shocks with our measure of cyclicality. Table A.2 in the Appendix provides summary statistics.

3.2 Persistent disparity and county characteristics

We estimate a vector containing 3,206 estimates of $\{\alpha_i, \beta_i\}$ pairs, one pair for each county in our sample. Full summary statistics for the α_i's and β_i's are in the last two rows of Table A.2 in the Appendix. The mean point estimate for α_i demonstrates an average gap in unemployment rates of 0.528 percentage points from the median county unemployment rate, with a minimum gap of -3.15 showing a county that outperforms the median county unemployment rate by more than 3 percentage points on average, and a maximum gap of 16.9—a county which experiences an unemployment rate that is on average nearly 17 percentage points higher than the median US county. The standard deviation is much smaller, 2.5, but nonetheless indicates considerable persistent dispersion in unemployment rates across counties.

[8] These two components of UGAP are labelled UNRATE and NROU in the Federal Reserve Economic Data database maintained by the Federal Reserve Bank of Saint Louis.

Figure 4: Average gap between county unemployment rate and median county unemployment rate, 1990-2018



Notes: Unemployment rates by county 1990-2018 from U.S. Bureau of the Census LAUS. Estimates of α_i from Eq.(2).

Figure 4 shows that these measures of persistent dispersion in county-level unemployment rates are also geographically disperse. Unemployment rates on average sit substantially higher than the median US county between 1990 and 2018 across certain counties in the Appalachian regions of West Virginia and Kentucky; across Mississippi, Alabama, and parts of Louisianna, Texas, and Arkasas; along California's Central Valley; and in northern Michigan and the eastern regions of Oregon. Other counties, especially in the mid-Atlantic, enclaves in the Northeast, and across much of the northern and central Great Plains, tend to have lower unemployment rates than the median county.

What characteristics of counties correlate with this dispersion in labor market outcomes? Table 1 shows the core results.

Table 1: Correlation of the average county-level unemployment gap with county characteristics

	Dependent variable: α_i						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
noHSdegPct1990	0.505***				0.417***	0.202*	0.441***
COLgradPct1990		-0.360***			-0.065	-0.146*	0.029
BlackPct1990			0.278***		0.111*	0.056	0.159**
PctEmpinMfg1990				0.202**	0.002	0.093	0.049
PctEmpinPubAdm1990						0.082*	0.065
PopPerSqMile1990						0.013	0.024
MedHomeValue1990						0.414***	0.056
MedHHMoneyInc1990						-0.436***	-0.302***
SavingsDepPerCap1990						-0.228***	-0.118*
N	3123	3123	3123	3123	3123	3099	3098
R^2	0.255	0.130	0.077	0.041	0.265	0.386	0.597
State FE	N	N	N	N	N	N	Y

Notes: Standardized beta coefficients; see Appendix for raw coefficients and standard errors. In any year t, the county-level unemployment gap is the county's unemployment rate minus the median county unemployment rate in that year. The dependent variable is the average county-level gap over the sample period (1990-2018) for each county, obtained from Eq. 2. Clustering by state. County characteristics from US Bureau of the Census *1994 County Data Book* (ICPSR DS80). See Data Appendix for detail. Standard errors are clustered at the state level in all specifications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

We first run simple univariate regressions using two measures of education (percent of the population with less than a high school degree and percent with a college degree) as well as the share of the population which is Black and the share of employment in manufacturing. Each variable on it own yields a coefficient that is highly statistically significantly different from zero. The magnitudes are expressed as standardized coefficients.[9] The standard deviation in the share of the population with less than a high school degree is ten percentage points. Column (1) therefore shows that counties that have a ten-percentage-point higher share of population with less than a high school degree have a persistently higher unemployment rate relative to the median county, increasing the average gap between a county's unemployment rate and the median by a magnitude of just over half a standard deviation, making it an additional 1.26 percentage points higher than the median county unemployment rate. Conversely, a six-and-a-half percentage point increase in the share

[9] In the Appendix, we report the raw coefficients and the standard errors clustered at the state level.

of the population with a Bachelor's degree is associated with 0.36 standard deviation lower gap (Column (2)), which translates to a nearly one percentage point lower unemployment rate gap. A ten-percentage point higher share of employment in manufacturing is associated with roughly a one-fifth standard deviation higher gap (Column (4)), which translates to a one-half percentage point higher unemployment rate gap.

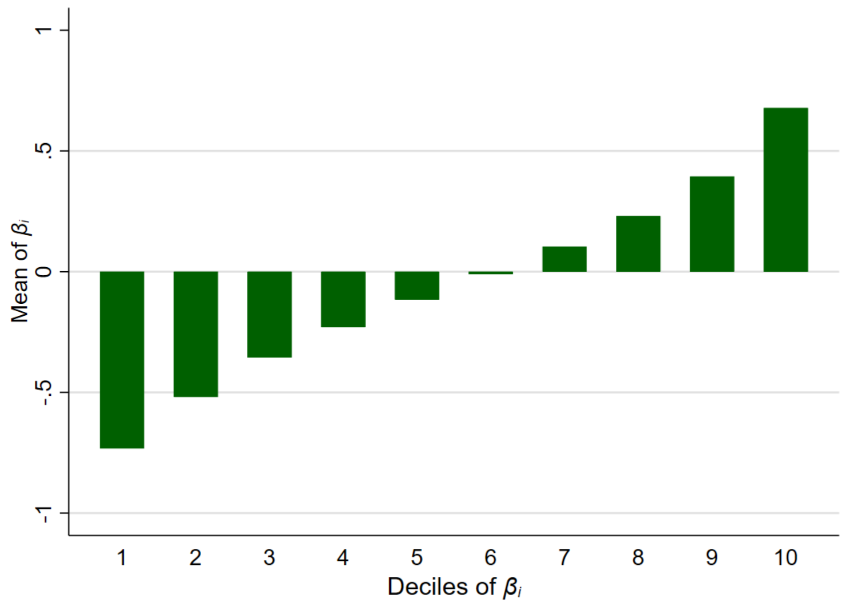
When all four variables are combined, only the share of a county's population without a high school degree and the share of the population which is Black are significant. When adding a range of controls for county income and wealth, higher household income and savings are associated with lower average levels of unemployment, though median house value is positively correlated. After adding these variables, the education variables retain significance. Inclusion of state fixed effects in Column (7) absorbs effects associated with residents' college education but again elucidates the significance of race. The correlation of the fraction of the population with no high school degree with the county unemployment gap retains its magnitude and significance even with state fixed effects.

In summary, we demonstrate that some US counties have persistently worse or better employment outcomes than others, with patterns significantly correlated with county demographic characteristics like high school completion, the manufacturing employment share, and race. Higher incomes, savings, and public sector jobs may have cushioned some areas against adverse outcomes, but including these controls is not enough in our regressions to eliminate the significance of education and race once we control for state policy through fixed effects.

3.3 Local cyclical sensitivity to national shocks

Figure 5 plots a histogram of the average β_i coefficient by deciles of β_i coefficients. The average β_i coefficient for counties in the top decile of β_i's is 0.7, meaning when the unemployment rate rises by one percentage point nationally, their unemployment rate rises by 1.7 percentage points relative to the median county. For the lowest decile, the average beta is -0.7, meaning that when the national unemployment rate rises, the unemployment rate in the lowest decile counties rises by substantially less than for the median county. There are eleven counties with a β_i below negative 1, implying their unemployment rate actually falls relative to the median when the national rate rises by one. Conversely, 18 counties have a β_i coefficient greater than 1, implying their unemployment rate rises (and falls) at more than twice the pace of the national unemployment rate gap. To be clear, this is not simply saying in a given recession some places fare worse than others, it is saying that systematically over the three decades leading up to the pandemic, some places have exhibited substantially elevated cyclical sensitivity: they face more pain in recessions.

Figure 5: Mean cyclical sensitivity of county unemployment rate gaps (β_i) by decile of β_i, 1990-2018



Notes: Unemployment rates by county 1990-2018 from U.S. Bureau of the Census LAUS; β_i's obtained from regressions of county unemployment rate minus median county unemployment rate on the national unemployment rate minus the CBO measure of the long run unemployment rate (Eq. 2), then sorted into deciles with the average across the betas in each decile reported here.

The top quintile of sensitivity has an average β_i of roughly 0.5 while the bottom quintile has an average β_i of -0.6. The gap between the two of 1.1 means that the 20 percent most cyclically sensitive counties in the United States relative to the least sensitive see their unemployment rates move with the business cycle by even more than the Black-White gap or High School-College gap as documented in the Aaronson et al (2019) study.[10] This is in no way intended to minimize the importance of those other gaps, but stands to show the quan-

[10] In Appendix Table A.1, we reproduce the group-level differences in cyclical sensitivity shown by Aaronson et al (2019). Furthermore, if contrasting the top quintile to bottom seems an inappropriate comparison for the Black White gap which compares a 1% population to a majority population, one could contrast the top quintile (0.5) to the bottom half of counties (-0.4) and still find a gap on par with the Black White gap.

titative relevance of the differing regional cyclical sensitivity.

In a comment on Aaronson et al (2019), Wolfers (2019) noted that when looking at groups, those with elevated cyclical sensitivity also had higher baseline levels of unemployment rates. That is, α_i and β_i were correlated in the above equation. Looking across 4 racial categories, 4 education categories, and 4 age categories, all groups with higher β_g also had higher α_g. There were no groups in the off diagonal squares of a 2 by 2 grid.

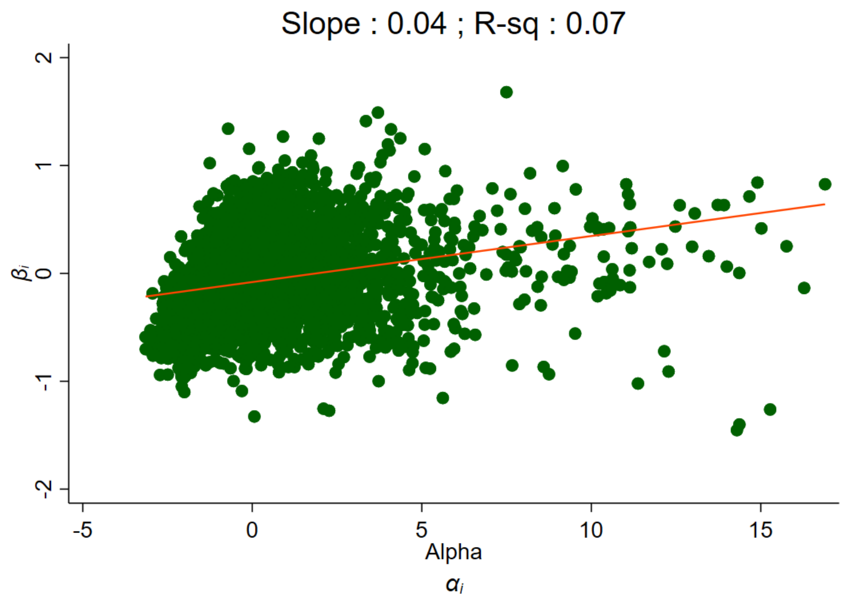
We repeat the exercise with counties and find there is a slight upward sloping relationship, but it is rather noisy (shown in Figure 6). For the case of counties, it is true that on average, those with higher average unemployment rates (higher α_i) over the sample period are also more cyclically sensitive (higher β_i), but there are many cases that do not fit the pattern. A large number of counties have negative β_i (they are less cyclically sensitive than the median county) but have α_i above zero, indicating higher-than-median steady state unemployment.[11]

How do these α's and β's relate to policy preferences in a current or prospective optimum currency area? In many ways the α_i's represent the prior concern of the literature. These are areas with persistently higher unemployment rates than the typical county. The β_i's represent a new concern in the currency union literature. Places with a higher β_i experience wider swings in the unemployment rate when the *national* economy has ups and downs. These are places most hurt by recessions and likely to suffer the most from slow recoveries. They may be hurt the most if the monetary policy authority responds to an adverse national shock with more restraint or for only a short period, meaning areas most sensitive to national shocks will not be cushioned in the same way as areas with smaller β_i's.

As documented above in Figure 2, and in Appendix Figures A.1 and A.3, the α's across U.S. states and counties are becoming more stratified (meaning the same places are increasingly likely to be found in the highest and lowest unemployment outcomes in any given year), even if Figure 1 shows that overall

[11] One might also ask whether counties with higher unemployment rates or higher cyclical sensitivity recover more slowly. Many studies computing half-lives in macroeconomics use quarterly or higher-frequency data. Our data are annual and we have only 29 periods, so we can get only a very rough estimate at best. We compute a half-life using the formula $H_i = \frac{\ln(0.5)}{\ln \rho}$, where ρ is the coefficient when regressing the local unemployment rate on its lag, ρas in Taylor (2001). A bar chart of average half-life by decile is included in the Appendix and shows considerable heterogeneity in the half-life across counties, indicating dispersion in the rates of recovery from shocks. The mean is 3.25 years, with a standard deviation of 1.51, a minimum of 0.28 and a maximum of 15.18. We see some slight positive correlation of the half-life with α_i and β_i, but with very little explanatory power. Explanatory power is greater (R-squared=11.9%) for Factor 1 from the PCA analysis below.

Figure 6: Average (α_i) versus cyclicality (β_i) of the county-level unemployment gap, 1990-2018



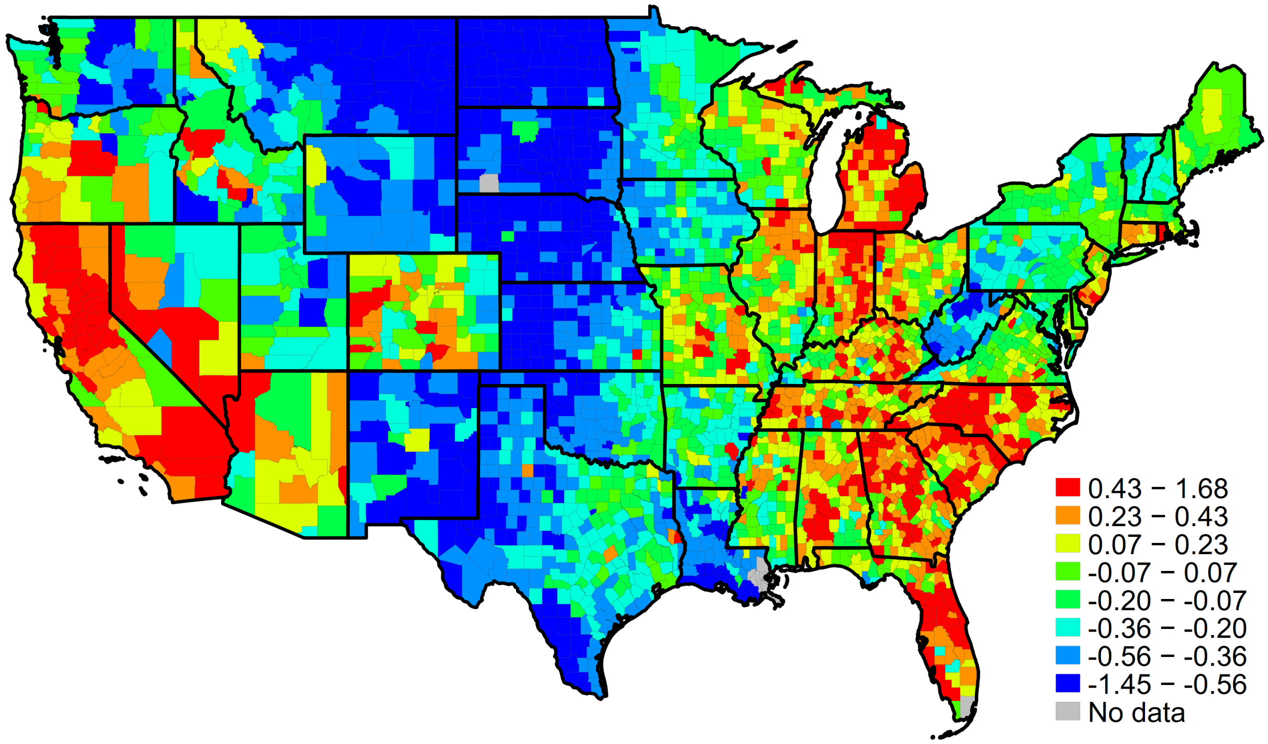
Notes: In any year t, the county-level unemployment gap is the county's unemployment rate minus the median county unemployment rate. Cyclicality of the county-level unemployment gap is the sensitivity of the county unemployment gap to the national unemployment gap, measured using Eq.(2), with the intercept being the conditional average unemployment rate.

dispersion his not widened. In addition, cyclical sensitivity varies considerably across places. Figure 7 shows that labor markets with higher cyclical sensitivity concentrated in the western portion of the Manufacturing Belt, southern Ohio River Valley, southern Appalachians, Florida, and California's Central Valley. In contrast, the Northeast, Pacific Northwest, and Great Plains regions are somewhat less subject to the vicissitudes of national shocks. In some areas, like West Virginia, along the southern border of Texas, and along the southern half of the Mississippi River, low cyclical sensitivity (β_i) coincides with persistently high unemployment rates (α_i).

We take the β_i's and regress them on county demographic and other characteristics, motivated by stylized facts on the importance of these variables for cyclical sensitivity discussed above. Results are in Table 2. The magnitudes are expressed as standardized coefficients.[12] Unlike for the average level of unemployment by county (the α_i's), the cyclical sensitivity of counties does not seem to be strongly associated with levels of education, beyond a possible small

[12]In the Appendix, we report the raw coefficients and the standard errors clustered at the state level.

Figure 7: Sensitivity of gap between county unemployment rate and median county unemployment rate to national unemployment gap, 1990-2018



Notes: Unemployment rates by county 1990-2018 from U.S. Bureau of the Census LAUS. National unemployment gap is the national unemployment rate minus the CBO measure of the long run unemployment rate, both from FRED. Estimates of β_i from Eq.(2).

cushioning effect from higher shares of college graduates once all controls and state fixed effects are taken into account. The share of the population without a high school degree is not correlated with cyclical sensitivity, and by itself, the share with a college degree is not either.

In contrast, the share of the population that is Black is consistently associated with greater county-level cyclical sensitivity. The share of the population working in manufacturing is also consistently associated with greater sensitivity. In the bivariate regression, an increase in the percentage of Black residents by one standard deviation (14 percentage points) is associated with an increase in cyclical sensitivity by nearly 0.28 standard deviation, meaning a β_i which is higher by 0.11. This is a large difference given that the mean β_i is -0.06. Counties with a ten-percentage-point larger share of employment in manufacturing exhibit extra sensitivity on the order of 0.55 standard deviation, so a β_i expected to be higher by 0.23. This latter finding may not be surprising as it is not uncommon for recessions to hit durable goods harder or generally to hit

Table 2: Correlation of cyclicality β_i of county-level unemployment gap with county characteristics

	Dependent variable: β_i						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
noHSdegPct1990	0.185				-0.012	-0.038	-0.128
COLgradPct1990		-0.099			0.084	-0.139*	-0.082**
BlackPct1990			0.277***		0.151*	0.140*	0.105*
PctEmpinMfg1990				0.550***	0.544***	0.494***	0.280***
PctEmpinPubAdm1990						0.016	-0.029
PopPerSqMile1990						-0.045	-0.013
MedHomeValue1990						0.362***	0.115
MedHHMoneyInc1990						-0.027	-0.076
SavingsDepPerCap1990						-0.114*	-0.028
N	3123	3123	3123	3123	3123	3099	3098
R^2	0.034	0.010	0.077	0.302	0.330	0.402	0.709
State FE	N	N	N	N	N	N	Y

Notes: Standardized beta coefficients; see Appendix for raw coefficients and standard errors. In any year t, the county-level unemployment gap is the county's unemployment rate minus the median county unemployment rate in that year. Cyclicality is the coefficient β_i for each county estimated from Eq.(2). Clustering by state. County characteristics from US Bureau of the Census *1994 County Data Book* (ICPSR DS80). See Data Appendix for detail. Standard errors are clustered at the state level in all specifications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

manufacturing industries harder. But, it does highlight that places with different employment shares will face different outcomes across the country because the share of the population that is Black and the share of workers in manufacturing are associated with a higher α_i and higher β_i. All else equal, this means these counties have persistently higher levels of unemployment and they face amplified cyclical shocks. So, they start with more unemployment, and then face a greater increase in unemployment during a recession, suggesting the localized damages from recessions could be quite high for them.

While the finding that a larger Black population is associated with greater cyclical sensitivity directly maps to the group-level differences noted in Aaronson et al. (2019), it is interesting that this is not the case for the share of workers without a high school degree. Furthermore, if shocks were equally distributed across counties (say, a shock requiring 4 percent of the population to lose its job) and Black workers were fired disproportionately, that would lead to group differences, but not a difference in the unemployment rate based on the racial make-up of counties. There is something broader at play where Black communities suffer more in downturns. The finding regarding counties with higher shares of Black individuals in the population opens an important aspect of the experience of Black workers in the U.S. economy. It is not simply that individual Black workers face discrimination, but Black communities in the aggregate fare worse in recessions. This result, as well as the association of manufacturing employment shares with cyclical sensitivity, remains even when including state-level fixed effects (Table 2, Col.(7)), so not fully mitigated by state policies.

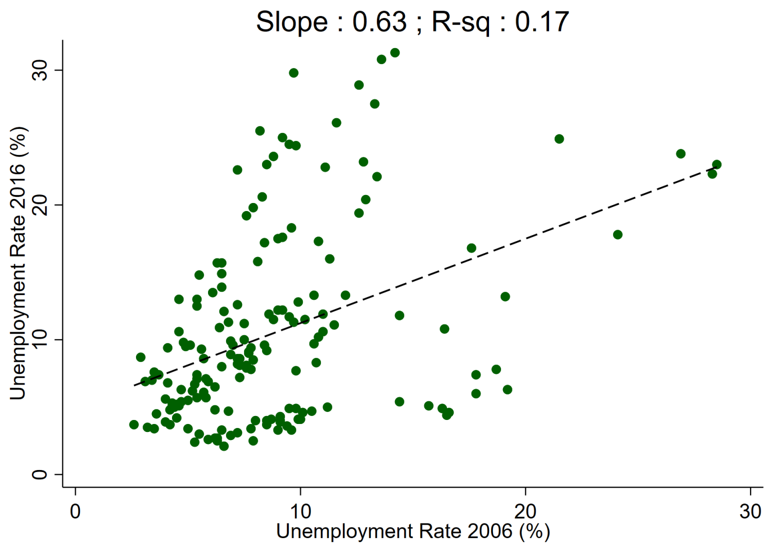
There are a number of possible reasons for this that extend beyond the scope of this paper. Hardy, Logan, and Parmon (2018) discuss a range of factors in how racial inequality combined with racial segregation can generate regional economic inequality. Lower levels of wealth in Black communities (Derenoncourt et al 2022) may leave Black communities more vulnerable to income shocks, leading to larger cuts in local consumption and hence larger employment shocks. In addition, differential access to the social safety net (see for example Hardy et al 2019) may mean Black communities have less income support in recessions, causing more employment losses as people cut back consumption. See also Hyclack and Stewart (1995) for a discussion of differential impacts of shocks. These systemic impacts fall outside the scope of this paper, but are an important consideration for why certain types of communities are more cyclically sensitive.

3.4 Europe

One might ask the same question Obstfeld and Peri (1998) raised, which is how similar might the behavior of local unemployment in the Euro Area (EA19) be to that in the United States? While there is no exact counterpart in Europe to US counties, we can look at provincial unemployment rates which are the NUTS2 level unemployment rates from EUROSTAT. Here, we see in Figure 8 that similar to our result in Figures 2 and Figure 3, unemployment is persistent at the provincial level. A one percentage point higher provincial unemployment rate in 2006 predicts an 0.63 percentage point higher unemployment rate in 2016.

Corresponding with our earlier analysis, we also can examine the behavior of gaps in province-level unemployment rates compared to the median province in the Euro Area 19, to measure non-adjustment across provinces (α_i) and cyclical sensitivity (β_i) as in Eq. (2). Here, we construct the EA19-wide national unemployment gap by extracting the cyclical component of the HP-filtered EA19

Figure 8: Provincial Unemployment Rates in the Euro Area 19, 2006 versus 2016



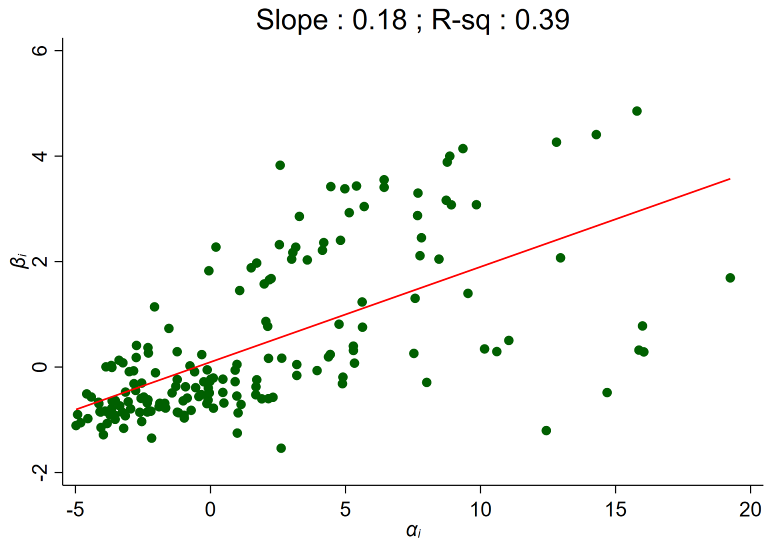
Notes: Unemployment rates by province 1999-2019 from EUROSTAT.

unemployment rate (called "total" in the EUROSTAT database), for the years 1999-2019. The average α_i across EA19 provinces is 1.63, almost three times higher than the mean of 0.58 we measured earlier for US counties 1990-2019. The standard deviation of this measure of non-adjustment is 5.15—twice a large as the dispersion across counties in the US.

As for cyclical senstitivity, the mean β_i across EA19 provinces is 0.39. The standard deviation of β_i across EA19 provinces is 1.48, three and a half times larger than measured above for US counties (0.41). As Figure 9 shows, regressing the β_i's on the α_i's produces a chart of striking similarity to Figure 6.

The correlation between non-adjustment and cyclical sensitivity in the EA19 is positive but quite low, though higher than observed in the US. Overall, this exercise suggests the presence of greater heterogeneity in cyclical sensitivity across provinces of EA19 countries and also a higher correlation between structural non-adjustment and cyclical sensitivity than we observe across counties within the US.

Figure 9: Average (α_i) versus cyclicality (β_i) of the province-level unemployment gap in EA19 countries



Notes: Estimates of α_i and β_i from Eq.(2) using EA19 province-level data. Unemployment rates by province 1999-2019 from EUROSTAT. National unemployment gap is the cyclical component extracted from Hodrick-Prescott-filtered EA19-wide unemployment rate.

4 A closer look at national shocks

One may worry that the national shocks we use are simply the aggregation of regional shocks. That is, they may not be hitting across the country, but just in large enough subsets of places that the national average rises. Rather than use the overall national average, one could use factor analysis to try to isolate shocks that truly are hitting a wide swath of counties, as suggested by Beyer and Smets (2015) for US states.

Therefore, instead of using only UGAP, we also construct common factors affecting US counties using principal component analysis (PCA). One advantage of this technique is it allows for multiple national factors. We standardize the county-level unemployment rate time-series, and extract two principal components as represented in Eq.(3):

$$u_t = \lambda_1 f_{1t} + \lambda_2 f_{2t} + \nu_t \tag{3}$$

where u_t is an $I \times 1$ vector of (standardized) county level unemployment rates at time t, $t = \{1990 \leq \mathbb{Z} \leq 2019\}$, with I the number of counties. λ_1 and λ_2 are $I \times 1$ vectors of county-level factor loadings on the first (f_{1t}) and the second (f_{2t}) common (national) factors, respectively, and ν_t is an $I \times 1$ vector of residuals.[13]

We find that the first two factors explain over 50 percent of variation observed in our panel of county unemployment rates. No other factor explains more than 10 percent, so we focus on these two factors. Figure A.4 in the appendix plots the percentage of variance explained by each of the ten extracted factors.

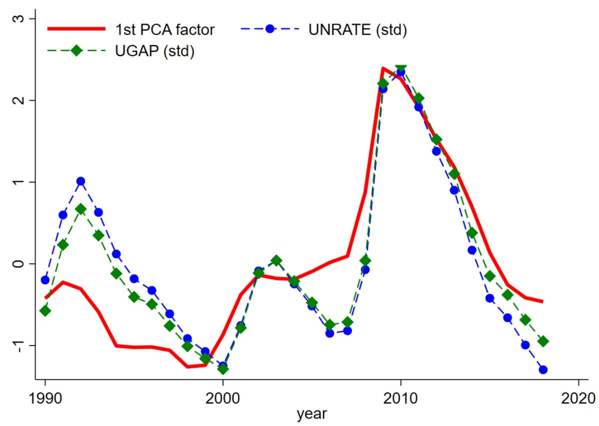
We plot the two principal factors in Figure 10, along with the national unemployment rate as well as the CBO-based unemployment gap. The first factor closely resembles the $UGAP$ measure (or for that matter, the raw unemployment rate) and accounts for more than one quarter of variation in county unemployment rates. Reassuringly, the $UGAP$ measure is strikingly similar to the first PCA factor, and hence its interpretation as a national shock is plausible. The correlation of $UGAP$ with the first and second PCA factors are 0.88 and 0.40, respectively. The correlation between the β_i coefficients noted above and the factor loadings on the first PCA factor is 0.88. While we borrowed the technique from Aaronson et al.'s (2019) group-level regressions at the national level, it seems it is appropriate for regional-level analysis as well.

Finally, in Figure 11 we show how the R-squared from the county-level regressions (e.g. which counties' variation in the county-level unemployment gap can be well described by $UGAP$) map to the variance explained by factors 1 and 2. Given the similarity of $UGAP$ and the first factor, it may not be surprising that the places whose variance is well-explained by $UGAP$ also have a high share of variance explained by the first factor (with a correlation of 0.66). The comparison of the R-squared with the variance explained by second factor highlights that there are counties that have a big response to the second factor, but do not respond to the national unemployment rate.

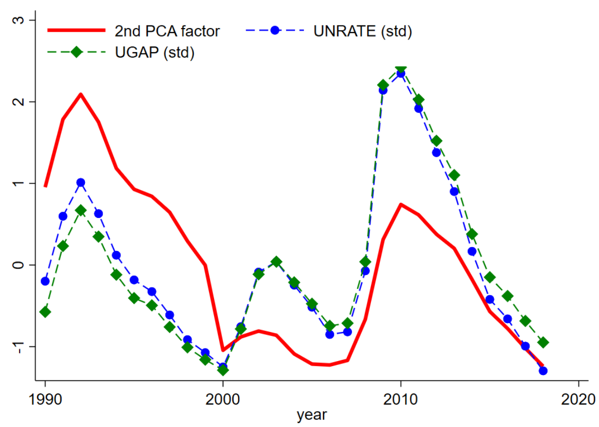
The second national factor generates different patterns relative to those documented for $UGAP$ based on Eq.(2). The correlation between loadings on the second factor (λ_{2i}) and the β_i coefficient from Eq.(2) is 0.31—substantial, but much lower than for the first factor. Table A.6 shows that in contrast to findings for λ_{1i}'s in Table A.5, unemployment rates in counties with more college-educated adults as a share of the population rise and fall less with the second

[13] Specifically, we combine the u_t vectors into a $T \times I$ matrix we call U, with T the number of years in our sample and I the number of counties. We then extract the principal components as described by Canova and Ferroni (2021). We use their toolkit to implement the PCA in Matlab, computing the eigenvectors and eigenvalues of $U'U$, then computing the factors as the first 10 eigenvectors multiplied by U.

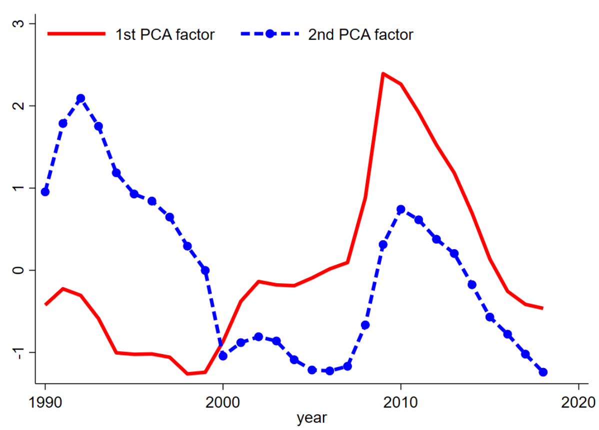
Figure 10: Principal components of county-level unemployment gaps versus the national unemployment gap



(a) First PCA factor and the National Unemployment Gap



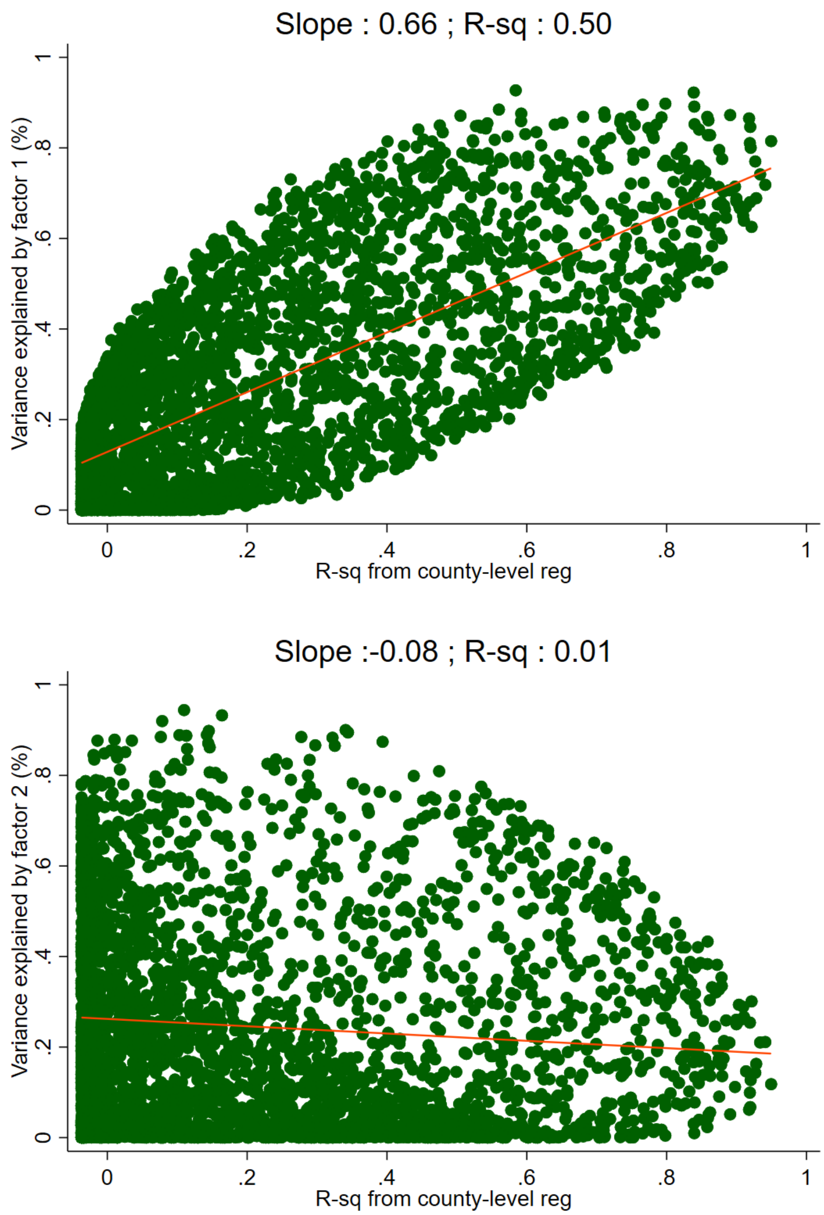
(b) Second PCA factor and the National Unemployment Gap



(c) PCA Factor 1 vs PCA Factor 2

Notes: County-level R-sq on the horizontal axes are from estimation of Eq.(2). Variance explained by PCA Factors 1 and 2 are from the process specified in the discussion of Equation (3).

Figure 11: Comparison of how well $UGAP$ versus principal components explain county-level unemployment gaps



Notes: County-level R-sq on x-axes is from estimation of Eqs.(2). Variance explained by Factors 1 and 2 on each y-axis is from Equation (3).

factor. Counties with a higher median home value have amplified sensitivity, while higher median household cash income and savings buffer against factor-2 shocks. These associations with college education and wealth are statistically indistinguishable from zero for the factor-1 shocks.

On net, the principal component analysis seems to support the regression analysis above, but adds a new dimension. There does appear to be a second non-trivial nationwide factor. This factor is not identical to the simple national unemployment rate or $UGAP$. And, the types of counties most affected by this factor are somewhat different from counties sensitive to the overall national factor embodied in $UGAP$ and factor 1 (f_{1t}). While education, race, and manufacturing are all associated with persistent gaps in county unemployment levels (as manifest in α_i), only race and share of manufacturing stand alone as significant when considering the cyclical sensitivity to both $UGAP$ and the first factor (β_i and λ_{1i}).[14] In contrast, education and levels of cash income and savings in the county are associated with cyclical sensitivity to this second factor (λ_{2i}), but race and manufacturing employment shares are not.

In addition, while the correlation between the first factor and $UGAP$ is quite high, a glance at Figure 11 suggests that this correlation is higher after 2000 than it is 1990-2000, and in fact this is true.[15] Combined with the fact that Factor 2 is less correlated with $UGAP$ than Factor 1, this suggests that phenomena driving cyclical fluctuations in a set of counties with higher loadings on Factor 2 are in some sense distinct from those driving the national unemployment rate, and that distinction may have grown around the year 2000.

While the factor extraction is by its nature an abstract exercise, we can conduct two analyses to examine this distinction. First, we regress our county factor loadings on α_i, our Obstfeld-Peri-inspired measure of non-adjustment at the county level. The α_i estimated from Eq.(2) are positively correlated with both factor loadings λ_{1i} and λ_{2i}, but the correlation with λ_{2i} is about four times higher. Regressing λ_{2i} on α_i yields an R-squared of 0.4 (see Figure A.10), but in unreported results the same regression with λ_{1i} shows less than one-tenth the explanatory power. Thus, it appears that the second factor may represent a national shock associated with more persistent adverse impacts on vulnerable local labor markets.

[14] Share of college graduates is significantly correlated with cyclical sensitivity to $UGAP$ (β_i) in Table 2 once controls and state fixed effects are added, but not on its own, and the impact is somewhat muted (a one standard deviation increase increases β_i by 0.03).

[15] Specifically, correlation between the first factor and $UGAP$ increases from 0.72 1990-2000 to 0.96 2000-2018.

Second, the increased correlation of the first factor with $UGAP$ after 2000 suggests some shift may have occurred around that time in the relative sensitivity of counties to Factor 1, or $UGAP$. Given recent research related to the persistence of the China shock by Autor, Dorn, and Hanson (2022), it is natural to examine whether this has any correlation with county-level exposure to the China shock or, as Eriksson et al. (2021) show, the product cycle as it manifests from North to South within the United States. With this in mind, we regress the factor loadings on measures of the county-level exposure to the China shock and historical product-cycle movement. We report the results in Appendix Tables A.7 through A.10.

Table A.7 shows that counties' level of exposure to the China shock by itself is significantly correlated with increased sensitivity to the first national factor (which tracks UGAP most closely). However its explanatory power is completely absorbed by education, race, and manufacturing. As in Table 2, education variables again have little robust correlation with the first factor when we include the China shock measure. Accounting for China shock exposure does not eliminate the positive and significant correlation of Factor 1 with the share of county employment in manufacturing or completely drown out its correlation with race.

Table A.8 shows that exposure to the China shock by itself has no clear correlation with counties' sensitivity to the Factor 2, with the exception of those least exposed. The least exposed quintile of counties are less cyclically sensitive to Factor 2, though this indicator variable appears to have low explanatory power— an R-squared of only 0.017 when included by itself. Eriksson et al. (2021) show that some counties with the lowest exposures were among those with the lowest concentrations of these industries as far back as 1910, with exposure rising until the late 1970s, even after the counties where the industries had spawned were shedding them. These places tended to have a low level of market access in 1890 as measured by Donaldson and Hornbeck (2016) and eventually took on these industries late in the industry product cycle. These results suggest that the differences between counties sensitive to Factor 2 but less so to Factor 1 observed in Figure 11 may be related to technological capacity and how connected these places historically have been to other markets.

We can examine product cycle effects more closely. Eriksson et al. (2021) show that observing which areas between 1960 and 1980 shifted employment toward versus away from the industries that would be hit by the surge in Chinese imports in 1990 can explain some of the adverse impacts on local employment rates between 1991 and 2007. That paper finds a "moving out" effect: places where China shock industries already had been moving out between 1960 and 1980—decades before the China shock began—saw additional bumps in both unemployment and detachment from the labor force. Here, we see in Table A.9 that places where China shock industries were moving out 1960 to 1980 appear more sensitive to Factor 1 even when including measures of county education, race, and manufacturing employment shares. Eriksson et al. (2021) show these places are concentrated in the manufacturing belt, and including state fixed effects absorbs the explanatory power of this move-out effect.

In contrast, Table A.10 suggests that counties where China shock industries were *moving in* 1960-1980 are more cyclically sensitive to Factor 2, even with all controls and state fixed effects included. The explanatory power as manifest by the R-squared in column 2 is rather low, only half of a percent. But the contrast is striking and holds up to state fixed effects, possibly because these places are more dispersed across the Southeast and parts of the Great Plains. Eriksson et al. (2021) show that these places tend to have been historically less connected to large markets, have fewer patents per capita and lower levels of education, and were areas with already more vulnerable labor markets prior to when the shock hit in 1990. Here, we see that they also appear more subject to a broad shock that is separate from the national unemployment gap that economists generally use to gauge the health of the national labor market. Recall that sensitivity to Factor 2 is more closely associated with non-adjustment. Interestingly, having a higher fraction of college-educated workers buffers counties against fluctuations in Factor 2 but not Factor 1. There appears to be something structurally different about places cyclically sensitive to the second national factor that is not captured in manufacturing shares but—based on their position in the US manufacturing product cycle and the buffering influence of college education—likely relates to their positioning relative to the secular path of innovation and the skill-set of local workers.

5 Summary and Discussion

Maury Obstfeld's work changed the face of international macroeconomics. His contributions to both theory and empirical results are among the most influential and most cited works in the last half century in the field. At the same time, he has made important contributions to practical questions in the field (as well as taking turns as a policymaker himself). In this paper, we have extended Obstfeld's pre-EMU work to consider new information about the United States labor market and extended the optimal currency union literature more broadly by considering regional cyclical sensitivity.

Different regions of the United States have had increasingly persistent differences in unemployment outcomes, and these differences tend to map to differences in education and race in the counties in question. Places with workers with less education and where Black residents make up a higher share of the population have had persistently worse outcomes, and on a relative basis, those gaps appear larger today than in the past. Shocks within the U.S. monetary union do not fade as quickly as they once appeared to do, serving as a cautionary tale for other more newly-formed—and perhaps less well-fitting–monetary unions.

At the same time, different types of places have experienced more cyclical sensitivity, with local unemployment rising and falling faster with the national unemployment rate. Race and industrial structure appear to be two important considerations for cyclical sensitivity, especially to the national shock largely embodied in fluctuations in the national unemployment gap. This raises important questions about both challenges faced by not just Black individuals in the labor market but by Black communities more broadly, and highlighting the differential impact of recessions across the geography of industrial structure. In addition to understanding more about implications of local industry mix, in future research it would be interesting to see if areas with greater cyclical sensitivity compensate workers for volatility in employment conditions with higher skill-adjusted wages.

We also show the existence of a second source of national fluctuations, separate from those largely embodied within the national unemployment gap. This factor is highly correlated with Obstfeld-Peri-style *non-adjustment* as manifest in higher average county unemployment relative to the median. We show that the phenomenon where production moves from innovative centers to places with lower-cost labor known as the product cycle may also help reveal which places are more sensitive to this factor versus more sensitive to Factor 1 and the national unemployment gap. Places that absorbed manufacturing activity late in the product cycle as manifest by increasing exposure between 1960 and 1980 to an import surge from a large low-wage country (China) that eventually hit in

1990 appear somewhat more cyclically sensitive to this secondary national factor.[16] Having a higher share of college-educated workers dampens sensitivity to this more pernicious shock. The association with non-adjustment and distinction from the drivers of sensitivity to the national unemployment gap suggests that the relationship of a place to the path of technological innovation and the skill-set of its workers is related as much to long-term structural factors as to fluctuations in disposable income that can be remedied by fiscal or monetary stimulus.

These results, therefore, push us to broaden the range of policies to consider in discussions of optimum currency areas from the industrial to the structural, given this insight into risk factors for sensitivity to a type of pernicious shock correlated with non-adjustment. It is not only the literature on monetary and fiscal multipliers or on industrial structure and mobility of trade or labor that is relevant. Instead, we must consider the deep-rooted literature on systemic social inequities and the emerging literature on spatial approaches to public policy. Studies like Cox (2010); Hardy, Logan, and Parmon (2018); von Lockette and Spriggs (2016); and Derenoncourt et al. (2022) provide insight into the former.

For the latter, since workers do not seem to move in response to adverse shocks as fluidly as they used to, the most relevant papers may be the new studies of what makes people with different skill-sets choose long-term to live where they do. The results here suggest that once we take joblessness into account, recommendations for workers to sort into skill-specialized cities as in Rossi-Hansberg, Sarte, and Schwartzman (2019) could exacerbate both non-adjustment and dispersion in non-adjustment. Many policymakers talk about the importance of investing in education, but a "brain drain" works against counties vulnerable to Factor 2 (Joint Economic Committee Republicans 2019, Li 2022). The literature on how to attract and keep the types of workers that dampen sensitivity to shocks associated with non-adjustment is thus germane.

Along these lines, the recent finding by Diamond and Gaubert (2022) that college-educated workers have moved away from cities centered on production and toward cities centered around consumption between 1980 and 2017 provide important insight. Some cities already have begun offering financial incentives to encourage in-migration of skilled workers (Liu 2021). Fajgelbaum and Gaubert (2020) outline a systematic tax schedule in a paper that provides a conceptual framework for considering such incentives. Rappoport (2009) pro-

[16] In contrast, places where the China shock industries were moving out 1960-1980 appears somewhat more sensitive to Factor 1, though the correlation is not robust to inclusion of the full set of controls.

vides a in-depth discussion of amenities and their importance in Americans' locational choice. Diamond (2016) examines the role of amenities in driving the sorting of skilled workers across places and Diamond and Moretti (2021) analyze the geography of amenities and the cost of living. Raj Chetty in various works demonstrates how amenities available at as granular a level as *neighborhoods* can substantially affect economic opportunity for the children of residents (see Chetty and Hendren 2018, for instance). Willingham and Ajilore (2021) challenge us to rethink rural development policy. Other disciplines also can offer insights into drivers of locational choice that may result in dispersion in our Obstfeld-Peri-style measure of non-adjustment (Curtis and Kulcsar 2019).

We hope the contributions and discussion above highlight the importance of Obstfeld's work across the field and raise interesting questions for future researchers.

References

Aaronson, S. R., M. C. Daly, W. L. Wascher, and D. W. Wilcox (2019). Okun Revisited: Who Benefits Most from a Strong Economy. *Brookings Papers on Economic Activity*, 333–371.

Almeida, A., A. Galiano, A. A. Golpe, and J. M. Martín (2020). Regional unemployment and cyclical sensitivity in Spain. *Letters in Spatial and Resource Sciences 13*, 187–199.

Amior, M. and A. Manning (2018). The persistence of local joblessness. *American Economic Review*, 1942–1970.

Austin, B., E. Glaeser, and L. Summers (2018). Jobs for the heartland: Place-based policies in 21st-century america. *Brookings Papers on Economic Activity*, 151–255.

Autor, D., D. Dorn, and G. Hanson (2021). On the persistence of the china shock. *Brookings Papers on Economic Activity*, 381–447.

Autor, D. H. (2019, January). Work of the past, work of the future. *Allied Social American Economics Association Annual Meeting Richard T. Ely Lecture*.

Autor, D. H., D. Dorn, and G. H. Hanson (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review 103*(6), 2121–2168.

Berry, C. and E. Glaeser (2005). The Divergence of Human Capital Levels Across Cities. *Papers in Regional Science 84*, 407–444.

Beyer, R. C. and F. Smets (2015). Shocks and migration. *Economic Policy 30*(84), 643–682.

Blanchard, O. and L. Katz (1992). Regional Evolutions. *Brookings Papers on Economic Activity 45*.

Bound, J. and H. J. Holzer (2000). Demand shifts, population adjustments, and labor market outcomes during the 1980s. *Journal of Labor Economics 18*(1), 20–54.

Byers, J. D. (1990). The Cyclical Sensitivity of Regional Unemployment: An Assessment. *Regional Studies 24*(5), 447–453.

Chetty, R. and N. Hendren (2018). The impacts of neighborhoods on intergenerational mobility i: Childhood exposure effects. *Quarterly Journal of Economics 133*(3), 1107–1162.

Cipolla, C. (1967). *Money, Prices, and Civilization in the Mediterranean World*. Gordian Press.

Cox, R. J. (2010). Crime, incarceration, and employment in light of the great recession. *Review of Black Political Economy 37*(1), 283–294.

Curtis, K. J. and L. J. Kulscar (2019). *Rural Demography*, Volume 22 of *Handbooks of Sociology and Social Research*. Springer.

Dao, M., D. Furceri, and P. Loungani (2017). Regional labor market adjustment in the United States: Trend and cycle. *Review of Economics and Statistics 99*(2), 243–257.

Debelle, G. and J. I. Vickery (2010). Labour market adjustment: Evidence on interstate labour mobility. *Australian Economic Review 32*(3), 249–263.

Decressin, J. and A. Fatas (1995). Regional labor market dynamics in europe. *European Economic Review 39*(9), 1627–1655.

Derenoncourt, E., C. H. Kim, M. Kuhn, and M. Schularick. Wealth of two nations: The U.S. racial wealth gap, 1860-2020. *Working Paper*.

Diamond, R. (2016). The determinants and welfare implications of us workers' diverging location choices by skill: 1980-2000. *American Economic Review 106*(3).

Diamond, R. and Gaubert (2022). Spatial sorting and inequality. *Annual Review of Economics 14*.

Diamond, R. and E. Moretti (2021). Where is standard of living the highest? local prices and the geography of consumption. *Manuscript, Stanford University*.

Donaldson, D. and R. Hornbeck (2016). Railroads and american economic growth: A "market access" approach. *Quarterly Journal of Economics 131*(2), 799–858.

Eriksson, K., K. N. Russ, J. C. Shambaugh, and M. Xu (2021). Trade shocks and the shifting landscape of u.s. manufacturing. *Journal of International Money and Finance 111*.

Fajgelbaum, P. and C. Gaubert (2020a). Optimal spatial policies, geography, and sorting. *Quarterly Journal of Economics 135*(2).

Fajgelbaum, P. D. and C. Gaubert (2020b). Optimal spatial policies, geography, and sorting. *Quarterly Journal of Economics 135*(2), 959–1036.

Ferroni, F. and F. Canova (2021). A hitchhiker's guide to empirical macro models.

Freeman, D. (2011). On (Not) Closing the Gaps: The Evolution of National and Regional Unemployment Rates by Race and Ethnicity. *The Review of Black Political Economy 39*, 1–18.

Freeman, R. B. (1972). *Labor Economics*. New Jersey: Prentice-Hall.

Ganong, P. and D. Shoag (2017). Why has regional income convergence in the u.s. declined? *Journal of Urban Economics 102*, 76–90.

Gaubert, C., P. Kline, D. Vergara, and D. Yagan (2021). Trends in u.s. spatial inequality: Concentrating affluence and a democratization of poverty. *American Economic Review Papers and Proceedings 111*.

Greenaway-McGrevy, R. and K. K. Hood (2016). Worker migration or job creation? Persistent shocks and regional recoveries. *Journal of Urban Economics 96*, 1–16.

Hardy, B., R. Samudra, and J. Davis (2019). Cash Assistance in America: The Role of Race, Politics, and Poverty. *The Review of Black Political Economy 46*, 306–324.

Hardy, B. L., T. D. Logan, and J. Parmon (2018). The Historical Role of Race and Policy for Regional Inequality. *The Hamilton Project Framing Pa*.

Herreno, J. and M. Pedemonte (2020). The geographic effects of monetary policy shocks. *Manuscript, University of California San Diego*.

Hershbein, B. and B. Stuart (2022). The Evolution of Local Labor Markets after Recessions. *Working paper*.

Holzer, H. and J. Bound (2000). Demand Shifts, Population Adjustments, and Labor Market Outcomes During the 1980s. *Journal of Labor Economics 18*, 20–54.

Holzer, H., S. Raphael, and M. Stoll (2006). Employers in the Boom: How Did the Hiring of Less-Skilled Workers Change during the 1990s? *The Review of Economics and Statistics 88*, 283–299.

Hoynes, H. (1999). The Employment, Earnings, and Income of Less Skilled Workers Over the Business Cycle. *NBER Working paper*.

Hyclak, T. and J. Stewart (1995). Racial Differences in the Unemployment Response to Structural Changes in Local Labor Markets. *The Review of Black Political Economy 23*, 29–42.

Kaplan, G., K. Mitman, and G. L. Violante (2020). Non-durable consumption and housing net worth in the Great Recession: Evidence from easily accessible data. *Journal of Public Economics 189*.

Kocherlakota, N. and T. Krueger (1998). Why do different countries use different currencies? *IMF Working Paper No. 98-7*.

Li, N. (2022). Innovation clusters and local brain drain. *Manuscript, University of California, Davis*.

Liu, J. (2021, March). Some cities are paying people up to $16,000 to move there. *CNBC.com*.

Mare, D. C., A. Grimes, and M. Morten (2009). Adjustment in local labour and housing markets. *Australasian Journal of Regional Studies 15*(2), 229–248.

Mill, J. (1894). *Principles of Political Economy, Volume II.* New York: John W. Parker.

Modestino, A. S., D. Shoag, and J. Ballance (2016). Downskilling: Changes in employer skill requirements over the business cycle. *Labour Economics 41*.

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

Moretti, E. (2011). Local Labor Markets. In O. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics*, Volume 4, Chapter 14, pp. 1237–1313. Elsevier.

Mundell, R. A. (1961). A Theory of Optimum Currency Areas. *American Economic Review 51*, 657–665.

Nunn, R., J. Parson, and J. Shambaugh (2018). The Geography of Prosperity". *The Hamilton Project Place Based Policies for Shared Economic Growth*.

Obstfeld, M. (1997). Europe's Gamble. *Brookings Papers on Economic Activity 2*, 241–317.

Obstfeld, M. (1998). EMU: Ready or Not. *International Economics Section, Departement of Economics Princeton University,, Princeton Essays in International Economics*.

Obstfeld, M. and G. Peri (1998). Regional Nonadjustment and Fiscal Policy. *Economic Policy 13*(26), 205–259.

Okun, A. M. (1973). Upward Mobility in a High-Pressure Economy. *Brookings Papers on Economic Activity 4*, 207–262.

Patterson, C. (2021). The Matching Multiplier and the Amplification of Recessions. *Working Paper*.

Republicans, J. E. C. (2019). Losing our minds: Brain drain across the united states. *SCP Report 2-19*.

Rossi-Hansberg, E., P.-D. Sarte, and F. Schwartzman (2019). Cognitive hubs and spatial redistribution. *NBER Working Paper 26267*.

Russ, K. N. and J. C. Shambaugh (2019, October). Education and unequal regional labor market outcomes: The persistence of regional shocks and employment responses to trade shocks. *Unpublished conference proceedings, Federal Reserve Bank of Boston 63rd Economic Conference, A House Divided: Geographic Disparities in Twenty-First Century America*.

von Lockette, N. D. and W. Spriggs (2016). Wage dynamics and racial and ethnic occupational segregation among less-educated men in metropolitan labor markets. *Review of Black Political Economy 43*, 35–56.

Willingham, C. Z. and O. Ajilore. Effective and ethical rural development. In A. Dumont and D. P. Davis (Eds.), *Investing in Rural Prosperity*. St. Louis, Missouri, USA: Federal Reserve Bank of St. Louis.

Wolfers, J. (2019). Comment on: Okun Revisited: Who Benefits Most from a Strong Economy. *Brookings Papers on Economic Activity*, 385–404.

A Revisiting Aaronson et al. (2019)

In this literature on cyclical sensitivity broken down by worker characteristics, the basic methodological setup is a regression of the gap in the unemployment rate between a group g at time t and some other group used as a benchmark on a measure of the business cycle:

$$UR_{g,t} - UR_{\text{benchmark},t} = \alpha_g + \beta_g(UGAP_t) + \epsilon_{g,t} \tag{4}$$

For example, a commonly estimated gap is the Black-White unemployment gap and which is then regressed on a measure of the business cycle ($UGAP$, typically the gap between the national unemployment rate and the CBO measure of the long run unemployment rate). A focus on gaps helps remove concerns around long-run trends and stationarity that have played a major role in some prior examinations of regional cyclical sensitivity discussed above.

A.1 Data

To provide context for our county-level analysis, we recreate the (national) Aaronson et al (2019) regressions using Eq.(4) and data from the U.S. Bureau of Labor Statistics,[17] here with the sample period 1976Q1-2019Q4 for black-white gaps, and 1992Q1-2019Q4 for education gaps due to a shorter series for measures of education.

For the male Black and male white unemployment rate, Labor Force Statistics from the Current Population Survey are aalso available at `https://www.bls.gov/cps/data.htm`. Click on link to the Data Finder for Labor Force Statistics and enter the series identifiers into the search box: LNS14000007 and LNS14000004. Adjust the sample to begin at 1972.

For other unemployment rates, one can use the same portal, or we used the FRED aggregator portal for convenience. Series identifiers for Black and white overall unemployment rate gaps are LNS14000006 and LNS14000006. Series identifiers for Less than High School Diploma ("<HS"), High School Graduates No College ("HS"), Some College or Associate Degree ("Some college"),

[17]Data for black male and white male (series LNS14000007 and LNS14000004) unemployment rates downloaded directly from *Labor Force Statistics from the Current Population Survey.* BLS data on unemployment rates for overall black and overall white and by educational group downloaded via Federal Reserve Economic Data database (LNS14000003, LNS14000006, LNS14027659, LNS14027660, LNS14027689, LNS14027662), as were the series for the natural rate of unemployment and national unemployment rate (series names NROU and UNRATE).

and Bachelor's Degree ("BA") are, respectively, LNS14027659, LNS14027660, LNS14027689, and LNS14027662.

In all regressions, the national unemployment rate (quarterly, seasonally adjusted) and long-term natural rate (quarterly) are from FRED, with series identifiers UNRATE and NROU. Since the long-term natural rate already is smoothed, it is not seasonally adjusted.

A.2 Cyclicality by demographic group

Table A.1 shows that the coefficient β_g in Eq.(4) for the gap between unemployment rates of Black versus White men is 0.9. For the overall Black-White gap, it is 0.7. In such a formulation, a β_g of zero means the two groups' unemployment rates move up and down together when the economy overall has a rising or falling unemployment rate. That is, there is no change in the gap between groups as the national unemployment rises or falls. A β-coefficient of nearly 1 for the Black-White unemployment rate gap means that the Black unemployment rate rises a full point more than the White rate whenever the economy overall has an unemployment rate that rises 1 point above the CBO long run rate. The constant (α) in the regression shows the base level of unemployment for the groups. The β_g-coefficient for the gap between workers with a less than a high school degree versus those with a college degree generate a β-coefficient of 1.0 while those with a high school degree have a β of 0.6, closing the gap somewhat.

The constant (α_g) in the Black-White regressions is 6, indicating a Black-White unemployment gap of 6 percentage points on average when the economy is overall at the CBO long run rate. It is somewhat higher than the constant for the gap between workers without a high school degree versus those with a Bachelor's degree, though the differences are not statistically distinguishable.

Table A.1: Regression of national unemployment rate gaps by demographic group on national unemployment gap

	1976 q1-2019 q4		1992 q1-2019 q4		
	Male Black - Male White	Black - White	<HS - college degree	HS - college degree	Some college - BA
Ugap	0.913***	0.711***	1.001***	0.621***	0.462***
	(0.0659)	(0.0753)	(0.0439)	(0.0159)	(0.0120)
Constant	6.077***	5.760***	5.399***	2.341***	1.502***
	(0.115)	(0.132)	(0.0810)	(0.0294)	(0.0222)
N	176	176	112	112	112
R^2	0.524	0.339	0.825	0.932	0.931

Notes: Regressions based on Aaronson et al. (2019). Data for black male and white male (series LNS14000007 and LNS14000004) unemployment rates downloaded directly from *Labor Force Statistics from the Current Population Survey.* BLS data on unemployment rates for overall black and overall white and by educational group downloaded via Federal Reserve Economic Data database (LNS14000003, LNS14000006, LNS14027659, LNS14027660, LNS14027689, LNS14027662), as were the series for the natural rate of unemployment and national unemployment rate (series names NROU and UNRATE). Sample periods are 1976Q1-2019Q4 for black-white gaps, and 1992Q1-2019Q4 for education gaps due to a shorter series for measures of education. See Data Appendix below for more detail. Standard errors in parentheses.

B Summary Statistics for US County-Level Data

Table A.2: County-Level Variables for Examination of Regional Adjustment in Eq.(2): Summary statistics

	N	Mean	S.D.	Min	Max
noHSdegPct1990	3132	30.37	10.37	4.5	68.4
COLgradPct1990	3132	13.52	6.58	3.7	53.4
BlackPct1990	3132	8.58	14.34	0	86.236
PctEmpinMfg1990	3132	18.49	10.60	0	53.7
PctEmpinPubAdm1990	3132	4.89	3.09	1.3	37.3
PopPerSqMile1990	3109	223.67	1435.22	1	52432
MedHomeValue1990	3132	54141.31	33572.52	14999	487300
MedHHMoneyInc1990	3132	23983.66	6605.36	8595	59284
SavingsDepPerCap1990	3131	10.46	5.28	0	98.348
Alpha	3206	0.58	2.50	-3.149	16.897
Beta	3206	-0.06	0.41	-1.453	1.680

Notes: Unconditional Alpha and Beta are coefficients from Eq.(2). County characteristics are from the US Bureau of the Census County Data Book digital format in ICPSR 2896 DS80: 100-var070, 100-var071, 100*(var010/var005), var136, var140, var004, var105, var079, and var197.

C Data Detail

C.1 Figures 1 and 2: State unemployment rates

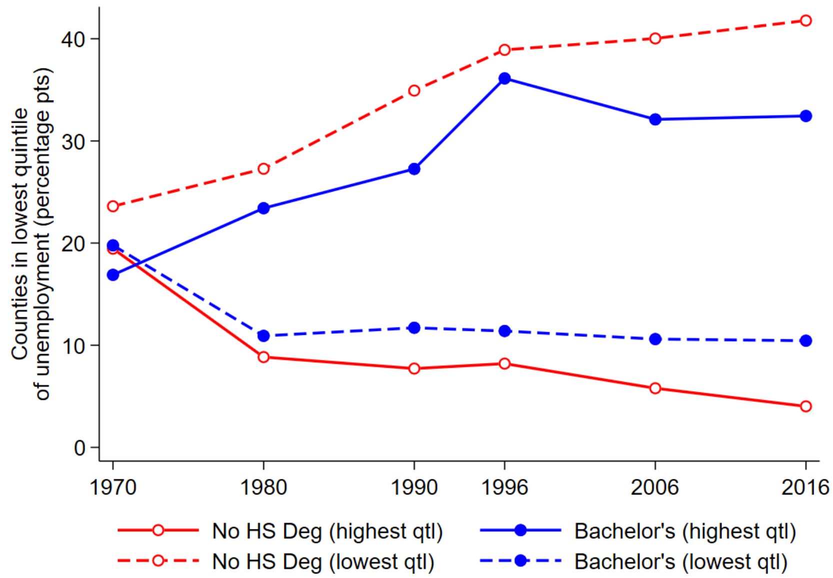
Data downloaded from the Federal Reserve Economic Data (FRED) aggregator portal at `https://fred.stlouisfed.org`. Series identifiers are 4 letters, with the first two letters the state's two-letter postal abbreviation and the second two letters "UR" for unemployment rate. Figures constructed in Excel.

C.2 County-level unemployment rates and county characteristics

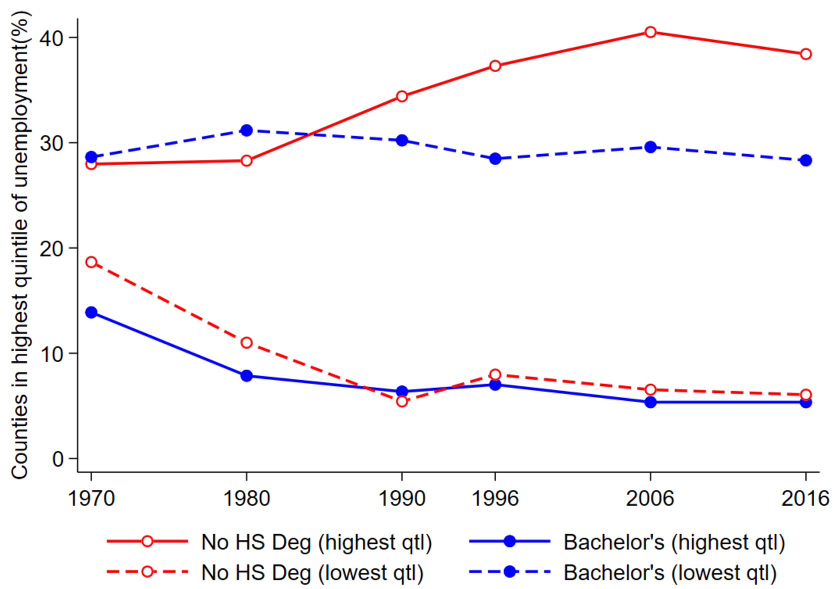
County-level unemployment rates for 1970 and 1980 are from the US Bureau of the Census County Data Books in digital format through ICPSR 2896, DS76 and DS78, available at `https://www.icpsr.umich.edu/web/ICPSR/studies/2896/datadocumentation`. County characteristics are all set to 1970 values and also from ICPSR 2896 DS76 (1972 County Data Book). Unemployment rates for 1990 onward are from the U.S. Bureau of Labor Statistics Local Area Unemployment Statistics (LAUS). Download County Data Tables by year at `https://www.bls.gov/lau/#tables`).

D Supplemental Figures

Figure A.1: Labor Market Outcomes in Counties, by Education Levels of Population in 1970



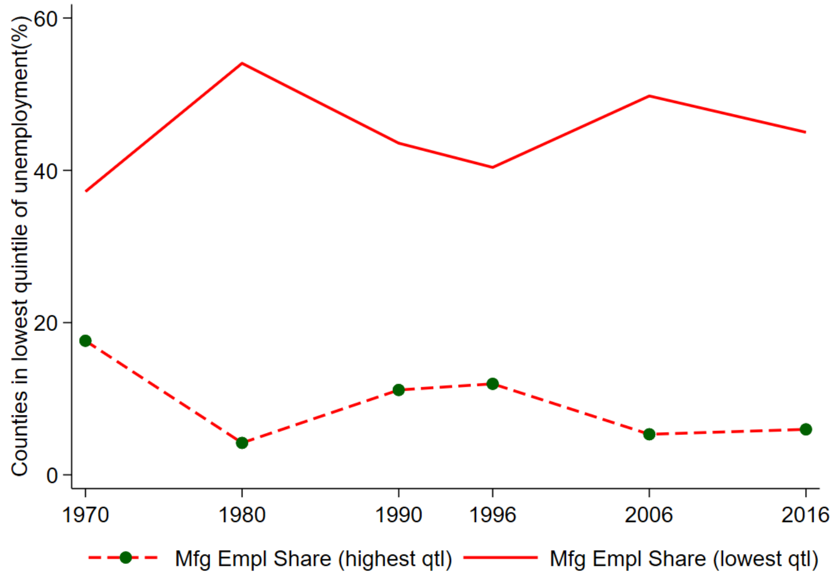
(a) Percentage of U.S. Counties in Bottom Quintile of Unemployment Rate 1970-2016



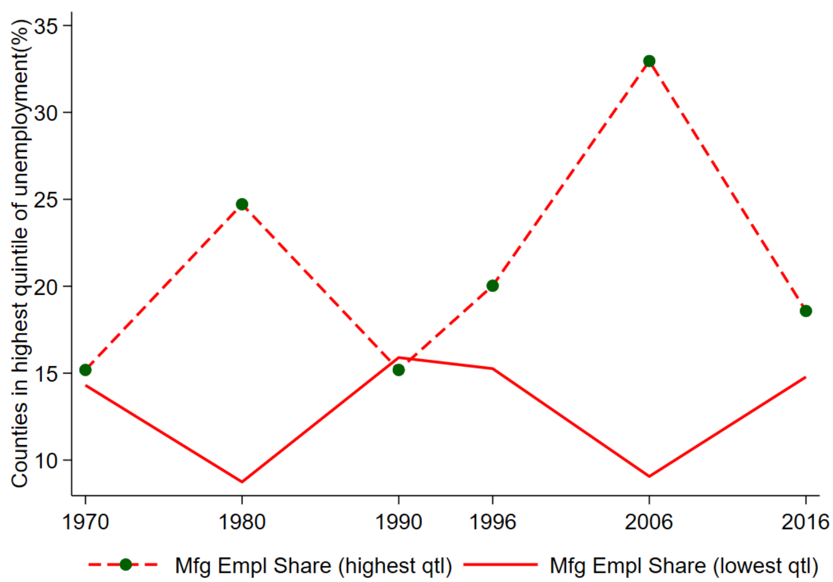
(b) Percentage of U.S. Counties in Top Quintile of Unemployment Rate 1970-2016

Source: Education levels by county in 1970 and unemployment rates in 1970 and 1980 from U.S. Bureau of the Census County Data Books, via University of Michigan ICPSR 2896; unemployment rates by county 1990-2016 from U.S. Bureau of the Census LAUS.

Figure A.2: Labor Market Outcomes in Counties, by Fraction of Employment in Manufacturing Industries in 1970



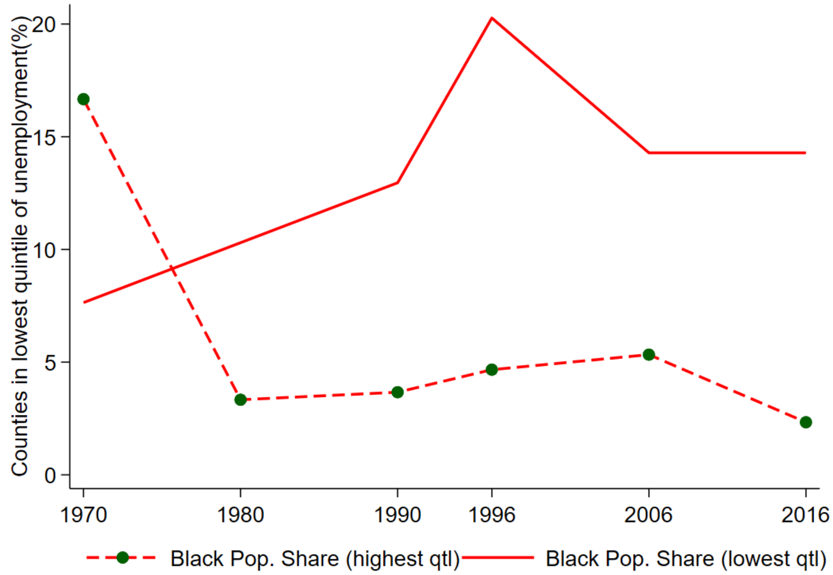
(a) Percentage of U.S. Counties in Lowest Quintile of Unemployment Rate 1970-2016



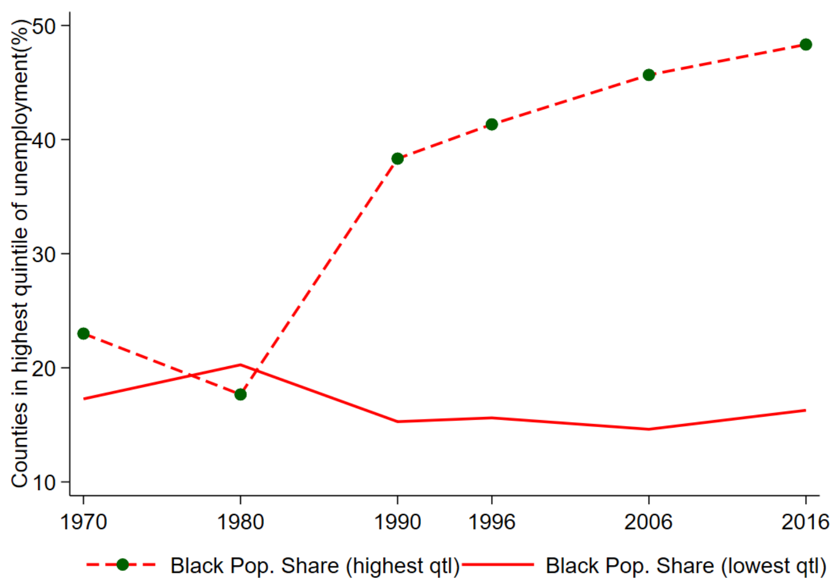
(b) Percentage of U.S. Counties in Top Quintile of Unemployment Rate 1970-2016

Notes: Fraction of workers in manufacturing by county in 1970 and unemployment rates in 1970 and 1980 from U.S. Bureau of the Census County Data Books, via University of Michigan ICPSR 2896; unemployment rates by county 1990-2016 from U.S. Bureau of the Census LAUS.

Figure A.3: Labor Market Outcomes in Counties, by Racial Composition of Population in 1970



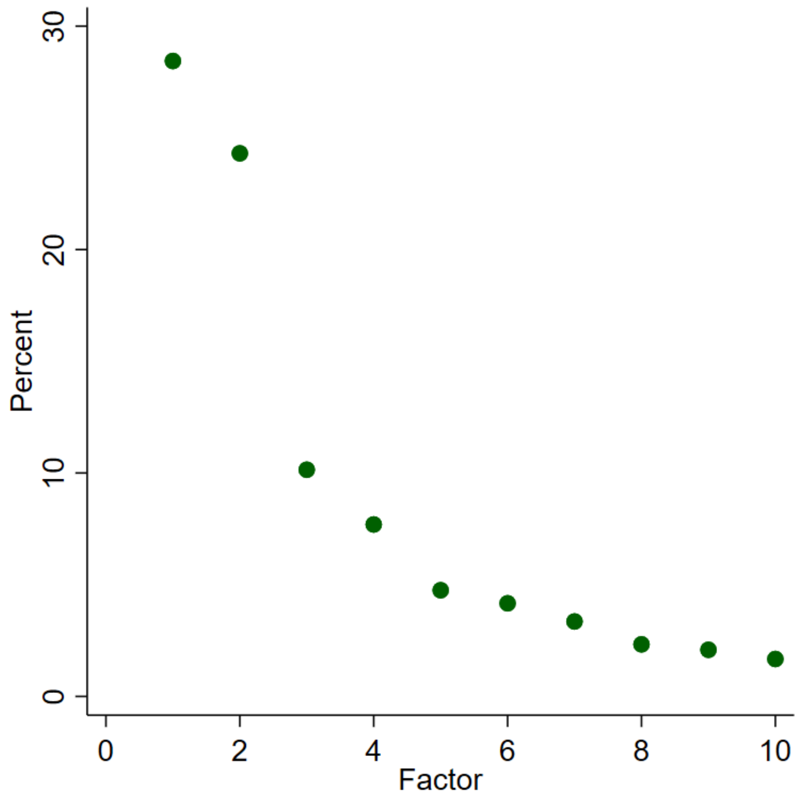
(a) Percentage of U.S. Counties in Lowest Quintile of Unemployment Rate 1970-2016



(b) Percentage of U.S. Counties in Top Quintile of Unemployment Rate 1970-2016

Notes: Fraction of Black residents by county in 1970 and unemployment rates in 1970 and 1980 from U.S. Bureau of the Census County Data Books, via University of Michigan ICPSR 2896; unemployment rates by county 1990-2016 from U.S. Bureau of the Census LAUS.

Figure A.4: Percentage of variance accounted for by each factor



Notes: First 10 factors extracted from the panel of county unemployment rates as described in Section 5.2.

Figure A.5: Heterogeneity in estimated half-life of adjustment in county-level unemployment

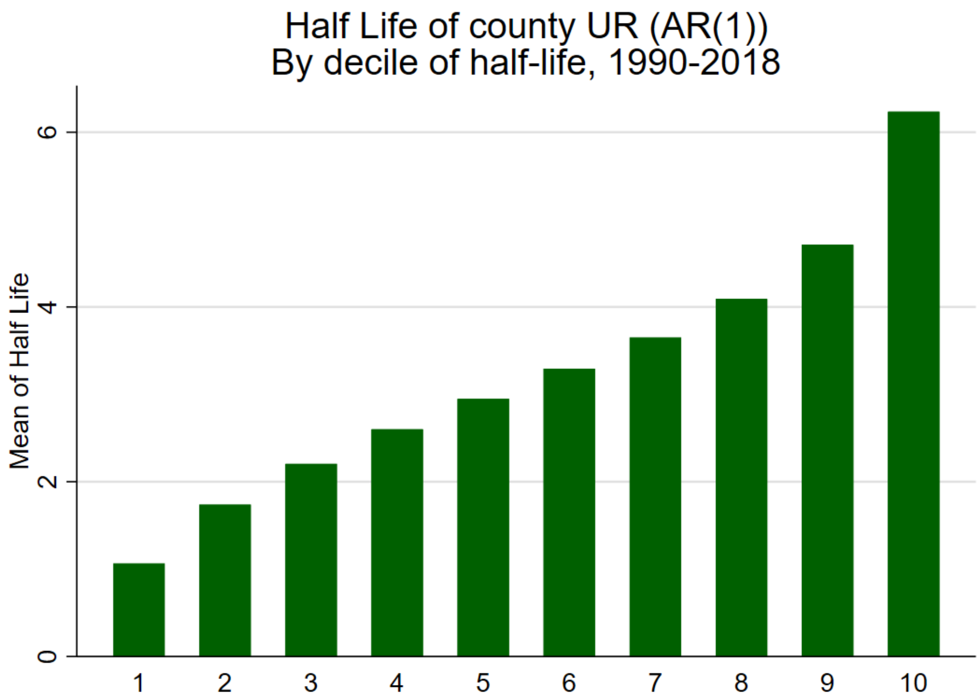


Figure A.6: Half-life of adjustment in county-level unemployment and α_i

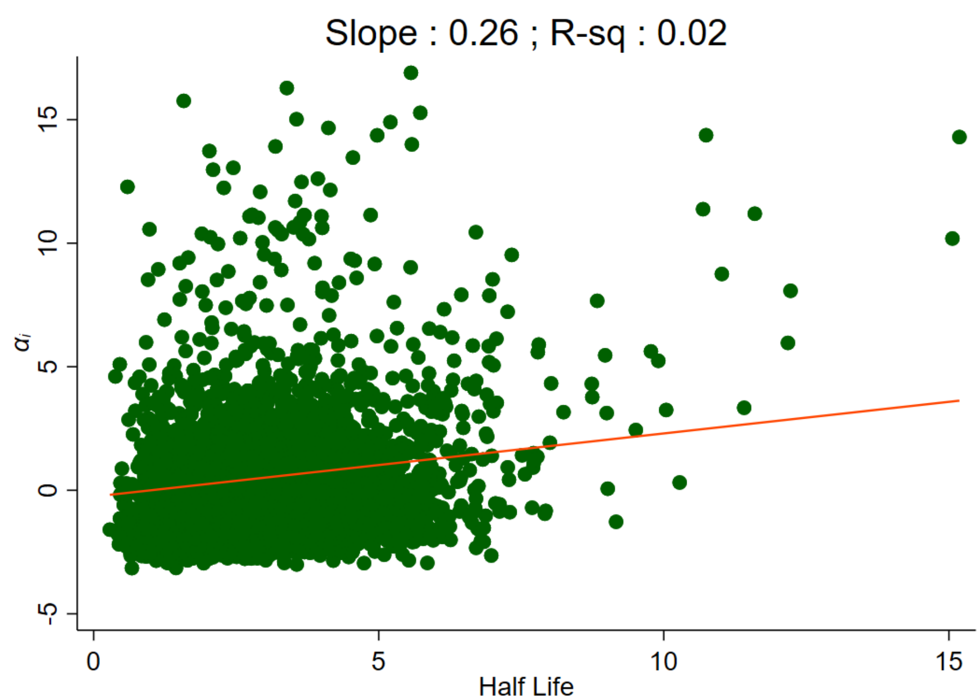


Figure A.7: Half-life of adjustment in county-level unemployment and β_i

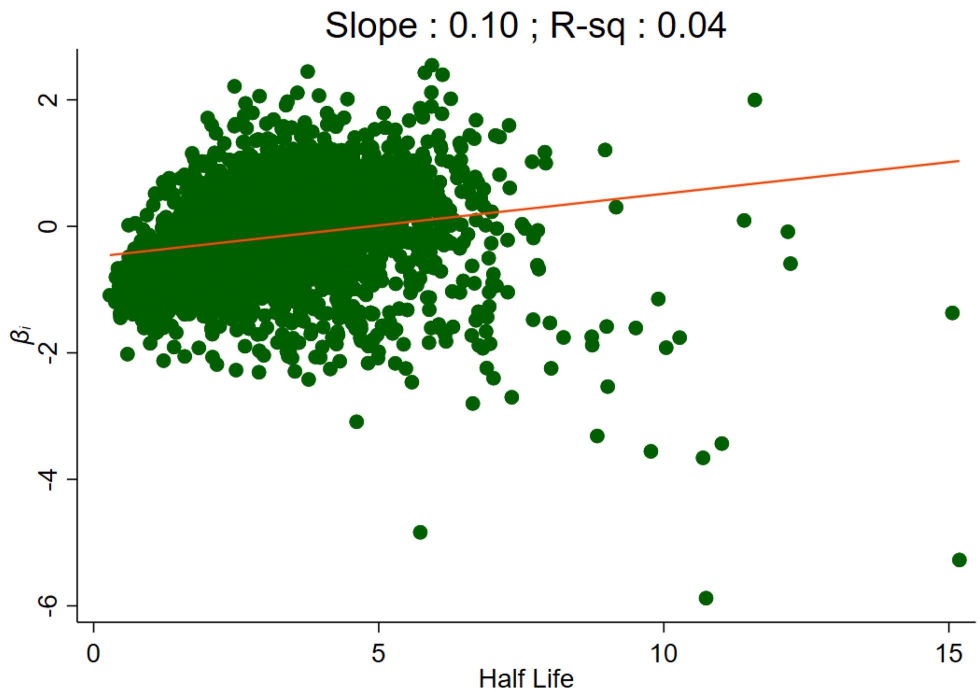


Figure A.8: Half-life of adjustment in county-level unemployment and $\lambda_1 i$

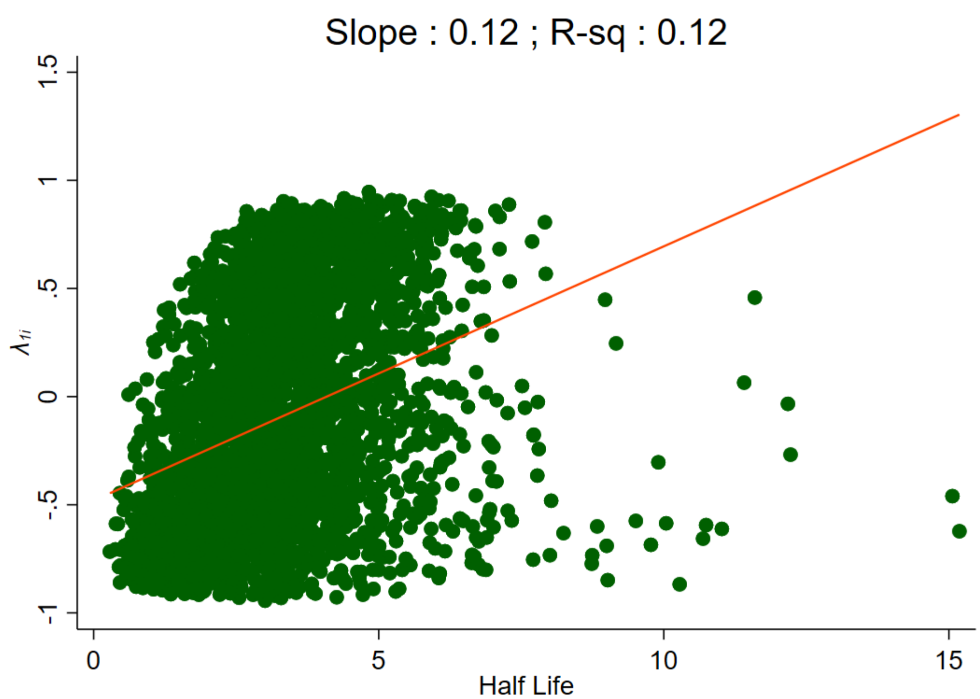


Figure A.9: Half-life of adjustment in county-level unemployment and $\lambda_2 i$

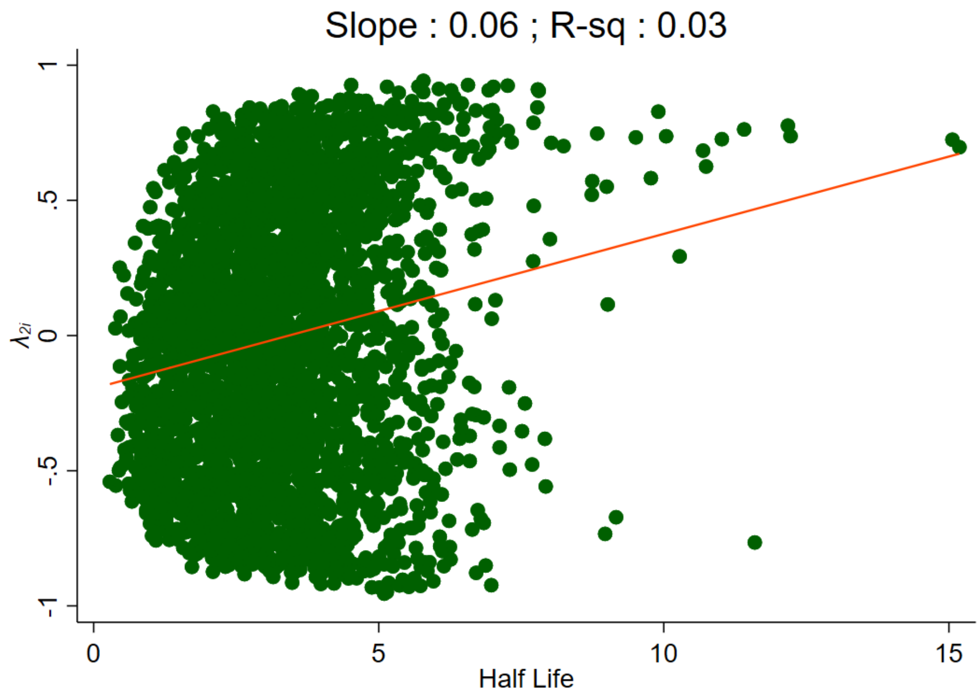
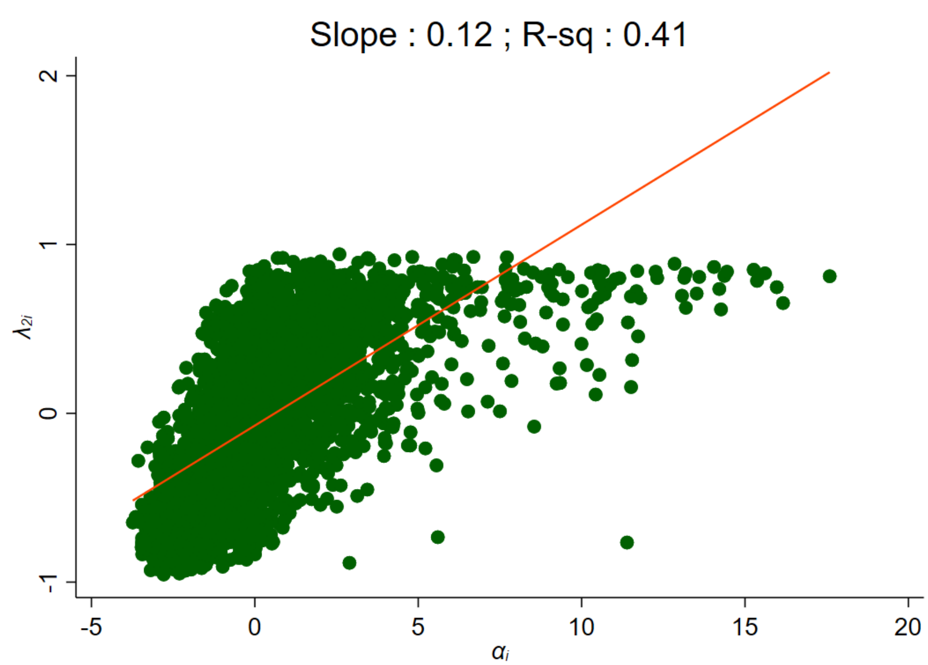


Figure A.10: Factor 2 Loadings and α_i



E Supplemental Tables

Table A.3: Correlation of the average county-level unemployment gap with county characteristics(raw coefficients)

	Dependent variable: α_i						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
noHSdegPct1990	0.0991***				0.0817***	0.0392*	0.0856***
	(0.00895)				(0.0144)	(0.0165)	(0.0173)
COLgradPct1990		-0.111***			-0.0203	-0.0447*	0.00882
		(0.00989)			(0.0189)	(0.0168)	(0.0176)
BlackPct1990			0.0396***		0.0158*	0.00788	0.0224**
			(0.00911)		(0.00740)	(0.00663)	(0.00658)
PctEmpinMfg1990				0.0387**	0.000451	0.0177	0.00937
				(0.0113)	(0.0115)	(0.00978)	(0.00864)
PctEmpinPubAdm1990						0.0558*	0.0444
						(0.0260)	(0.0242)
PopPerSqMile1990						0.0000180	0.0000336
						(0.0000386)	(0.0000348)
MedHomeValue1990						0.0000248***	0.00000335
						(0.00000301)	(0.00000746)
MedHHMoneyInc1990						-0.000134***	-0.0000928***
						(0.0000240)	(0.0000231)
SavingsDepPerCap1990						-0.0876***	-0.0454*
						(0.0201)	(0.0189)
_cons	-2.659***	1.857***	0.0131	-0.365	-1.999*	1.860	-0.455
	(0.348)	(0.252)	(0.205)	(0.320)	(0.830)	(0.992)	(0.930)
N	3123	3123	3123	3123	3123	3099	3098
R^2	0.255	0.130	0.077	0.041	0.265	0.386	0.597
State FE	N	N	N	N	N	N	Y

Notes: In any year t, the county-level unemployment gap is the county's unemployment rate minus the median county unemployment rate in that year. The dependent variable is the average county-level gap over the sample period (1990-2018) for each county, obtained from Eq. 2. Clustering by state. County characteristics from US Bureau of the Census *1994 County Data Book* (ICPSR DS80). See Data Appendix for detail. Standard errors are in parentheses and clustered at the state level in all specifications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: Correlation of cyclicality β_i of county-level unemployment gap with county characteristics (raw coefficients)

	Dependent variable: β_i						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
noHSdegPct1990	0.00736				-0.000493	-0.00151	-0.00507
	(0.00410)				(0.00440)	(0.00445)	(0.00275)
COLgradPct1990		-0.00621			0.00525	-0.00870*	-0.00515**
		(0.00315)			(0.00398)	(0.00387)	(0.00184)
BlackPct1990			0.00800***		0.00436*	0.00403*	0.00303*
			(0.00225)		(0.00169)	(0.00168)	(0.00115)
PctEmpinMfg1990				0.0214***	0.0212***	0.0193***	0.0109***
				(0.00270)	(0.00262)	(0.00258)	(0.00148)
PctEmpinPubAdm1990						0.00219	-0.00410
						(0.00313)	(0.00278)
PopPerSqMile1990						-0.0000130	-0.00000386
						(0.00000704)	(0.00000450)
MedHomeValue1990						0.00000443***	0.00000140
						(0.000000784)	(0.000000904)
MedHHMoneyInc1990						-0.00000167	-0.00000474
						(0.00000464)	(0.00000298)
SavingsDepPerCap1990						-0.00896*	-0.00221
						(0.00335)	(0.00198)
_cons	-0.286*	0.0213	-0.131*	-0.459***	-0.548**	-0.403	0.0156
	(0.119)	(0.0871)	(0.0614)	(0.0741)	(0.184)	(0.213)	(0.126)
N	3123	3123	3123	3123	3123	3099	3098
R^2	0.034	0.010	0.077	0.302	0.330	0.402	0.709
State FE	N	N	N	N	N	N	Y

Notes: In any year t, the county-level unemployment gap is the county's unemployment rate minus the median county unemployment rate in that year. Cyclicality is the coefficient β_i for each county estimated from Eq.(2). Clustering by state. County characteristics from US Bureau of the Census *1994 County Data Book* (ICPSR DS80). See Data Appendix for detail. Standard errors are clustered at the state level in all specifications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.5: Regression of Factor 1 Loadings on County Characteristics

	Dependent Variable: λ_{1i}						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
noHSdegPct1990	0.130				-0.008	0.060	-0.086
COLgradPct1990		-0.040			0.138*	0.007	0.007
BlackPct1990			0.229**		0.108	0.110*	0.042
PctEmpinMfg1990				0.508***	0.529***	0.460***	0.203***
PctEmpinPubAdm1990						0.004	-0.017
PopPerSqMile1990						-0.036	-0.013
MedHomeValue1990						0.110	0.030
MedHHMoneyInc1990						0.166	0.082
SavingsDepPerCap1990						-0.065	-0.005
N	3123	3123	3123	3123	3123	3099	3098
R^2	0.017	0.002	0.052	0.258	0.287	0.321	0.662
State FE	N	N	N	N	N	N	Y

Notes: Standardized beta coefficients. Factor 1 loadings are coefficients from Eq.(3). County characteristics are from the US Bureau of the Census County Data Book digital format in ICPSR 2896 DS80: 100-var070, 100-var071, 100*(var010/var005), var136, var140, var004, var105, var079, and var197. Standard errors clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.6: Regression of Factor 2 Loadings on County Characteristics

	Dependent Variable: λ_{2i}						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
noHSdegPct1990	0.327***				0.278**	0.079	0.102
COLgradPct1990		-0.260***			-0.052	-0.341***	-0.248***
BlackPct1990			0.111		-0.014	-0.058	0.021
PctEmpinMfg1990				0.168**	0.055	0.069	0.040
PctEmpinPubAdm1990						0.052	-0.031
PopPerSqMile1990						-0.019	0.002
MedHomeValue1990						0.681***	0.298**
MedHHMoneyInc1990						-0.395***	-0.368***
SavingsDepPerCap1990						-0.198***	-0.118**
N	3123	3123	3123	3123	3123	3099	3098
R^2	0.107	0.067	0.012	0.028	0.112	0.293	0.497
State FE	N	N	N	N	N	N	Y

Notes: Standardized beta coefficients. Factor 2 loadings are coefficients from Eq.(3). County characteristics are from the US Bureau of the Census County Data Book digital format in ICPSR 2896 DS80: 100-var070, 100-var071, 100*(var010/var005), var136, var140, var004, var105, var079, and var197. Standard errors clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.7: Regression of Factor 1 Loadings on county China shock exposure

	Dependent Variable : λ_{1i}					
	(1)	(2)	(3)	(4)	(5)	(6)
ChinaShock	0.230***					
highest_ChinaShock		0.241***		0.003	0.021	0.004
lowest_ChinaShock			-0.298***	-0.019	-0.011	0.007
noHSdegPct1990				-0.008	0.059	-0.087
COLgradPct1990				0.133*	0.001	0.007
BlackPct1990				0.107	0.110*	0.043
PctEmpinMfg1990				0.517***	0.443***	0.205***
PctEmpinPubAdm1990					0.004	-0.018
PopPerSqMile1990					-0.036	-0.013
MedHomeValue1990					0.109	0.031
MedHHMoneyInc1990					0.168	0.081
SavingsDepPerCap1990					-0.067*	-0.005
N	3097	3123	3123	3123	3099	3098
R^2	0.053	0.058	0.089	0.287	0.321	0.662
State FE	N	N	N	N	N	Y

Notes: Standardized beta coefficients. Factor 1 loadings are coefficients from Eq.(3). ChinaShock is the measure of the change of imports per worker weighted by county-level employment shares constructed by Autor, Dorn, and Hanson (2013, labelled dipw9107 in their replication package). The prefix "highest" (lowest") indicates a county is in the top (bottom) quintile for ChinaShock. County characteristics are from the US Bureau of the Census County Data Book digital format in ICPSR 2896 DS80: 100-var070, 100-var071, 100*(var010/var005), var136, var140, var004, var105, var079, and var197. Standard errors clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.8: Regression of Factor 2 Loadings on county China shock exposure

	Dependent Variable : λ_{2i}					
	(1)	(2)	(3)	(4)	(5)	(6)
ChinaShock	0.080					
highest_ChinaShock		0.074		0.001	0.019	0.020
lowest_ChinaShock			-0.131**	-0.132***	-0.107**	-0.074***
noHSdegPct1990				0.282**	0.085	0.113
COLgradPct1990				-0.079	-0.361***	-0.264***
BlackPct1990				-0.023	-0.064	0.016
PctEmpinMfg1990				-0.019	-0.001	-0.006
PctEmpinPubAdm1990					0.053	-0.029
PopPerSqMile1990					-0.018	0.003
MedHomeValue1990					0.668***	0.293**
MedHHMoneyInc1990					-0.386***	-0.356***
SavingsDepPerCap1990					-0.202***	-0.122**
N	3097	3123	3123	3123	3099	3098
R^2	0.006	0.005	0.017	0.124	0.301	0.501
State FE	N	N	N	N	N	Y

Notes: Standardized beta coefficients. Factor 2 loadings are coefficients from Eq.(3). ChinaShock is the measure of the change of imports per worker weighted by county-level employment shares constructed by Autor, Dorn, and Hanson (2013, labelled dipw9107 in their replication package). The prefix "highest" (lowest") indicates a county is in the top (bottom) quintile for ChinaShock. County characteristics are from the US Bureau of the Census County Data Book digital format in ICPSR 2896 DS80: 100-var070, 100-var071, 100*(var010/var005), var136, var140, var004, var105, var079, and var197. Standard errors clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.9: Regression of Factor 1 Loadings on county product cycle characteristics

	Dependent Variable : λ_{1i}					
	(1)	(2)	(3)	(4)	(5)	(6)
prodcycle	-0.017					
move_in_1960_1980		0.103*		-0.006	0.006	-0.002
move_out_1960_1980			0.236***	0.119**	0.090*	0.030
noHSdegPct1990				-0.002	0.051	-0.090
COLgradPct1990				0.129*	0.011	0.007
BlackPct1990				0.126*	0.123*	0.044
PctEmpinMfg1990				0.491***	0.438***	0.202***
PctEmpinPubAdm1990					0.005	-0.017
PopPerSqMile1990					-0.043*	-0.013
MedHomeValue1990					0.113	0.030
MedHHMoneyInc1990					0.137	0.075
SavingsDepPerCap1990					-0.060	-0.002
N	3095	3123	3123	3123	3099	3098
R^2	0.000	0.011	0.056	0.300	0.328	0.663
State FE	N	N	N	N	N	Y

Notes: Standardized beta coefficients. Factor 1 loadings are coefficients from Eq.(3). The variable "product cycle" is the difference between ChinaShock exposure in 1980 and 1960, as computed by Eriksson et al. (2021). The variable "move in" indicates the top quintile of product cycle movement (experienced the greatest increase in exposure to the China shock between 1960 and 1980), while "move out" indicates the bottom quintile, which have negative values. Other county characteristics are from the US Bureau of the Census County Data Book digital format in ICPSR 2896 DS80: 100-var070, 100-var071, 100*(var010/var005), var136, var140, var004, var105, var079, and var197. Standard errors clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.10: Regression of Factor 2 Loadings on county product cycle characteristics

	Dependent Variable : λ_{2i}					
	(1)	(2)	(3)	(4)	(5)	(6)
prodcycle	0.012					
move_in_1960_1980		0.074**		0.023	0.036	0.052***
move_out_1960_1980			0.055	0.063	0.047	-0.018
noHSdegPct1990				0.279**	0.074	0.109
COLgradPct1990				-0.057	-0.341***	-0.248***
BlackPct1990				-0.008	-0.055	0.015
PctEmpinMfg1990				0.029	0.048	0.026
PctEmpinPubAdm1990					0.052	-0.032
PopPerSqMile1990					-0.022	0.003
MedHomeValue1990					0.681***	0.296**
MedHHMoneyInc1990					-0.405***	-0.355***
SavingsDepPerCap1990					-0.199***	-0.126**
N	3095	3123	3123	3123	3099	3098
R^2	0.000	0.005	0.003	0.115	0.295	0.500

Notes: Standardized beta coefficients. Factor 2 loadings are coefficients from Eq.(3). The variable "product cycle" is the difference between ChinaShock exposure in 1980 and 1960, as computed by Eriksson et al. (2021). The variable "move in" indicates the top quintile of product cycle movement (experienced the greatest increase in exposure to the China shock between 1960 and 1980), while "move out" indicates the bottom quintile, which have negative values. Other county characteristics are from the US Bureau of the Census County Data Book digital format in ICPSR 2896 DS80: 100-var070, 100-var071, 100*(var010/var005), var136, var140, var004, var105, var079, and var197. Standard errors clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$