

SECULAR LABOR REALLOCATION AND BUSINESS CYCLES*

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Abstract

We revisit an old question: does industry labor reallocation affect the business cycle? Our empirical methodology exploits variation in a local labor market's exposure to industry reallocation based on the area's initial industry composition and national industry employment trends for identification. Applied to confidential employment data over 1980-2014, we find sharp evidence of reallocation contributing to higher local area unemployment if it occurs during a national recession, but little difference in outcomes during an expansion. A multi-area, multi-sector search and matching model with imperfect mobility across industries and downward nominal wage rigidity can reproduce these cross-sectional patterns.

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1. Introduction

Industries experience idiosyncratic shocks, generating changes in the distribution of employment. Whether such industry labor reallocation matters quantitatively in causing, amplifying, or propagating the business cycle has important implications for our understanding of business cycles, labor markets, and the scope for policy. Yet, the issue remains unsettled.

We study the consequences of secular labor reallocation, defined as the change in an economy’s allocation of labor in response to mean-preserving, long-lasting idiosyncratic industry shocks. We make two main contributions. First, we propose a novel method to estimate how secular labor reallocation affects local labor markets and implement it using confidential administrative employment data. Different from much of the literature exploring the “sectoral shifts” hypothesis, we examine whether the consequences of reallocation depend on the phase of the business cycle. We find they do. More reallocation implies higher unemployment during a recession, but roughly neutral effects when it occurs during an expansion. Second, we show that a multi-area, multi-sector search-and-matching model featuring realistic frictions to sectoral mobility and downward wage rigidity can rationalize this result.

Our analysis starts in Section 2 with a description of our empirical identification strategy. A number of challenges arise. First, the small number of national business cycles in periods with high frequency, high quality industry level data limit inference based only on national variation. Second, realized reallocation within a business cycle may reflect cyclical sensitivities that vary across industries (Abraham and Katz, 1986), and business cycles can cause permanent reallocation of inputs (Schumpeter, 1942). Third, we generally do not observe pure cross-industry dispersion shocks which do not also affect the mean of variables such as productivity. To circumvent the small number of national business cycles, we use variation in reallocation and business cycle outcomes across broadly defined local labor markets in the United States. To isolate long-lasting shocks, our metric of reallocation sums the absolute value of industry employment share changes between the start and end of a recession-recovery or expansion cycle, thereby filtering out cyclical changes which occur during a recession but reverse during a recovery. We address the endogeneity of reallocation to local conditions by developing a Bartik-style measure of predicted reallocation based on a local area’s initial industry composition and industry employment changes in the rest of the country and use this measure as an instrument for actual reallocation. Finally, we account for non mean-preserving industry shifts by controlling directly for the Bartik predicted employment growth rate given an area’s industry composition. Thus, our empirical specification regresses local area unemployment on local area reallocation, controlling for predicted growth and with reallocation instrumented using predicted reallocation. Intuitively, the research design compares outcomes in areas with the same predicted employment growth but different predicted reallocation.

We implement our exercise using confidential employment data by local area and industry from the Bureau of Labor Statistics Longitudinal Database merged with the public use counterpart of these data, the QCEW. We use the public use version to extend the analysis back to 1979. The resulting data set tracks industry reallocation in more than 200 urban local labor markets. We describe these data in detail in Section 3.

Section 4 contains our empirical analysis. Predicted reallocation is a strong instrument for actual reallocation except around the 1990 recession due to a change in the data collection procedure at that time. We therefore introduce a two sample two stage least squares design where we estimate the first stage excluding the 1990 episode but include it in the second stage and derive the standard error formula appropriate to this setting. Our formula should prove useful in other settings where researchers encounter missing data.

We obtain two main empirical results. First, higher reallocation causes higher unemployment. Second, this average response masks a crucial asymmetry. During a recession-recovery, a one standard deviation increase in predicted reallocation raises unemployment by roughly 0.5 p.p. at the national recession trough, with the effect then dissipating over the subsequent recovery. In contrast, reallocation does not affect unemployment during an expansion. These results are statistically strong, are not driven by particular sectors or areas, and are robust to inclusion of local area time-varying control variables or local area fixed effects.

Section 5 introduces a multi-sector, multi-area model of reallocation and unemployment to provide a structural interpretation of our results. Each area in the model contains a number of industries consisting of firms and workers who interact according to a search and matching framework subject to a downward nominal wage constraint. The shares of workers and firms in each industry depend on industry-specific productivity and consumer preferences. In line with the data, the model features two-way gross flows of workers across industries each period. We shock the model with an increase in the cross-sectional variance of industry-level productivities and estimate the same regression in the model as in the data. Specifically, we estimate the marginal effect of reallocation on unemployment during an “expansion,” in which the increase in the cross-sectional variance of industry productivity constitutes the only set of shocks, and a “recession,” in which borrowers simultaneously face an increase in the interest rate.

Without any labor market or wage-setting frictions, reallocation across industries would occur instantaneously and without generating any unemployment. Allowing for only within-industry search and matching frictions, the mean-preserving spread in industry productivities generates a small increase in unemployment regardless of whether it occurs coincident with a demand-induced recession or not. Incorporation of frictions to moving across industries and empirically plausible downward wage rigidity breaks this symmetry. Intuitively, during expansions higher wages draw job seekers into the expanding sectors, while wage compression during recessions pushes the adjustment into a larger difference in job finding rates. We construct

impulse response functions of the cross-area marginal effect of reallocation on unemployment in model-simulated data and find they accord well with our empirical results.

Related literature. The paper relates to literatures on the causes and consequences of input reallocation and business cycles. In an early and influential contribution, [Lilien \(1982\)](#) argued that sectoral shifts were responsible for much of the fluctuations in unemployment in the 1970s, a point subsequently disputed by [Abraham and Katz \(1986\)](#) and [Murphy and Topel \(1987\)](#). Their critiques inform our methodological approach. Debate over the importance of sectoral reallocation has renewed in the context of the slow recoveries from the most recent two national recessions.¹ Different from the [Lilien \(1982\)](#) question of whether business cycle downturns coincide with more restructuring, we find a connection between reallocation and the business cycle because of the greater ease with which labor markets absorb a given amount of reallocation when it occurs during an expansion rather than a recession-recovery.

Methodologically, our paper follows [Autor, Dorn, and Hanson \(2013\)](#) and [Charles, Hurst, and Notowidigdo \(2014\)](#) in using industry shocks to local labor markets. Our paper differs in its focus on business cycles outcomes. As such, we construct a Bartik measure that does not rely on a specific source of sectoral reallocation. We validate our identification strategy following recommendations in [Goldsmith-Pinkham, Sorkin, and Swift \(2018\)](#) and [Borusyak, Hull, and Jaravel \(2018\)](#). Our results complement work on the consequences of reallocation at the worker level ([Jaimovich and Siu, 2014](#); [Fujita and Moscarini, 2013](#); [Davis and Haltiwanger, 2014](#)).

Our general equilibrium search-and-matching model with nominal frictions builds on [Christiano, Eichenbaum, and Trabandt \(2016\)](#) and earlier work by [Walsh \(2005\)](#). We incorporate an industry structure and labor reallocation frictions following [Kline \(2008\)](#), [Pilossoph \(2014\)](#), and [Dvorkin \(2014\)](#). Downward nominal wage rigidity has recently been emphasized by [Schmitt-Grohé and Uribe \(2016\)](#), and [Daly and Hobijn \(2014\)](#), and following [Hall \(2005\)](#), our implementation does not violate bilateral efficiency conditions.

The importance of wage rigidity in our model leads to some conclusions which differ from existing literature. A popular account suggests that desired reallocation must engender high wages in the growing sector and falling wages in the declining sector (see e.g. [DeLong, 2010](#); [Krugman, 2014](#)). While strictly true in our model, the magnitude of this wage differential can be quite small. Moreover, it is precisely when this wage differential is small that the

¹See e.g. [Groschen and Potter \(2003\)](#); [Koenders and Rogerson \(2005\)](#); [Berger \(2014\)](#); [Garin, Pries, and Sims \(2013\)](#); [Mehrotra and Sergeyev \(2012\)](#) for papers which highlight the importance of input reallocation, and [Aaronson, Rissman, and Sullivan \(2004\)](#); [Pilossoph \(2014\)](#); [Dvorkin \(2014\)](#); [Hall and Schulhofer-Wohl \(2015\)](#) for an opposing view. [Sahin, Song, Topa, and Violante \(2014\)](#) stake a middle ground using an empirical decomposition. A related literature views secular sectoral shocks as inevitable and a diversified industrial base as a necessary condition for a city to be able to reinvent itself when such shifts occur ([Glaeser, 2005](#)). Our results do not dispute the long-run benefits of having a diversified industrial base but instead point out that the cost of undergoing such a reinvention depends on the phase of the business cycle.

unemployment response to desired reallocation is magnified. Reallocation in the model also causes total vacancies to fall, a result at odds with the claim in [Abraham and Katz \(1986\)](#) that rising vacancies are the signature of reallocation. Closer to our mechanism, [Jackman and Roper \(1987\)](#); [Shimer \(2007\)](#); [Sahin et al. \(2014\)](#) also emphasize “mismatch unemployment” caused by a dispersion in job finding rates across sectors.

2. Measurement and Empirical Strategy

We define a measure of reallocation across industries and then discuss our empirical strategy.

2.1. Measure of Reallocation

We define an index of reallocation based on the dispersion in industry employment growth rates as in [Lilien \(1982\)](#). The economy consists of A areas, each with I industries. Let $e_{a,i,t}$ denote employment in area a and industry i at time t , $e_{a,t} = \sum_{i=1}^I e_{a,i,t}$ total employment in the area, $s_{a,i,t} = e_{a,i,t}/e_{a,t}$ industry i 's employment share, $g_{a,i,t,t+j} = \frac{e_{a,i,t+j}}{e_{a,i,t}} - 1$ the area-industry employment growth rate, and $g_{a,t,t+j} = \frac{e_{a,t+j}}{e_{a,t}} - 1$ total local area employment growth. Reallocation in area a between months t and $t + j$ is:

$$R_{a,t,t+j} = \frac{12}{j} \frac{1}{2} \sum_i^I s_{a,i,t} \left| \frac{1 + g_{a,i,t,t+j}}{1 + g_{a,t,t+j}} - 1 \right|. \quad (1)$$

The measure $R_{a,t,t+j}$ is easily interpreted. The term $\frac{1}{2} \sum_{i=1}^I \left| \frac{1 + g_{a,i,t,t+j}}{1 + g_{a,t,t+j}} - 1 \right|$ equals zero if employment grows at an identical rate in every industry between t and $t + j$ and one if all industries with positive employment in t disappear by $t + j$. In general, this term is between zero and one, with higher realizations indicating more reallocation. The ratio $12/j$ translates the reallocation between t and $t + j$ into an annualized monthly flow, such that $R_{a,t,t+j} \subseteq [0, 12/j]$.²

2.2. Econometric Approach

We assume unemployment and reallocation in local area a evolve according to:

$$\Delta u_{a,t,t+j} = \beta_j R_{a,t,t+k} + \mathcal{G}(\{s_{a,i,t}\}; \{\eta_{i,t,t+j}\}) + \Gamma^U X_{a,t} + \varepsilon_{a,t,t+j}, \quad (2)$$

$$R_{a,t,t+k} = \mathcal{C}(u_{a,t}, u_{a,t+1}, \dots, u_{a,t+k}) + \mathcal{R}(\{s_{a,i,t}\}; \{\eta_{i,t,t+k}\}) + \Gamma^R X_{a,t} + \nu_{a,t,t+k}, \quad (3)$$

where $\Delta u_{a,t,t+j} = u_{a,t+j} - u_{a,t}$, $\mathcal{G}(\{s_{a,i,t}\}; \{\eta_{i,t,t+j}\})$ and $\mathcal{R}(\{s_{a,i,t}\}; \{\eta_{i,t,t+k}\})$ are functions which relate cumulative idiosyncratic industry-level shocks $\{\eta_{i,t,t+k}\}$ and local area employment shares

²The measure defined in Equation (1) has an equivalent representation in terms of changes in industry employment shares, $R_{a,t,t+j} = \left(\frac{12}{j}\right) \left(\frac{1}{2} \sum_{i=1}^I |s_{a,i,t+j} - s_{a,i,t}|\right)$. The measure differs slightly from [Lilien \(1982\)](#); [Lilien](#) measures reallocation only period-by-period, corresponding to $R_{a,t,t+1}$, and [Lilien](#) sums the squares of industry growth rate dispersion whereas we sum absolute values to reduce sensitivity to outliers. The measure $R_{a,t,t+1}$ also equals the [Davis and Haltiwanger \(1992\)](#) cross-industry job reallocation rate if total employment remains unchanged between the two periods. Appendix B contains additional details.

to local area unemployment and reallocation, $X_{a,t}$ contains time t measurable observed variables which affect unemployment or reallocation, and $\varepsilon_{a,t,t+j}$ and $\nu_{a,t,t+k}$ are unobserved area-specific determinants. We write $\eta_{i,t,t+k}$ without an a subscript to emphasize that these shocks occur at the national level; shocks to an industry specific to a particular area are subsumed in $\nu_{a,t,t+k}$. While we do not need to specify the functional forms of \mathcal{G} and \mathcal{R} , it is natural and convenient to think of \mathcal{G} as a function solely of the weighted mean shock in an area $\sum_i s_{a,i,t} \eta_{i,t,t+j}$ and \mathcal{R} as a function of the weighted dispersion in $\{\eta_{i,t,t+k}\}$.

Our object of interest is β_j , the effect of reallocation on unemployment. The prior literature has emphasized two sources of causality running instead from unemployment to reallocation, captured by the $\mathcal{C}(\cdot)$ function in Equation (3). First, a low opportunity cost of restructuring during periods of high unemployment and weak demand may lead to higher reallocation (Schumpeter, 1942; Berger, 2014). Second, a demand-induced recession can cause cyclical reallocation across industries if industries differ in their cyclical sensitivities (Abraham and Katz, 1986). More generally, both unemployment and reallocation may depend on common determinants, as captured by the common arguments in the \mathcal{G} and \mathcal{R} functions. For example, an area with a large manufacturing base in 1980 may have had high unemployment directly as a result of concentrating in industries which had negative labor demand shocks while also experiencing substantial reallocation over the past few decades.

Double-Bartik. We introduce a “double Bartik” strategy to overcome these difficulties. Following Bartik (1991) and a large subsequent literature, we define *Bartik predicted employment growth* as the employment growth in local area a if employment in each local industry grew at exactly the same rate as employment in that industry in the rest of the country,

$$g_{a,t,t+j}^b = \frac{12}{j} \sum_{i=1}^I s_{a,i,t} g_{-a,i,t,t+j}, \quad (4)$$

where $e_{-a,i,t}$ denotes employment in industry i at time t summing over all areas other than area a and $g_{-a,i,t,t+j} \equiv \frac{e_{-a,i,t,t+j}}{e_{-a,i,t}} - 1$ is the leave-one-out employment growth rate for industry i . Substituting $g_{-a,i,t,t+j}$ and $g_{a,t,t+j}^b$ into Equation (1), we analogously define *Bartik predicted reallocation* as the reallocation which would obtain in area a if employment in each local industry grew at exactly the same rate as employment in that industry in the rest of the country,

$$R_{a,t,t+k}^b = \left(\frac{12}{k}\right) \left(\frac{1}{2} \sum_{i=1}^I s_{a,i,t} \left| \frac{1 + g_{-a,i,t,t+k}}{1 + g_{a,t,t+k}^b} - 1 \right| \right). \quad (5)$$

We believe this second Bartik measure is original.³

³The closest antecedent of which we are aware comes from Davis and Haltiwanger (2014) who develop an instrument for cross-establishment job reallocation based on the interaction of lagged industry employment shares and the job reallocation rate within each industry.

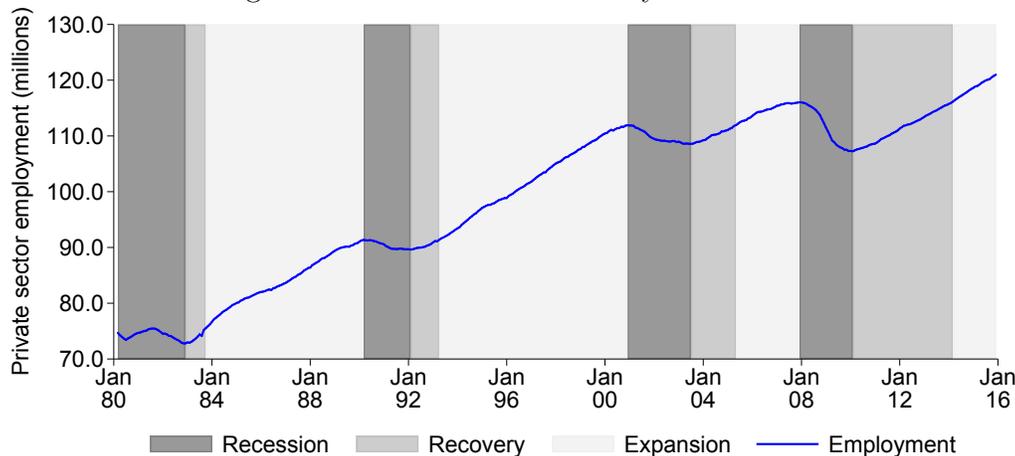
We use Bartik predicted reallocation $R_{a,t,t+k}^b$ as an excluded instrument for $R_{a,t,t+k}$ and Bartik predicted employment growth as a control (i.e., included instrument) in a specification including period fixed effects. To understand this specification, suppose we knew the functions \mathcal{G} and \mathcal{R} and observed $\{\eta_{i,t,t+k}\}$. Then so long as \mathcal{G} and \mathcal{R} were not collinear, estimating Equations (2) and (3) with \mathcal{R} an excluded instrument and \mathcal{G} an included instrument would identify β_j from the part of local reallocation due to \mathcal{R} and after controlling for the direct effect of industry shocks on local area unemployment which occur through the function \mathcal{G} . Since we do not actually observe these shocks or know these functions, we assume instead that Bartik growth and reallocation, measured over appropriate time spans, can proxy for the functions \mathcal{G} and \mathcal{R} . Indeed, Bartik reallocation being a good proxy for \mathcal{R} implies the relevance condition $\text{Cov}(R_{a,t,t+k}, R_{a,t,t+k}^b | g_{a,t,t+k}^b, X_{a,t}, \alpha_t) > 0$. The exclusion restriction $\text{Cov}(\varepsilon_{a,t,t+j}, R_{a,t,t+k}^b | g_{a,t,t+k}^b, X_{a,t}, \alpha_t) = 0$ requires that Bartik growth absorb all direct effects of industry shocks on unemployment which occur through \mathcal{G} . Furthermore, specifying predicted reallocation as an excluded instrument solves the problem of feedback from local unemployment to reallocation because (with time fixed effects) predicted reallocation does not depend on local outcomes after time t , while including $g_{a,t,t+k}^b$ controls for both the area’s industrial cyclical sensitivity and the possibility that predicted reallocation concentrates in areas also undergoing secular decline or expansion. Intuitively, the research design compares areas with the same predicted growth but different predicted reallocation.

Reallocation timing. If labor market frictions impede reallocation, then the pattern of national industry employment growth could lag shifts in $\{\eta_{i,t,t+k}\}$ and make Bartik growth and reallocation, which depend on realized national industry employment growth rates, poor proxies for the functions of the underlying shocks. To address this potentiality, we measure both actual and predicted reallocation over two separate, multi-period windows. The first window begins at a national employment peak and lasts through the course of a national recession and subsequent labor market recovery. The second window begins when the labor market has fully recovered and ends at the start of the next recession. Therefore, we assume that *actual* national employment reallocation between the start and end of a recession-recovery and over an expansion fully reflects the reallocation which would eventually occur as a result of the idiosyncratic industry shocks, so that the Bartik reallocation instrument embodies the reallocation in an area implied by the national industry shocks.⁴ This timing also filters out temporary reallocation induced by differing cyclical sensitivities.

We define a national labor market recession as the period between a private sector employment peak and lasting until the employment trough, a recovery as the period from the trough until the economy regains its previous peak level, and an expansion as the period be-

⁴This is the case in our model, as we show in appendix figure 8.

Figure 1 – National Business Cycle Partition



tween the end of a recovery and the start of the next recession. Thus, we measure reallocation over the 2005-08 expansion using the growth rates of industry employment between June 2005 and the private sector employment peak in January 2008 and reallocation during the 2008-14 recession-recovery using the growth rates of industry employment between January 2008 and March 2014 when employment first regains its January 2008 level. Figure 1 illustrates the labor market recessions, recoveries, and expansions in our sample. (We treat the 1980-82 period as a single long recession.) The view of cyclical tightness as the same at the start and end of each recession-recovery and expansion cycle echoes the “gaps” view of business cycles advocated by DeLong and Summers (1988). Our main results are not sensitive to this particular partitioning.⁵ We apply the same national timing to all local areas to compute predicted and realized reallocation, allowing for the interpretation of our regressions as pooled cross-sections.⁶

By construction, national reallocation during a recession-recovery cycle is mean-preserving in overall employment. Measuring reallocation between two periods when total employment

⁵We use the term “recession” to refer to the period between the private sector employment peak and trough with the understanding that this definition differs from the periods designated by the NBER. We report robustness to other timing conventions in Section 4.3. We prefer the timing procedure described above for two reasons. First, when $e_t = e_{t+j}$, the predicted reallocation measure $R_{a,t,t+j}^b$ has a natural interpretation as described shortly. Second, we do not see an obvious alternative for how to adjust for demographic trends. For example, not only had the national employment-population ratio not recovered its pre-recession level as of the end of 2016, the peak of the series predates the 2000 recession as well. Similarly, the employment-population ratio for prime age males did not regain its previous peak following *any* downturn since 1975.

⁶Using local business cycle timing could induce a feedback from local demand/supply shocks to predicted reallocation through the length of the local cycle and thereby reintroduce reverse causality. Because national and local cycles are highly correlated, our partitioning captures much of the variation in local business cycles. For example, applying the same recession-recovery/expansion partition to local areas, in our sample a monthly average of 75% of local areas are in a local recession-recovery cycle when the national economy is in a recession-recovery cycle and 68% of local areas are in a local expansion when the national economy is in an expansion.

remains unchanged facilitates a natural economic interpretation, since

$$R_{a,t,t+T}|_{e_{a,t}=e_{a,t+T}} = \frac{12}{T} \frac{1}{2} \sum_{i=1}^I \left| \frac{e_{a,i,t+T} - e_{a,i,t}}{e_{a,t}} \right|. \quad (6)$$

Equation (6) rewrites $R_{a,t,t+T}$ as the minimum fraction of total period t employment that changes industries between t and $t + T$, expressed as a monthly flow at an annual rate. When $e_{-a,t} = e_{-a,t+T}$, a derivation similar to Equation (6) shows that predicted reallocation $R_{a,t,t+T}^b$ has the interpretation of the predicted net quantity of industry employment reshuffling between t and $t + T$ as a share of total employment at t , expressed at an annual rate.

Other specification details. An important element of our analysis will be to allow the effect of reallocation on unemployment to vary by the phase of the business cycle. We argue in Section 5 that the differences in β across business cycle phases are informative about the underlying economic mechanisms.

Finally, varying the horizon of the unemployment response holding fixed the horizon over which reallocation occurs traces out an impulse response function. That is, for months t which mark the start of a recession or an expansion and letting T denote the length of the recession-recovery or the expansion, we estimate for $c \in \{\text{Recession-recovery}, \text{Expansion}\}$:

$$\Delta u_{a,t,t+j} = \beta_{j,c} R_{a,t,t+T} + g_{a,t,t+T}^b + \Gamma_{j,c}^{u'} X_{a,t} + \varepsilon_{a,t,t+j}. \quad (7)$$

2.3. Discussion

The Bartik research design has the advantage of not requiring the researcher to take a stand on the deep industry-level determinants of reallocation in any given period (the η_i in our notation), such as changes in technology, consumer tastes, exchange rates, or trade policy. Rather, the evolution of employment nationally summarizes the consequences of the combination of these deep determinants for reallocation. The Bartik approach simply requires that the deep determinants produce a common component of industry employment growth across areas, and that, after residualizing with respect to predicted area growth, these determinants affect local areas only through their effect on reallocation. Not needing to link reallocation to a primitive shock makes this approach well-suited to the study of business cycle frequency outcomes which span multiple cycles, each with its own unique deep determinants of reallocation.

This aspect of the research design also introduces two important limitations. First, we study the consequences of reallocation but do not attempt to identify its primitive causes and therefore cannot answer how a policy maker might manipulate reallocation if desired. Related, the representation (2) and (3) may not uniquely characterize the system, as ultimately unemployment depends on the underlying shocks. Nonetheless, our results shed light on a

long-running debate about whether the frictional reallocation of labor exerts an independent impact on unemployment and the frictions which give rise to such effects. Second, despite the common usage of the phrase “Bartik shock” (which we have purposefully avoided), neither Bartik predicted employment growth nor predicted reallocation necessarily constitutes a shock in the standard meaning of being unanticipated and orthogonal to previous outcomes. In our setting, anticipation effects —knowledge of the industry shocks $\{\eta_{i,t,t+k}\}$ before time t —would complicate the interpretation of β if unemployment begins to rise before the reallocation occurs. In our empirical work we test for differential pre-trends to diagnose such anticipation effects and find little evidence for them. The model in Section 5 expands on both of these issues by providing a concrete example of a set of primitive shocks $\{\eta_{i,t,t+k}\}$ which give rise to our measure of reallocation. Finally, two recent contributions, [Goldsmith-Pinkham et al. \(2018\)](#) and [Borusyak et al. \(2018\)](#), formalize identification arguments and recommend validation procedures in a Bartik setting.⁷ We carry out their recommendations as part of our robustness exercises and find results favorable to our identification strategy.

3. Data and Summary Statistics

We implement our exercise in broadly defined local labor markets in the United States.

3.1. Data

Data on employment by county and industry come from the Bureau of Labor Statistics Longitudinal Database (LDB) and Quarterly Census of Employment and Wages (QCEW). The LDB reports employment by establishment and month starting in 1990. The source data come from quarterly reports employers file with state employment security agencies as part of the unemployment insurance system; as a result, the LDB contains essentially universal coverage of private sector employment. Each establishment in the LDB has a 6 digit NAICS code associated with its primary activity. Our LDB sample contains 42 states which allow access to their data through the BLS visiting researcher confidential data access program. These data are uniquely suited to measuring reallocation because they do not contain sampling error which would artificially increase reallocation rates.

The QCEW is the public use version of the LDB. It reports monthly employment at the industry-county level for all 50 states starting in 1975, subject to disclosure limitations to

⁷[Goldsmith-Pinkham et al. \(2018\)](#) use an equivalence result between a shift-share instrumental variable and a weighted sum of coefficients from just-identified IV regressions each with the area share in one industry as the excluded instrument to characterize exogeneity of local industry-shares as a sufficient condition for identification. [Borusyak et al. \(2018\)](#) show that exogeneity of national industry trends is also sufficient for validity of a Bartik estimator. The equivalence results in these papers do not directly apply to the reallocation Bartik defined in Equation (5) because $R_{a,t,t+k}^b$ does not have a shift-share structure due to the location-specific subtraction of the Bartik growth rate inside the absolute value. They do apply to a close variant which contains only the national growth rate inside the absolute value in Equation (5).

prevent the release of identifying information regarding single establishments.⁸ We use the QCEW to extend the sample back to 1979 and to fill in states not in our LDB sample.

Two details of the data collection procedure merit mention as they affect our analysis. First, the Federal Unemployment Compensation Amendments of 1976 expanded the number of industries and establishments covered by unemployment insurance laws, with the result that the QCEW expanded its coverage of employment between 1976 and 1980.⁹ We exclude data prior to 1978 because the staggered implementation of the coverage expansion across states produces substantial measurement difficulties during that period. In effect, we exclude the 1976-1980 expansion from the analysis. Second, in 1990 and 1991 the BLS lowered the threshold requirements for multi-establishment employers to report employment by single establishment (Farmer and Searson, 1995). As a result, an unusually high number of establishments change industry code during those years. While predicted reallocation between the 1990 peak and 1993 last-peak should remain mostly unaffected by the reclassifications as long as the changes roughly net out at the national level, actual reallocation at the local level has sufficient measurement error to render it unusable.¹⁰ We instead develop a two-sample 2sls estimator where we estimate the first stage excluding the 1990-93 period as described further below.

We combine the LDB data with NAICS 3 digit employment from the QCEW for counties in states not in the LDB and with 2 digit SIC data for 1975-2000.¹¹ We seasonally adjust all series at the industry-county level using the multi-step moving average approach contained in the Census Bureau's X-11 algorithm. Relative to other data sets with employment by geography and industry such as the Census Bureau's County Business Patterns or Longitudinal Business Database (LBD), the BLS data have the important advantage for business cycle analysis of providing monthly rather than annual frequency. We choose SIC 2/NAICS 3 as our level of industry detail because our measure of reallocation does not distinguish between movement across similar or dissimilar industries. The SIC 2/NAICS 3 level allows for enough industry detail (roughly 80 industries) to generate variation in reallocation across areas while ensuring that all such reallocation occurs across broadly defined industries. A finer level of detail would

⁸Even at the NAICS 2 digit level and with counties already aggregated into metropolitan statistical areas (MSAs), roughly one-fifth of potential cells get suppressed for disclosure reasons; the suppressed share rises to 35% for MSA-industry cells at the NAICS 3 digit level.

⁹See <http://www.bls.gov/cew/cewbultncur.htm#Coverage>.

¹⁰We are grateful to Jessica Helfand and David Hiles of the BLS for helping to clarify the issues related to the 1990 and 1991 reporting change. Separately, the NAICS version of the QCEW also contains a number of transcription errors prior to 2001 which do not appear in the LDB and which we hand correct.

¹¹The QCEW reports employment by county and SIC 2 digit industry beginning in 1975 and by 3 and 4 digit industry for 1984-2000. We date the 1980s expansion as beginning in October 1983, making the introduction in 1984 of the SIC 3 and 4 digit industry detail redundant for our analysis. The 1987 revision of the SIC made large changes to a handful of industry definitions which if uncorrected would result in spurious reallocation. We adjust for the classification changes by combining each of SIC 36 and 38, SIC 60 and 61, and SIC 73, 87, and 89 into a single composite industry. In our analysis, we always interact period fixed effects with the classification (NAICS or SIC) to account for any level differences in reallocation across the two systems.

also diminish our ability to make any use of the public data.

We aggregate county-level data into Core Based Statistical Areas (CBSAs) using the 2013 OMB county classifications. The Office of Management and Budget (OMB) defines CBSAs as areas “containing a large population nucleus and adjacent communities that have a high degree of integration with that nucleus” and distinguishes between Metropolitan (MSA) and Micropolitan (MiSA) areas depending on whether the urban core contains at least 50,000 inhabitants. We further aggregate CBSAs into Combined Statistical Areas (CSAs). CSAs consist of adjacent CBSAs that have “substantial employment interchange” and thus better capture the local labor market. Not all CBSAs belong to a CSA. For example, the San Diego MSA is not part of a CSA, but the Boston-Cambridge-Newton MSA is one of five MSAs in the Boston-Worcester-Providence CSA.

Our main outcome variable is the local unemployment rate and comes from the Bureau of Labor Statistics Local Area Unemployment Statistics (LAUS) program. We combine published data starting in 1990 with unpublished data available from the LAUS office for 1976-89. For 1990-present, the LAUS provide seasonally-adjusted data for MSAs; we augment these data by seasonally adjusting the county data using the same procedure described above for the 1976-89 period and for counties not in an MSA and aggregate up to the MSA or CSA level. While the construction of county and MSA unemployment rates involves imputation, any noise is likely to be classical left hand side error and the unemployment rate offers conceptual advantages by reducing the effect of migration on the analysis.

Our final sample includes all MSAs and CSAs containing at least one MSA, with employment of at least 50,000 in one month, an agricultural share of employment of less than 20%, and where we observe at least 95% of private sector employment at the industry level.¹² The final sample contains 1,314 of the 3,144 counties in the United States and covers 86% of 2013 employment.

3.2. Trends in National Reallocation

An overview of reallocation at the national level provides useful context for what follows. Table 1 reports national reallocation for each recession-recovery and expansion and at various levels of industry aggregation. The shaded rows indicate the recession-recovery episodes. We measure reallocation using SIC definitions for the episodes between 1975 and 2000 and using NAICS definitions for the episodes beginning after 1990. It helps to group SIC 2 with NAICS 3, and SIC 4 with NAICS 6, based on similarity in the number of industries. Reallocation measures for the overlapping episodes appear roughly comparable across these definitions.

A number of interesting patterns emerge. First, cross-industry reallocation occurs all the

¹²We exclude areas with a large agricultural share because of the particular difficulty of seasonally adjusting agricultural employment. The 95% coverage restriction binds because of disclosure limits in CSAs/MSAs located at least partly in states not in our LDB sample and for the period 1980-89 when we do not have confidential data. As a result, our sample contains fewer CSAs/MSAs in the 1980-89 period than thereafter.

Table 1 – Reallocation by Episode and Industry Detail

Epsiode	Months Expansion		Industry definition						
			SIC 1.5	NAICS 2	SIC 2	NAICS 3	NAICS 4	SIC 4	NAICS 6
Mar80-Oct83	43	No	1.14		1.29			1.68	
Oct83-Mar90	77	Yes	0.71		0.93				
Mar90-Apr93	37	No	0.82	1.04	0.97	1.15	1.32	1.34	1.56
Apr93-Dec00	92	Yes	0.42	0.60	0.85	0.77	0.95	1.14	1.13
Dec00-May05	53	No		0.80		0.97	1.25		1.42
May05-Jan08	32	Yes		0.60		0.73	1.00		1.20
Jan08-Mar14	74	No		0.64		0.71	0.87		1.03
$R^2 : \frac{1}{j} \Delta s_{i,t,t+j} = \alpha_i + \varepsilon_{i,t,t+j}$			0.72	0.71	0.73	0.59	0.65	0.75	0.65
Industry count			18	20	73	92	305	963	1028

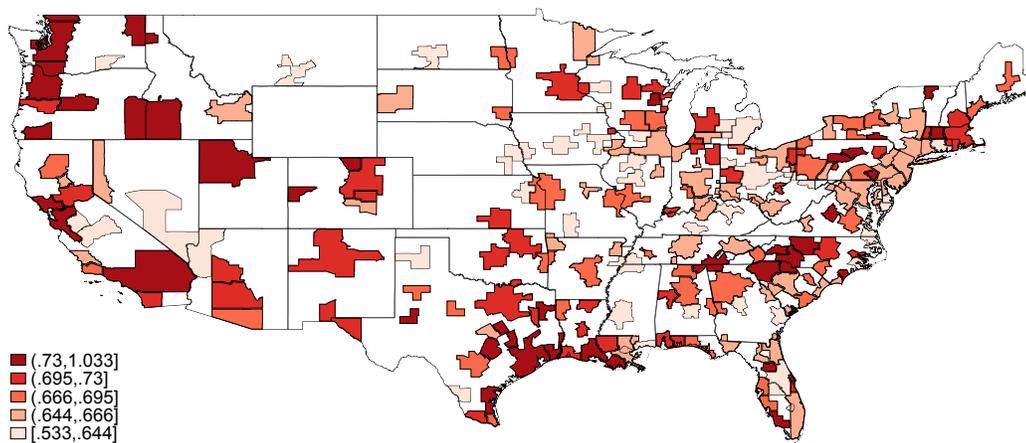
Notes: The table reports values of $R_{us,t,t+j}$ for all complete national recession-recovery and expansion cycles between 1975 and 2014, and at varying levels of industry detail. The table omits the entry for SIC 4 between 1983 and 1990 because of the SIC classification revision in 1987.

time. Since [Lilien \(1982\)](#), a debate has continued about whether sectoral employment shifts concentrate “enough” during periods of low economic activity to explain fluctuations in the business cycle. The problem identified by [Abraham and Katz \(1986\)](#) of how to account for different industry cyclical sensitivities during recessions makes answering this question difficult. By filtering out cyclical reallocation which occurs during a recession but reverts during a recovery, our timing approach provides one way around the [Abraham and Katz \(1986\)](#) critique.¹³ Using our approach, more secular reallocation does occur during episodes containing recessions, qualitatively consistent with the [Lilien](#) conjecture.

Second, consistent with a downward trend in a number of measures of labor market flows ([Davis, Faberman, and Haltiwanger, 2012](#); [Molloy, Smith, Trezzi, and Wozniak, 2016](#)), the rate of reallocation has trended down. For example, 4.6% ($1.29 \times 43 / 12$) of employment changed SIC 2 digit industry between the March 1980 private sector employment peak and the October 1983 last-peak. The same fraction changed NAICS 3 digit industry between the January 2008 peak and the February 2014 last-peak, despite the latter episode lasting 30 months longer. As a result, monthly reallocation fell from 1.29% (at an annual rate) during the 1980-83 episode to 0.74% during the 2008-14 episode. The decline in between is monotonic for recession-recoveries. Despite the widespread attention to industry reallocation during the 2008-2014 episode, our measure of secular reallocation suggests a decline in reallocation intensity during the Great

¹³Alternatively, see [Brainard and Cutler \(1993\)](#); [Aaronson et al. \(2004\)](#); [Mehrotra and Sergeyev \(2012\)](#) for articles that apply parametric time series models to either the cyclical or trend component of employment shares to address this question. Note however that the comparison of recession-recoveries and expansions in Table 1 does not exclude the possibility that secular reallocation concentrates during recession-recoveries because of Schumpeterian restructuring. That is, while our timing solves the [Abraham and Katz \(1986\)](#) critique, it does not address other endogeneity concerns. For that we turn to local variation.

Figure 2 – Map of Predicted Reallocation Per Year, 2008-2014 Cycle



Notes: the figure shows the geographic distribution predicted reallocation per year for the national employment peak in January 2008. Due to disclosure limitations, for this figure only we use only data from the public-use QCEW and require a minimum industry employment coverage of 80%.

Recession period (see also [Foster, Grim, and Haltiwanger, 2016](#)).¹⁴

Third, a large amount of reallocation occurs across broadly-defined industries. For example, of the 6.5% (1.06% per year multiplied by 6.08 years) of employment changing 6 digit NAICS industry between the January 2008 peak and the March 2014 last-peak, 4.1 p.p. constituted movement across 2 digit industries.

Fourth, while individual industries exhibit persistence in their contribution to national reallocation, the explanatory power of this relationship lies well below one. We establish this fact by reporting in the penultimate line of the table the R^2 from the regression: $j^{-1}|\Delta s_{i,t,t+j}| = \alpha_i + \varepsilon_{i,t}$. For example, at the NAICS 3 level, the R^2 of this regression equals 0.59. Thus, individual industry trends leave unexplained 40% of the variation in the contribution of industries to national reallocation. This time variation in industry employment trends will in turn contribute to substantial variation over time in the predicted reallocation in individual areas.

3.3. Local Reallocation

Figure 2 shows a map of the variation in predicted reallocation during the 2008-2014 recession-recovery cycle.¹⁵ We split the MSA/CSA observations into quintiles based on their Bartik reallocation and mark higher reallocation levels with darker shades of red. The map shows that predicted reallocation is not easily explained by geographic factors.

¹⁴Interpreted through the lens of our empirical exercises and our model, the decline in reallocation intensity during the Great Recession translates into a similar increase in unemployment due to reallocation. This is because the larger aggregate shock during the Great Recession tightens the downward wage constraint more than in an average recession. Therefore, a given amount of reallocation generates more unemployment during the Great Recession, which compensates for the decline in reallocation intensity.

¹⁵For data confidentiality reasons, the map uses only the public-use QCEW data. Greater disclosure limitations prior to 2008 make it impossible to report maps at the same level of industry detail for earlier cycles.

Table 2 – Correlation of Predicted Reallocation Across Episodes

	1980-83	1983-90	1990-93	1993-00	2000-05	2005-08	2008-14
1980-1983	1.00						
1983-1990	0.24	1.00					
1990-1993	0.21	0.09	1.00				
1993-2000	-0.02	0.52	-0.16	1.00			
2000-2005	0.30	0.26	0.07	0.43	1.00		
2005-2008	0.17	0.35	0.04	0.43	0.52	1.00	
2008-2014	0.10	0.15	0.05	0.26	0.49	0.71	1.00

Table 2 reports the pairwise correlations in predicted local reallocation across each national recession-recovery and expansion. Predicted reallocation has a modest correlation across most episodes. These patterns inform our analysis in three ways. First, in some specifications we will exploit the absence of perfect serial correlation by including area fixed effects. Second, we will always cluster all standard errors by CSA/MSA to account for arbitrary correlation within an area over time.¹⁶ Third, in interpreting our findings and in the model in Section 5, we will not assume reallocation at the start of a cycle is unanticipated.

4. Empirical Results

4.1. First-Stage and Two-Sample 2sls

Table 3 presents first stage regressions of actual on predicted reallocation, controlling for predicted growth and period fixed effects. Column (1) pools over the three recession-recovery cycles 1980-83, 2000-05, and 2008-14. Predicted reallocation has strong explanatory power with a partial F-statistic of 15.5. As discussed in Section 3.1, the change between 1990 and 1993 in the minimum employment level requiring multi-establishment employers to report employment separately for each establishment renders actual reallocation at a local level during that period too noisy to use. Column (2) illustrates the problem. Including the 1990-93 episode in the regression lowers the first stage coefficient from 0.98 to 0.21 and yields a partial F-statistic below one, far too small to provide reliable second stage estimates.

In order to include the 1990-93 episode in the subsequent analysis, we introduce a two sample instrumental variables framework (Angrist and Krueger, 1992). Two sample two-stage least squares (ts2sls) estimates the first stage regression in one sample and applies the estimated first stage coefficients to the instruments in a second sample used for the second stage analysis. Thus, for recession-recovery episodes the first stage regression will exclude the 1990-93 cycle while the second stage will include it. Implicitly, we assume that the true first stage coefficient

¹⁶Because we control for Bartik growth, which uses all the information in national industry employment growth rates, our standard errors do not suffer from the criticism raised in Adão, Kolesár, and Morales (2018).

Table 3 – First Stage Regressions

	Dependent variable: actual reallocation			
	Recession-recoveries		Expansions	Pooled
	(1)	(2)	(3)	(4)
Right hand side variables:				
Predicted reallocation	0.98** (0.25)	0.21 (0.24)	0.66** (0.22)	0.80** (0.18)
Episodes	Ex. 1990-93	All	All	Ex. 1990-93
National cycle FE	Yes	Yes	Yes	Yes
Predicted growth	Yes	Yes	Yes	Yes
R^2	0.38	0.08	0.22	0.38
CSA-MSA clusters	217	218	218	220
Observations	534	748	557	1091

Notes: The dependent variable is actual reallocation, R_a . Predicted reallocation is the reallocation measure R_a^b . Standard errors in parentheses and clustered by CSA-MSA. ** indicates significance at the 1% level.

does not differ during the 1990-93 cycle. While not directly testable, supportive evidence comes from the tight range of coefficients (between 0.88 and 1.08) obtained from estimating the first stage regression separately in each of the other recession-recovery cycles.

Column (3) shows the first stage for the expansion cycles. The partial F-statistic lies just below the [Staiger and Stock \(1997\)](#) rule-of-thumb of 10. Including covariates, as we will do shortly, raises the first-stage partial F-statistic substantially. Finally, column (4) shows the first stage pooling over the recession-recovery (excl. 1990-93) and expansion episodes.

This setup requires an econometric contribution which we briefly describe. We differ from the typical ts2sls framework in which the first and second stage samples contain entirely separate observations and the regression residuals are assumed to be independent across the two samples. Appendix A derives the asymptotic variance of the second stage coefficients when independence does not hold. The expression we derive is to our knowledge original and nests formulae in [Inoue and Solon \(2010\)](#) and [Pacini and Windmeijer \(2016\)](#) when the two samples are independent.

4.2. Effects of Reallocation

We start by reporting the effects of reallocation without distinguishing by the phase of the business cycle. Table 4 reports ts2sls regressions of the form:

$$\text{Second stage:} \quad u_{a,t+j} - u_{a,t} = \beta \hat{R}_{a,t,t+T} + \Gamma' X_{a,t} + \alpha_t + \varepsilon_{a,t,t+j}, \quad (8)$$

$$\text{First stage:} \quad R_{a,t,t+T} = \pi_1 R_{a,t,t+T}^b + \pi_2' X_{a,t} + \delta_t + \eta_{a,t,t+T}, \quad (9)$$

where $u_{a,t+j} - u_{a,t}$ is the change in the area a unemployment rate between the national recession peak and trough (recession-recovery episode) or during the first 30 months of the national

Table 4 – Homogenous Effects over Cycle

	Dep. var.: change in unemployment rate		
	(1)	(2)	(3)
Right hand side variables:			
Reallocation	0.44 ⁺ (0.25)	0.39* (0.15)	0.60** (0.18)
National cycle FE	Yes	Yes	Yes
Predicted growth	Yes	Yes	Yes
First stage coefficient	0.80	1.18	1.11
First stage F stat.	18.8	67.7	29.5
CSA-MSA clusters	220	220	220
First stage observations	1,091	1,091	1,091
Second stage observations	1,305	1,305	1,305

Notes: The table reports ts2sls regressions. The dependent variable is the change in the unemployment rate between the national recession peak and trough (recession-recovery episode) or during the first 30 months of the national expansion. Additional controls in column (2) are: lags of employment growth, population growth, and house price growth, each measured from 5 years to 1 year prior to the cycle start; area size, measured by the log of sample mean employment; and the Herfindahl of industry concentration at the cycle start. Standard errors in parentheses and clustered by CSA-MSA. +, *, ** indicate significance at the 10%, 5%, and 1% levels.

expansion and $\hat{R}_{a,t,t+T} = \hat{\pi}_1 R_{a,t,t+T}^b + \hat{\pi}_2' X_{a,t} + \hat{\delta}_t$ is the cross-sample fitted value of reallocation obtained by applying the first stage regression coefficients to the variables in the second stage sample. The 30 month horizon corresponds to the mean peak-to-trough length in our sample. The endogenous variable $R_{a,t,t+T}$ and excluded instrument $R_{a,t,t+T}^b$ measure the monthly flow of reallocation and predicted reallocation, respectively, between the beginning and end of the national recession-recovery or expansion. Both our simulated model in Section 5 and the empirical impulse response function point to the national trough as the point at which the effect of reallocation reaches its maximum impact during a recession-recovery, so we start our analysis at this horizon. We will shortly report the impulse response function for recession-recoveries.

Table 4 shows that on average over the business cycle reallocation results in higher unemployment. Column (1) is our most parsimonious specification and includes in $X_{a,t}$ only predicted growth variables measured over the same horizon as reallocation and over the same horizon as the dependent variable. In anticipation of our next result showing how the effects of reallocation vary by phase of the business cycle, we interact each covariate with an indicator for national recession-recovery or expansion, so that any difference between the effects of reallocation in this table and the next comes only from allowing the effect of reallocation to vary. The coefficient of 0.44 means that a marginal 1 p.p. of reallocation per year over the course of a cycle causes unemployment to rise by $0.44 \times 2.5 = 1.1$ p.p. during the first 30 months of the cycle. Column (2) adds the following control variables, described in detail in Appendix C: lags of employment

Table 5 – Heterogeneous Effects over Cycle

	Dep. var.: change in unemployment rate		
	(1)	(2)	(3)
Right hand side variables:			
Reallocation X Expansion	−0.40 (0.35)	−0.10 (0.16)	−0.32 (0.34)
Reallocation X Recession-Recovery	0.87** (0.25)	0.87** (0.23)	0.91** (0.21)
P-value of equality	0.004	0.001	0.004
National cycle FE	Yes	Yes	Yes
Predicted growth	Yes	Yes	Yes
Additional controls	No	Yes	No
Area FE	No	No	Yes
CSA-MSA clusters	220	220	220
First stage coefficient, recession	1.01	1.06	1.28
First stage coefficient, expansion	0.66	1.28	0.98
First stage F-statistic, recession	16.7	20.2	13.3
First stage F-statistic, expansion	8.5	66.7	15.4
First stage observations	1,091	1,091	1,091
Second stage observations	1,305	1,305	1,305

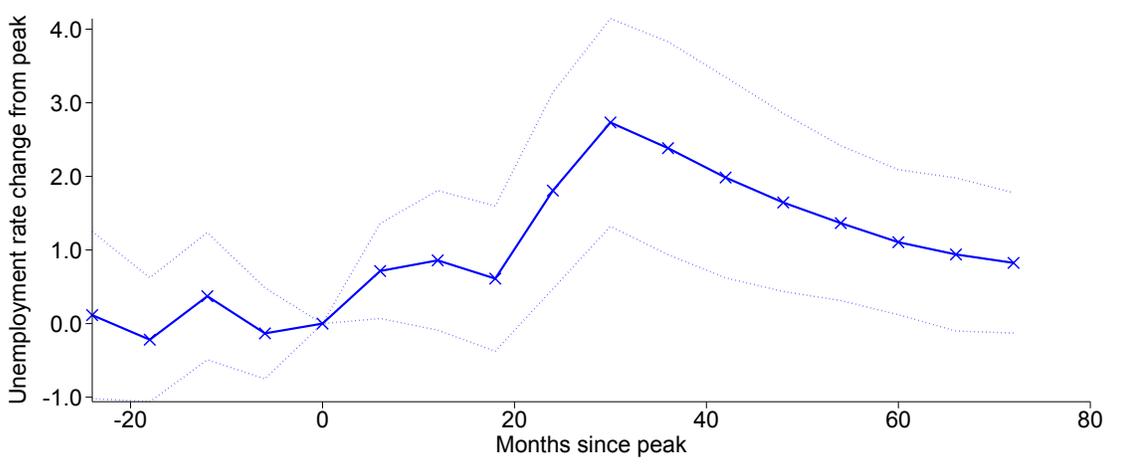
Notes: The table reports ts2sls regressions. The dependent variable is the change in the unemployment rate between the national recession peak and trough (recession-recovery episode) or during the first 30 months of the national expansion. Additional controls in column (2) are: lags of employment growth, population growth, and house price growth, each measured from 5 years to 1 year prior to the cycle start; area size, measured by the log of sample mean employment; and the Herfindahl of industry concentration at the cycle start. All controls and fixed effects are interacted with an indicator variable for recession-recovery period. Standard errors in parentheses and clustered by CSA-MSA. ** indicates significance at the 1% level.

growth, population growth, and house price growth, each measured from 5 years to 1 year prior to the cycle start; area size, measured by the log of sample mean employment; and the Herfindahl of industry concentration at the cycle start.¹⁷ Column (3) adds area fixed effects. Inclusion of both area and time fixed effects restricts the variation in predicted reallocation to coming from within a CSA/MSA and relative to the national mean. In columns (2) and (3), the added controls produce stronger first stage fits and smaller second stage standard errors. Importantly, the point estimate for the effect of reallocation remains stable across columns.

Table 5 presents the main empirical result of the paper. The specifications mirror those in Table 4 except that we allow the effects of reallocation (and any covariates) to vary according to whether it occurs during a recession-recovery or an expansion. Accordingly, the first stage regression includes two excluded instruments, one for predicted reallocation during a recession-recovery and the other for predicted reallocation during an expansion. All coefficients are exactly equal those from estimating regressions during recession-recovery and expansion

¹⁷We further describe and report the coefficients and standard errors on the control variables in Appendix C.

Figure 3 – Timing of Effects on Unemployment During Recession-Recovery



Notes: The solid line plots the coefficients on reallocation from a regression of the change in the unemployment rate at different horizons on reallocation. The dashed lines plot the 95% confidence interval for each horizon.

phases separately. Reallocation during a recession-recovery increases unemployment by an economically large and statistically significant amount. Across columns, the data reject zero effect of reallocation during a recession-recovery at the 1% level, with t-statistics ranging from 3.5 to 4.3. In economic magnitude, a one standard deviation increase in predicted reallocation causes an unemployment rate 0.5 p.p. higher (2.5 years \times 0.87 p.p. per year \times 0.23 s.d.) by the time national employment reaches its trough. In contrast, the data do not reject zero effect of reallocation on unemployment during expansions, with the point estimates slightly negative. The data therefore strongly reject equality of coefficients during a recession-recovery and expansion.

Figure 3 shows the full timing of the effects of reallocation on unemployment during a recession-recovery. The solid line in Figure 3 plots the coefficients β_j from a local projection of the change in the unemployment rate on reallocation, that is, the coefficients β_j from estimating Equations (8) and (9) allowing j to vary in 6 month increments. The coefficients trace out a hump-shaped impulse response function. Areas undergoing reallocation during a national recession-recovery cycle experience a relative rise in unemployment while national employment is falling. The effect crests at the national employment trough and reverses as the economy recovers. The coefficients for one and two years before the national peak indicate little evidence of areas with large predicted reallocation during the recession-recovery experiencing differential unemployment rate trends immediately prior to the national peak. The absence of pre-trends means that even if reallocation does not come as a surprise shock at the start of a recession, anticipation effects do not contaminate our estimates of what happens during the recession.

4.3. Robustness

Table 6 groups together a number of sensitivity exercises to assess the robustness of the finding that reallocation affects unemployment during recessions. Each row of the table reports

Table 6 – Robustness

Specification	Recession-Recovery			CSAs	Obs.
	β	s.e.	P(equality)		
1. Baseline	0.87**	0.25	0.004	220	1305
2. Bartik growth vigintiles	0.98**	0.30	0.404	220	1305
3. Control for age shares	1.10**	0.23	0.000	220	1305
4. Predicted growth by period	0.94**	0.26	0.008	220	1305
5. Predicted growth by region	0.99**	0.30	0.043	220	1305
6. Drop if area has large industry	0.86**	0.29	0.002	203	1107
7. Drop if high manufacturing share	1.25**	0.45	0.007	193	960
8. Drop if high construction share	1.11**	0.27	0.000	206	966
9. Drop if high resources share	1.04**	0.35	0.160	177	973
10. Drop if high health care share	0.70*	0.33	0.031	198	987
11. Drop persistent industries	1.47**	0.37	0.004	220	1305
12. Drop 1990-93	0.86**	0.31	0.008	220	1091
13. Drop 2008-14	1.10**	0.32	0.002	220	1101
14. HP filter dating	0.88**	0.28	0.040	220	1291
15. NAIRU dating	1.15*	0.58	0.399	221	1246
16. Expand window \pm 3 months	0.71*	0.28	0.067	218	1125
17. Peak-to-peak reallocation	0.82*	0.41	0.030	220	1305

Notes: Each row of the table reports the coefficient and standard error for recession-recovery periods and the p-value of equality of coefficients in a recession-recovery and an expansion from a separate regression described in the first column. All rows additionally include the controls from column (1) of Table 5. The first row, labeled “Baseline”, reproduces column (1) of Table 5. Row 2 controls for episode-specific indicator variables for belonging to each of twenty quantiles of predicted growth. Row 3 controls for the share of the population in 5-year age bins at the start of the cycle. Rows 4 and 5 allow the coefficients on predicted growth to vary by cycle and by region, respectively. Row 6 excludes observations where the area contains at least one industry with employment of 5% or more of the national total in that industry at the cycle start. Rows 7-10 exclude observations in the cycle’s top quartile of employment share in the industry indicated. Row 11 excludes from the construct of predicted reallocation any industry which either expands or contracts nationally in every cycle in our data. Row 12 drops the 1990-93 cycle. Row 13 drops the 2008-14 cycle. In row 14, a recovery ends when the cyclical component of an HP filter of national employment (smoothing parameter 129,600) equals zero. In row 15, a recovery ends when the national unemployment rate first equals the CBO’s estimate of the NAIRU. In row 16, the recession-recovery window is extended by 3 months on each side. Row 17 constructs predicted reallocation on a peak-to-peak basis. **, * denote significance at the 1% or 5% level.

for a separate regression the coefficient and standard error for recession-recovery periods and the p-value of equality of coefficients in a recession-recovery and an expansion. The first row, labeled “Baseline”, reproduces column (1) of Table 5.

Rows 2 to 5 further expand the control variables in the regression. Row 2 adds non-parametric controls for the Bartik predicted growth rate over the cycle by adding episode-specific indicator variables for belonging to each of twenty quantiles of predicted growth. This specification compares the evolution of unemployment across areas with different predicted reallocation but in the same vigintile of predicted growth. Row 3 controls for the share of the population in 5-year age bins at the start of the cycle. Rows 4 and 5 allow the coefficients on

predicted growth to vary by cycle and by region, respectively. The effects of reallocation during recession-recoveries increase slightly in each of these specifications and with the exception of row 2 the difference in coefficients between recession-recoveries and expansions remain significant at the 5% level.¹⁸

Row 6 removes from the sample areas which contain an industry with employment relative to national employment in that industry above 5%. If employment in an industry concentrates in a few areas (for example, auto manufacturing employment in Detroit and Birmingham), and if the firms in different areas engage in strategic interaction (for example, negative shocks to plants in Detroit induce expansion at plants in Birmingham), then local industry employment in an area may correlate with elsewhere employment in that industry because of a strategic response to shocks specific to another local area’s industry rather than because of the common response to a common set of shocks. In practice, the small size of CSA/MSAs relative to the national economy – the median CSA/MSA has total employment in 2013 of 113,000, or less than 0.1% of national private sector employment - makes such concentration scarce. Indeed, the restriction removes 17 CSA/MSAs from the sample (primarily the largest ones) but has almost no effect on the estimated coefficients.

Rows 7-10 assess sensitivity to excluding areas with large employment shares in manufacturing, construction, resources extraction, and health care. [Goldsmith-Pinkham et al. \(2018\)](#) show the equivalence of a shift-share IV estimator to a “Rotemberg”-weighted sum of IV coefficients using area shares in each individual industry and period as the excluded instrument in separate just-identified regressions. The Rotemberg weights characterize which industries have the largest influence on the IV coefficient. To assess the sensitivity to reducing the influence of these industries, we first compute the Rotemberg weights for a close variant of our baseline regression which has the shift-share structure.¹⁹ Of the five largest (in absolute value) weights

¹⁸The specifications in rows 2, 9, and 15 of the table cannot reject equality of coefficients at the 10% level. In each of these cases, the larger p-value reflects a large increase in the standard error for the expansion coefficient rather than convergence of the point estimates, the increase in the standard error in turn reflects a weak first stage for the expansion subsample, and (not shown) including the baseline controls strengthens the first stage and yields a rejection of equality at least at the 5% level.

¹⁹The variant contains only the national growth rate inside the absolute value in Equation (5). The 2sls recession-recovery coefficient in this specification is 1.05 (s.e.=0.30), close to that of our baseline coefficient. The weight formula for industry i in period t is $(\tilde{R}^b R^\perp)^{-1} |g_{i,t}| Z'_{i,t} R^\perp$, where \tilde{R}^b is the $AP \times 1$ vector of Bartik reallocation in each area $a \in A$ and period $t = 1, 2, \dots, P$, R^\perp is the $AP \times 1$ vector of actual reallocations orthogonalized with respect to covariates, $g_{i,t}$ is the growth rate of national employment in industry i in period t , and $Z_{i,t}$ is an $AP \times 1$ vector consisting of zeros in all rows not corresponding to period t and the location-industry initial employment shares in industry i for the rows corresponding to period t . Because construction of the Rotemberg weights requires computing the covariance of shares and the endogenous variable, we exclude the 1990-93 cycle from this exercise. Appendix Table C.3 reports additional statistics related to the Rotemberg weights. We can alternatively motivate the robustness exercises in rows 7-11 as reducing the influence of industries which made the largest contributions to national reallocation over the past decades, consistent with the identification approach in [Borusyak et al. \(2018\)](#). In this vein, row 10 shows the robustness to excluding areas with large shares in health care.

for a recession-recovery period, two correspond to manufacturing industries, two to natural resources extraction, and one to construction. We then remove from the sample areas in the top quartile of beginning-of-cycle employment share in each of these sectors. Excluding these areas reduces substantially the Rotemberg weight associated with the particular industry and addresses directly the concern raised by Goldsmith-Pinkham et al. (2018) of high Rotemberg weight industries concentrating in areas which experience other shocks. The coefficients from these restricted samples remain close to the baseline.

Row 11 follows Notowidigdo (2011) and keeps all areas but removes from the construction of predicted reallocation any industry which either increases or decreases national employment in each cycle in our data.²⁰ Thus, the variation in row 11 comes only from industries experiencing persistent but not permanent expansions or contractions. Row 12 excludes the 1990-93 cycle from the second sample and reports the coefficient from a conventional 2sls regression. Row 13 shows that excluding the Great Recession has a small effect on the results.

Rows 14 to 17 explore robustness to the precise timing definition. Row 14 defines the end of the recovery as the first month following a peak in which the cyclical component of an HP filter (smoothing parameter 129,600) of national private sector employment turns positive. In row 15, we define the end of the recovery as the first month in which the national unemployment rate falls to or below the Congressional Budget Office estimate of the NAIRU. Row 16 expands the recession-recovery window symmetrically by 3 months on each side. Finally, row 17 redefines the reallocation timing to measure reallocation between two national employment peaks.²¹ The basic pattern of a statistically significant positive coefficient during recession-recoveries and a smaller coefficient during expansions remains robust to these alterations.

5. Quantitative Model

The previous section demonstrated that reallocation causes an increase in unemployment if it occurs during a national recession-recovery, but not if it occurs during an expansion. The rise in the unemployment rate concentrates during the recession part of the cycle, with maximum impact around the national employment trough. We now study a model economy to better understand these patterns. The model illustrates what types of primitive shocks could give rise to our empirical setup and how frictions to labor mobility and downward wage rigidity allow the model to match the empirical patterns in the data.

²⁰More specifically, we exclude a NAICS (SIC) industry if national employment expands or contracts during each cycle in which NAICS (SIC) employment is reported. This procedure identifies 47 of the 165 SIC 2 or NAICS 3 digit industries in our data: 113, 114, 313-316, 322, 323, 325 (NAICS, shrinking); 112, 485, 488, 493, 541, 562, 611, 621-624, 712, 722 (NAICS, expanding); 09, 11, 12, 21-23, 31, 66 (SIC, shrinking); 02, 07, 08, 47, 58, 62, 64, 67, 72, 73, 75, 79-84 (SIC, expanding). These industries overlap substantially with the set of industries with high Rotemberg weights, with five of the ten largest (in absolute value) Rotemberg weights in persistently shrinking or expanding industries.

²¹For the 2008-14 cycle, we measure reallocation between the peak in January 2008 and December 2016.

5.1. Setup

Time is discrete. The economy consists of \mathcal{A} islands, each of which has \mathcal{I} industries. We assume no aggregate uncertainty and perfect consumption insurance within (but not across) islands, which implies an island-specific discount factor $m_{a,t,t+1}$.

5.1.1. Labor market The labor market in each area-industry operates according to search and matching principles. At the beginning of period t , industry i in area a contains $(1 - \delta_{t-1})e_{a,i,t-1}$ workers employed in the previous period and still attached to their firm, $x_{a,i,t}$ workers searching for a job, and $v_{a,i,t}$ job vacancies. Hiring occurs at the beginning of the period, with $n_{a,i,t}$ new matches formed. The $e_{a,i,t} = (1 - \delta_{t-1})e_{a,i,t-1} + n_{a,i,t}$ workers employed in t engage in production. At the end of the period, $\delta_t e_{a,i,t}$ of the employed workers exogenously separate from their employer. We let $u_{a,i,t} = x_{a,i,t} - n_{a,i,t}$ denote the number of unemployed workers in period t after the matching process has taken place. Following [Christiano et al. \(2016\)](#), this concept of unemployment allows for job-to-job transitions by workers who separate at the end of $t-1$ but get newly hired at the beginning of t . We let $l_{a,i,t} = e_{a,i,t} + u_{a,i,t} = (1 - \delta_{t-1})e_{a,i,t-1} + x_{a,i,t}$ denote the total labor force in industry i in area a at time t . We fix the economy-wide labor force at $\sum_{a=1}^{\mathcal{A}} \sum_{i=1}^{\mathcal{I}} l_{a,i,t} = 1$.

The firm vacancy posting condition and matching process are standard. Firms post $v_{a,i,t}$ vacancies in industry i at cost κ per vacancy. A free entry condition drives the expected value of a vacancy to zero. The matching function takes the Cobb-Douglas form $n_{a,i,t} = M v_{a,i,t}^{1-\alpha} x_{a,i,t}^\alpha$. Letting $\theta_{a,i,t} = \frac{v_{a,i,t}}{x_{a,i,t}}$ denote the vacancy-searcher ratio, or industry labor market tightness, searching workers find jobs at rate $f_{a,i,t} = M \theta_{a,i,t}^{1-\alpha}$, and firms fill vacancies at rate $q_{a,i,t} = M \theta_{a,i,t}^{-\alpha}$. Thus, the value of a filled job to the firm, $J_{a,i,t}$, and the free entry condition are,

$$J_{a,i,t} = (p_{a,i,t} - w_{a,i,t}) + (1 - \delta_t)m_{a,t,t+1}J_{a,i,t+1}, \quad (10)$$

$$\kappa = q_{a,i,t}J_{a,i,t}, \quad (11)$$

where $p_{a,i,t}$ is the real marginal product and $w_{a,i,t}$ is the real wage.

Unemployed workers search in one industry and one area at a time. Their choice of where to search plays an important role. In line with recent literature, we assume semi-directed search ([Kline, 2008](#); [Artuç, Chaudhuri, and McLaren, 2010](#); [Kennan and Walker, 2011](#); [Pilossoph, 2014](#); [Dvorkin, 2014](#)). Specifically, at the end of period t , employed workers transition into unemployment in their same industry at rate $\delta_t - \lambda_t$. Both unemployed and employed workers receive an industry reallocation shock $\Lambda_{a,i,t}$ at exogenous rate λ_t . An industry reallocation shock $\Lambda_{a,i,t}$ consists of an immediate job separation if previously employed, \mathcal{I} time-invariant sector-specific taste parameters $\{\psi_{a,j}\}_{j=1}^{\mathcal{I}}$, and a draw of I idiosyncratic taste shocks $\{\varepsilon_{j,t}\}_{j=1}^{\mathcal{I}}$ from a distribution $F(\varepsilon)$. These taste parameters and shocks enter additively into the worker's value function for searching in each sector $j = 1, \dots, \mathcal{I}$. The value functions of an employed

worker, $W_{a,i,t}$, and an unemployed worker, $U_{a,i,t}$, are then,

$$W_{a,i,t} = w_{a,i,t} + m_{a,t,t+1} \{[(1 - \delta_t) + (\delta_t - \lambda_t) f_{a,i,t+1}] W_{a,i,t+1} + (\delta_t - \lambda_t) (1 - f_{a,i,t+1}) U_{a,i,t+1}\} \\ + m_{a,t,t+1} \lambda_{a,t} \left(\mathbf{E} \max_j \{(1 - f_{a,j,t+1}) U_{a,j,t+1} + f_{a,j,t+1} W_{a,j,t+1} + \psi_{a,j} + \varepsilon_{j,t}\} \right), \quad (12)$$

$$U_{a,i,t} = z + m_{a,t,t+1} \{(1 - \lambda_t) [f_{a,i,t+1} W_{a,i,t+1} + (1 - f_{a,i,t+1}) U_{a,i,t+1}]\} \\ + m_{a,t,t+1} \lambda_{a,t} \left(\mathbf{E} \max_j \{(1 - f_{a,j,t+1}) U_{a,j,t+1} + f_{a,j,t+1} W_{a,j,t+1} + \psi_{a,j} + \varepsilon_{j,t}\} \right), \quad (13)$$

where z is the worker's flow opportunity cost of employment and \mathbf{E} the expectations operator.

The parameter λ determines the share of unemployed re-optimizing their industry search market. Equivalently, λ has the interpretation of a stochastic death or retirement shock, with a new generation of workers of mass λ born each period and choosing afresh their industry of search. Holding the share re-optimizing below unity provides one important friction allowing reallocation shocks to affect employment. The $\psi_{a,j}$ parameters can be interpreted as permanent preferences to work in particular sectors. The ε_j shocks have the interpretation of transitory taste shocks which make some individuals prefer to work in certain sectors, or of noise shocks which give individuals private (mis)information about the returns to searching in each sector. Inclusion of these shocks generates two-way gross labor flows across industries. Existence of gross flows in excess of the net reallocation flows induced by non steady-state dynamics captures an important feature of reality. Thus, consistent with [Pilossoph \(2014\)](#), net reallocation in our model occurs without requiring changes in the amount of gross flows. The level of λ and the volatility of the process generating ε_j together govern the magnitude of gross flows and the directness of search across industries.²²

We denote the transition probability from industry i to industry j conditional on an industry reallocation shock by $\pi_{a,ij,t}$. This probability does not depend on the worker's previous employment status or industry, $\pi_{a,ij,t} = \pi_{a,kj,t} = \pi_{a,j,t}$. We have three laws of motion for the evolution of job seekers, employment, and unemployment:

$$x_{a,i,t} = \delta_{t-1} e_{a,i,t-1} + u_{a,i,t-1} - \lambda_{t-1} l_{a,i,t-1} + \pi_{a,i,t-1} \lambda_{t-1} l_{a,t-1}, \\ e_{a,i,t} = (1 - \delta_{t-1}) e_{a,i,t-1} + f_{a,i,t} x_{a,i,t}, \\ u_{a,i,t} = (1 - f_{a,i,t}) x_{a,i,t}.$$

²²The assumption of time dependent, stochastic reallocation shocks $\Lambda_{a,i,t}$ rather than a state-dependent reallocation decision and a fixed cost of moving makes the quantity of gross flows exogenous. In an aggregate steady state, the two approaches are isomorphic. The assumption of time dependent shocks is more computationally tractable for a large number of industries. Quantitatively, the volatility of the preference shocks matters more for our results than the level of gross flows. Further, since we study the response to very long-lasting industry dispersion shocks, we do not think that allowing for "rest" unemployment as in [Alvarez and Shimer \(2011\)](#) would meaningfully affect the model's conclusions. We also abstract from geographical mobility. In appendix D.10, we extend the model to incorporate area reallocation. This extension yields quantitatively larger employment responses, due to the migration channel, but very similar effects of reallocation on local area unemployment.

Wages follow a Nash bargain between the firm and worker, subject to exogenously imposed downward nominal wage rigidity. This rigidity takes the form

$$w_{a,i,t} = \max\{w_{a,i,t}^*, (1 - \chi^w) w_{a,i,t-1}/\Pi_{a,t}\}, \quad (14)$$

where $w_{a,i,t}^*$ is the Nash bargained real wage, $\Pi_{a,t}$ is gross producer price inflation, and χ^w is a parameter specifying the maximum permitted decline in the nominal wage. Following [Hall \(2005\)](#) and [Chodorow-Reich and Karabarbounis \(2016\)](#), exogenous wage rigidity allows the model to generate realistic unemployment fluctuations without violating bilateral efficiency conditions or requiring counterfactual assumptions on the sources of wage rigidity. A large literature reports evidence of downward nominal wage rigidity in the data ([Kahn, 1997](#); [Card and Hyslop, 1997](#); [Goette, Sunde, and Bauer, 2007](#); [Dickens, Goette, Groshen, Holden, Messina, Schweitzer, Turunen, and Ward, 2007](#); [Daly and Hobijn, 2014](#)).²³

5.1.2. General equilibrium Output of industry i in area a is

$$Q_{a,i,t} = \eta_{i,t} e_{a,i,t}, \quad (15)$$

where $\eta_{i,t}$ is (strictly exogenous) labor productivity in industry i which does not vary across islands. Industry output is sold under perfect competition at real price $P_{a,i,t}^Q$ to a wholesaler. The wholesaler combines local industry output into an area-specific good $Q_{a,t}$ using the technology

$$Q_{a,t} = \left[\sum_i \tau_{a,i,t}^{\frac{1}{\zeta}} Q_{a,i,t}^{\frac{\zeta-1}{\zeta}} \right]^{\frac{\zeta}{\zeta-1}}, \quad (16)$$

giving rise to a downward sloping industry-level demand curve $Q_{a,i,t} = \tau_{a,i,t} \left(\frac{P_{a,i,t}^Q}{P_{a,t}^Q} \right)^{-\zeta} Q_{a,t}$, and where $\zeta \geq 1$ and $P_{a,t}^Q = \left[\sum_i \tau_{a,i,t} (P_{a,i,t}^Q)^{1-\zeta} \right]^{\frac{1}{1-\zeta}}$. In our calibration, we vary the parameters $\{\tau_{a,i,t}\}$ across islands to generate variation in steady state employment shares.

The real marginal revenue product $p_{a,i,t}$ arising in Equation (10) is the product of industry productivity and the real price of industry i 's good:

$$p_{a,i,t} = \eta_{i,t} P_{a,i,t}^Q. \quad (17)$$

With downward sloping demand, the decline in output engendered by a decline in $\eta_{i,t}$ induces a rise in the real price $P_{a,i,t}^Q$, such that following a negative productivity shock the marginal revenue product $p_{a,i,t}$ changes little but output and employment in sector i fall.

²³Still, this assumption is not without controversy. [Pissarides \(2009\)](#) shows in the context of a search model with exogenous separations that what matters for unemployment fluctuations is the wage rigidity of new hires. [Daly and Hobijn \(2014\)](#) and [Gertler, Huckfeldt, and Trigari \(2015\)](#) provide evidence of rigidity on this margin, including of downward wage rigidity.

Closing the model requires specifying the determination of the set of real industry prices $P_{a,i,t}^Q$, overall inflation, and the discount factor $m_{a,t,t+1}$. We assume that product prices are determined competitively. An Euler equation for each household determines consumption and the discount factor. While agents enjoy perfect consumption insurance within an area, asset markets across areas allow only for trade of a nominal bond. A central bank follows a standard interest rate rule that satisfies the Taylor principle. Finally, we allow for a wedge μ_t between the policy interest rate and the interest rate faced by households, and use an increase in the wedge to generate a demand-induced recession. We provide a detailed discussion and formal statement of the equations of the remainder of the model in appendix D.

5.2. Calibration

We calibrate a version of the model with two areas and ten industries, $\mathcal{A} = 2$ and $\mathcal{I} = 10$, at monthly frequency. The two areas allow for one small (infinitesimal) area which we treat as representative of a single local CSA/MSA, and one large area representative of the rest of the economy. Our choice of ten industries represents a balance between computational feasibility and ensuring that national industry trends are representative of local industry trends.²⁴

We briefly describe the calibration of the labor market block of the model, shown in Table 7. The parameters are the same in the small and the large area. Appendix D contains further details and our procedure for finding the model steady state. We obtain a target for the steady state job finding rate f appropriate to a two state labor market model of 0.5 by updating the procedure described in [Shimer \(2012\)](#), and for the job filling rate q of 0.75 from [Davis, Faberman, and Haltiwanger \(2013\)](#). Using the longitudinally linked monthly CPS files, we find a monthly job separation rate of 0.066. This separation rate exceeds that implied by the procedure in [Shimer \(2012\)](#) because it includes job-to-job transitions and therefore is more appropriate for our labor market setting. We also use the longitudinally linked monthly CPS files to calculate that 60% of “EUE” spells end with the worker employed in a different 3 digit NAICS industry. This fraction together with the job finding and separation rates determines the reallocation intensity λ . Given that our model has neither aggregate productivity growth nor trend inflation, we set the downward wage rigidity parameter χ^w to the 0.35% average monthly increase in nominal hourly earnings of production and non-supervisory employees. This value allows nominal wages to fall by 0.35% each month relative to trend, corresponding to zero nominal wage growth. We parameterize the idiosyncratic shocks $F(\varepsilon)$ as Type I $EV(-\rho\tilde{\gamma}, \rho)$, where $\tilde{\gamma}$ is Euler’s constant. The parameter ρ governs the directness of search and does not have an easily observed counterpart—it determines the ratio of net reallocation to gross reallocation given an increase in dispersion of industry labor demand—and the existing literature provides

²⁴Recall our first-stage coefficient of roughly 1 in Table 3. With $\mathcal{I} = 2$ and one location having a near-100% employment share in the expanding sector, clearly the employment share could not grow at the same rate locally as it does nationally. We found that $\mathcal{I} \geq 10$ largely eliminates such cases.

Table 7 – Calibrated Labor Market Parameters

Name	Description	Value	Source
f	Job finding rate	0.5	Shimer (2012)
q	Job filling rate	0.75	Davis et al. (2013)
δ	Separation rate	0.066	Matched monthly CPS
λ	Industry reallocation	0.043	Matched monthly CPS
ρ	Industry reallocation noise	0.95	Peak unemployment effect in recessions
D	Discount factor	0.997	4% annual rate
β	Bargaining power	0.6	
χ^w	Downward-wage rigidity	0.0035	Average monthly nominal wage growth
z	Opportunity cost	0.55 p	Chodorow-Reich and Karabarbounis (2016)

a wide range of estimates. We therefore infer ρ together with the shocks, as we describe in the following section. This yields $\rho = 0.95$. We parameterize the fixed reallocation utilities $\{\psi_{aj}\}_{j=1}^{\mathcal{I}}$ such that the steady-state allocation of labor is efficient.

5.3. Quantitative Exercise

We conduct a just-identified indirect inference to recover ρ , $\{\frac{\eta_{i,t+\mathcal{I}}}{\eta_{i,t}}\}$, and μ_t such that the model matches the following empirical targets over a full recession-recovery cycle: (1) the average employment share changes,²⁵ (2) the average unemployment increase and duration of the cycle, and (3) the peak cross-sectional effect of reallocation on unemployment (figure 3).

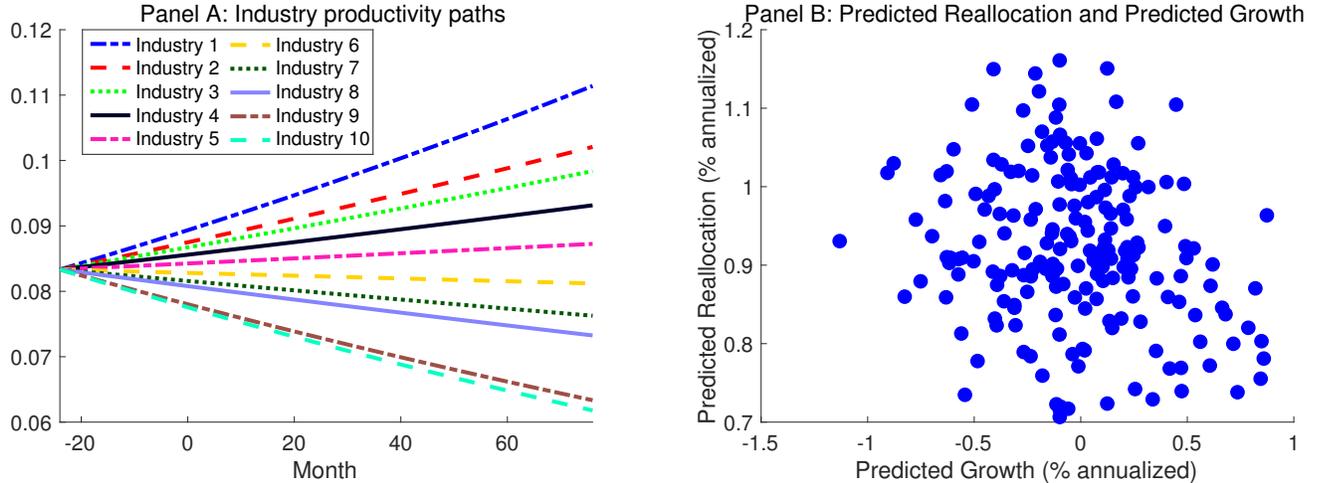
We restrict the $\mathcal{I} = 10$ productivity paths to be log-linear and mean-preserving, so that they can be (heuristically) identified from ten employment share changes. The left panel of figure 4 plots the productivity paths with industries in decreasing order of productivity change. The dispersion begins in period -24 and reaches full spread after 135 months. Period 0 will correspond to the national employment peak before the recession. The remaining duration (111 months) corresponds to the average duration of a full peak-to-peak cycle. We solve the model under perfect foresight, so the productivity paths are known as of $t = -24$. Thus, our calibration features predictable industry-specific trends before, during, and after the recession.

We create a demand-driven recession with a temporary increase in the wedge μ_t between the central bank’s policy interest rate and the interest rate available to households. To avoid conflating news of the recession with news of reallocation, agents learn of the wedge shock 25 months after the reallocation shock, at $t = 1$. The wedge equals $\mu_t = 0.0057$ for $1 \leq t \leq 36$, where its size and duration are heuristically identified by the average unemployment rate increase (3.5 percentage points) and recession-recovery duration (53 months). The national unemployment peak occurs after 24 months, close to the 30 months in the data.

In appendix Appendix D.9, we verify that industry employment growth in the large area over

²⁵We sort the 93 NAICS-3 sectors into 10 quantiles based on their employment share changes, and then calculate the average employment share change for each quantile.

Figure 4 – Productivity Paths and Local Predicted Growth and Reallocation



Notes: Panel A displays the perfect-foresight productivity paths η_i of each of the $i = 1, \dots, 10$ sectors. The productivity paths are mean-preserving in logs. Panel B displays the cross-section of predicted growth and predicted reallocation in our simulated local areas over a recession-recovery cycle.

a full recession-recovery cycle is highly correlated with the idiosyncratic industry shocks. We also show that by the end of the recession-recovery the industry employment distribution has reached the new steady state level implied by the idiosyncratic productivity shocks. Thus, our timing assumption ensures that the Bartik instrument reflects the desired amount of reallocation and not temporary frictions to employment or mobility.

We simulate the model 200 times for different initial employment share in the small area.²⁶ We construct the initial employment shares from ten independent draws from a uniform distribution, $U[0.06, 1]$, scaled to sum to one. The positive lower bound on the distribution rules out zero sectoral employment shares as well as employment shares above 65%. The right panel of figure 4 plots a cross-section of the implied predicted growth rates and the predicted reallocation rates for each local area.

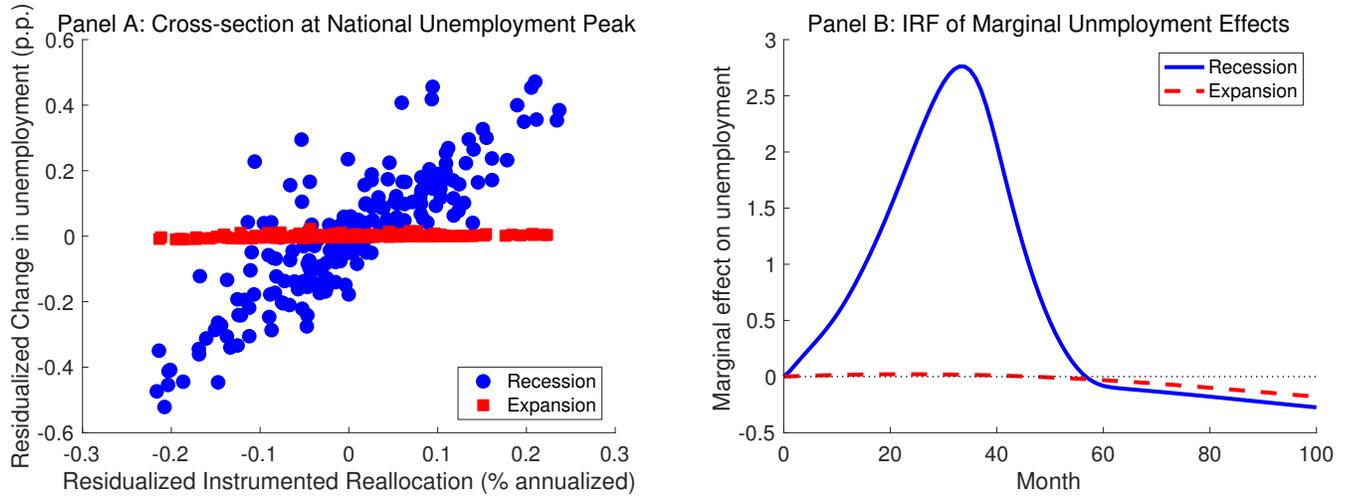
The above describes the shocks during the *recession-recovery* scenario. In the *expansion scenario* we turn off the interest rate wedge shock. We solve the model by reversing the shocks after 250 periods and working backward from the initial steady state equilibrium.²⁷

The left panel of figure 5 plots the residualized change in local unemployment from $t = 1$ to $t = 24$ (the national unemployment peak) against the residualized instrumented reallocation for the local area. Both variables are residualized with respect to predicted growth over the respective cycle and a constant, which corresponds to the second stage of our empirical estimates. The figure highlights a strong positive relationship between (residualized) unemployment and (residualized) instrumented reallocation in a recession, whereas there is no economically significant relationship in an expansion.

²⁶Since the small area is infinitesimal, the solution for the large area is identical in each simulation.

²⁷Allowing for a longer time before reversal has little effect on our results.

Figure 5 – Model Impulse Response Function and Marginal Effect



Notes: Panel A displays the cross-section of the residualized increase in unemployment from period 0 to 24 against the residualized instrumented reallocation, separately for the recession-recovery scenario and the expansion scenario. Panel B displays the marginal effects of realized reallocation based on an IV regression at different horizons.

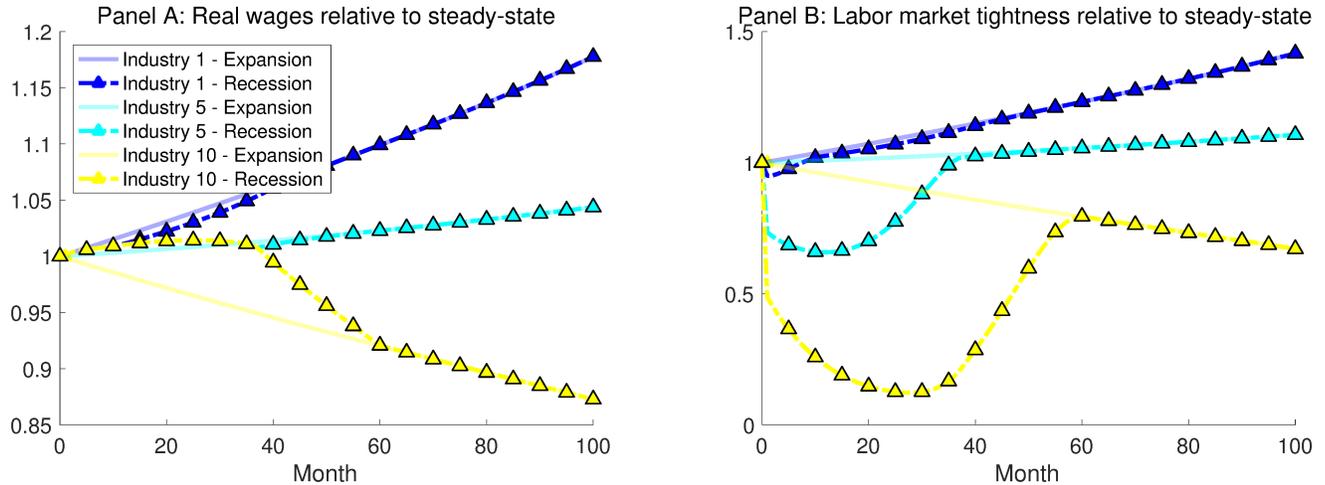
The right panel plots the marginal effect of reallocation on unemployment for the expansion and recession-recovery scenarios. These are the IV coefficients from running regressions of the change in unemployment on realized reallocation instrumented with predicted reallocation, controlling for predicted growth and a constant. The marginal effects for $t = 24$ (the national unemployment peak) correspond to the best-fit lines through the points in panel A. These marginal effects of reallocation on unemployment have their data-analog in Table 5 and the plot in Figure 3. In the model, as in the data, the marginal effect of reallocation on unemployment is significantly larger and more persistent in recession-recoveries than in expansions. The maximum marginal effect during the recession-recovery peaks at 2.73 after 34 months, consistent with the empirical impulse response function in Figure 3. In contrast, the maximum marginal effect during the expansion is small (0.02), falling within the range of point estimates reported in Table 5 (after multiplying the latter by 2.5). While the model fits the peak effect in recessions by construction, the model is corroborated by the dynamics of the marginal effects and the asymmetry of the expansion results.

5.4. Mechanism

The model replicates the finding that reallocation generates a quantitatively large increase in local unemployment if it occurs during a recession but not if it occurs during an expansion. Compression of the wage distribution during recessions forms a key mechanism underlying this difference.²⁸ In expansions the wage constraint does not bind, so real wages rise in the

²⁸Our focus on wage rigidity does not mean that we reject other possible mechanisms. Recent work has highlighted two: the possibility of search inefficiency or job retraining associated with industry switchers (e.g. [Jaimovich and Siu, 2014](#)), and changes in the pool of job seekers during recessions (e.g. [Ahn and Hamilton,](#)

Figure 6 – Model Impulse Response Functions of Real Wages and Labor Market Tightness



Notes: Panel A plots the impulse response functions of real wages relative to the initial steady-state in the large area of the currency union. Panel B displays the corresponding impulse response functions for labor market tightness. For ease of exposition, we only plot results for three sectors.

expanding sector and fall in the declining sector commensurate with the rate of the productivity change. This is shown by the unmarked lines in the left panel of figure 6. Due to imperfect labor mobility, tightness diverges as shown in the right panel of figure 6, causing a decrease in matching efficiency and reducing employment. However, the divergence in tightness is small as higher wages draw workers into the expanding sectors, increasing the number of job seekers in the expanding sectors and reducing the number in the contracting sectors.

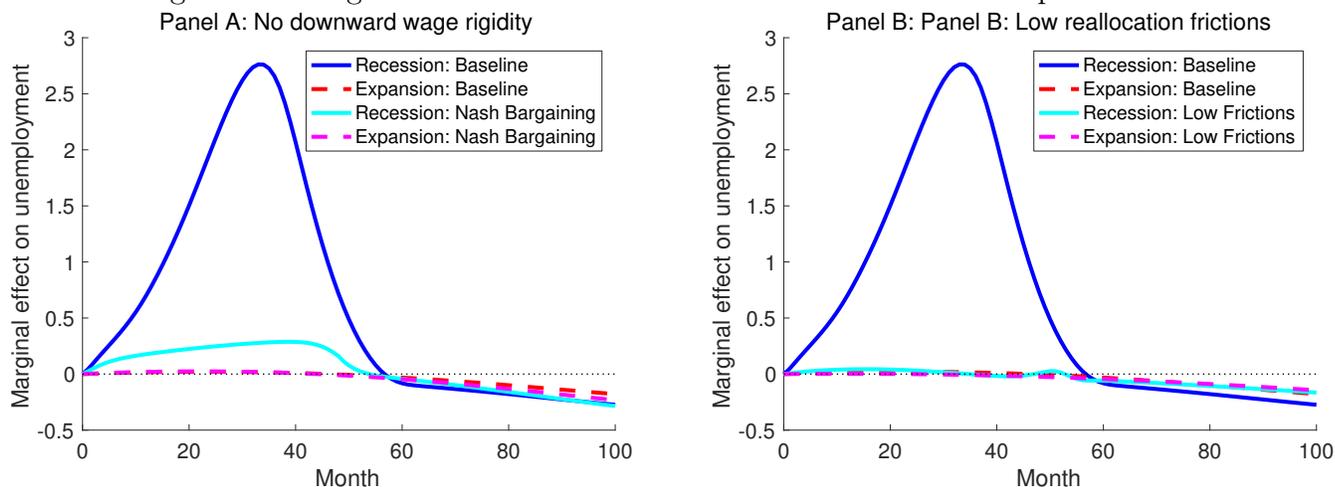
In a recession the downward nominal wage constraint becomes binding. However, the extent to which it binds differs across sectors, as illustrated by the triangle-hash lines in the left panel of figure 6. The wage constraint binds most tightly in the industries experiencing both secular decline and the cyclical recession, further compressing job values and disincentivizing vacancy creation, while rising wages in the expanding industry limit the increase in job values and therefore vacancy posting.²⁹ The decline in total vacancies causes unemployment to increase.³⁰ In addition, a constant returns to scale matching function means that the sharp divergence in labor market tightness and hence job finding rates across sectors generates additional “mismatch” unemployment beyond that accounted for by the decline in aggregate vacancies (Sahin

2014; Hall and Schulhofer-Wohl, 2015). Pilossoph (2014) and Dvorkin (2014) criticize the inefficient search explanation on the grounds that gross flows of workers across industries vastly exceed net flows and appear mostly unresponsive to changes in net flows, a fact consistent with our model.

²⁹Throughout these dynamics the job surplus in each sector remains positive, so that the downward nominal wage constraints respect bilateral efficiency. This follows from our calibration of the worker’s opportunity cost such that the steady-state surplus of a job is relatively large.

³⁰The decline in vacancies in our model contradicts the argument in Abraham and Katz (1986) that the decline in vacancies during recessions necessarily limits the potential role for reallocation shocks. Their logic rests on a downward sloping Beveridge curve (a negative relationship between unemployment and vacancies) absent sectoral shifts, while reallocation shocks which shift the Beveridge curve induce positive comovement of vacancies and unemployment. Hosios (1994) first challenged the robustness of this logic.

Figure 7 – Marginal Effect of Reallocation in Alternative Model Specifications



Notes: Panel A displays the marginal effect of reallocation on unemployment in the baseline model and when period-by-period Nash bargaining replaces the downward nominal wage rigidity assumption. Panel B contrasts the baseline model with a parameterization that sets the area and industry reallocation noise parameters to 20 percent of their baseline values, which weakens reallocation frictions and makes labor search more directed. In each case we parameterize the reallocation and recession shocks to hit the same targets as in our baseline.

et al., 2014; Barnichon and Figura, 2015).³¹

In Table E.1 of the online appendix, we test for the asymmetry of wage compression during recessions and expansions using national hourly wages by industry from the CPS and QCEW employment share changes. Consistent with the model’s mechanism, we find that industries with rising employment shares have rising wage differentials during expansions, but that there is no economically or statistically significant relationship between the change in the wage premium during a recession and industry share growth.

To illustrate quantitatively the model’s key frictions, panel A of Figure 7 plots the baseline marginal coefficient impulse response function (the solid blue line) along with counterfactual marginal coefficients obtained by selectively changing features of the model. The dash-dot light blue line shows the marginal effects in recession-recoveries with wages determined by Nash bargaining in each period. Since this experiment does not feature any nominal rigidity, we induce a recession with a negative productivity shock, calibrated to hit the same recession targets as our baseline. Without downward wage rigidity, the effects are much smaller and of similar magnitude across business cycle states.³²

³¹Constant returns to scale makes job finding rates concave in tightness so that minimizing unemployment holding the number of vacancies fixed requires equalizing job finding rates across sectors. The magnitude of mismatch unemployment in our model calibrated to features of the Great Recession (employment share changes, depth, duration, and inflation rate) is 1.15 p.p., within the range reported in table 1 of Sahin et al. (2014).

³²We kept the baseline ρ in the experiment with Nash Bargaining, since raising ρ to hit the peak marginal unemployment effect resulted in much wider dispersion in the productivity paths, causing negative job surplus in the contracting sector. Appendix Figure 10 displays the comparison with a higher $\rho = 4$, such that the surplus remains positive in all sectors. In this case, the marginal effects of reallocation on unemployment under Nash Bargaining are too large in expansions, too small in recessions, and counterfactually increase with the

Panel B of Figure 7 illustrates the importance of reallocation frictions. The teal and pink dashed lines report the impulse response functions of the marginal coefficients when the variance of the reallocation taste shocks ε_j is reduced to 20% of its baseline values. This change makes the industry and location choice much more directed. A greater directedness of search per se has only a minor effect on the employment response to a given set of productivity processes. However, it implies that the same employment share changes across sectors require much less dispersion in productivity. This limits the dispersion of labor market tightness and the extent to which wage constraints bind asymmetrically across sectors, which results in marginal coefficients of nearly zero in both expansions and recessions. Conversely, appendix figure 11 shows that an increase in labor market fluidity (Davis and Haltiwanger, 2014) mitigates the adverse employment consequences of a reallocation shocks.

6. Conclusion

Reallocation of workers across industries matters asymmetrically over the business cycle. To establish this fact, we develop a methodology to isolate the secular component of industry dispersion. The methodology identifies reallocation in a local area predicted by the local area’s industry composition and national trends and orthogonalizes this predicted reallocation with respect to the direct growth rate consequences of the local industry composition. We apply the methodology to local labor markets over a 35 year period. Areas subjected to more reallocation have worse local recessions if national employment is depressed, but similar outcomes during national expansions.

We interpret the empirical results through the lens of a model of the labor market featuring decisions by job-seekers of which industry to search for work. The model delivers the following insights. First, absent labor market frictions or mechanisms which generate sticky wages, reallocation does not much affect labor market outcomes. Intuitively, when workers can seamlessly transition across industries, dispersion shocks result in immediate transitions to a new steady state. Second, plausible frictions result in marginal reallocation effects of similar magnitude to those found in our empirical exercises. Third, compression of wage differentials during recessions can explain the asymmetric response of aggregate employment to reallocation during recession-recoveries and expansions.

Our analysis has implications for policy not explored in this paper. The idiosyncratic industry shocks which underlie secular industry reallocation include real shocks such as dispersion in productivity levels or consumer taste trends. Nonetheless, the ease with which reallocation occurs depends sharply on the state of the business cycle. This interaction suggests a possible role for monetary policy in accommodating such shocks to “grease the wheels” of reallocation with

horizon.

higher inflation. Likewise, the interaction between worker fluidity and industry reallocation in our model suggests a possible role for policy in increasing the fluidity of labor markets to mitigate against the consequences of industry reallocation shocks. We leave further development of these conjectures and other implications to future work.

A. Standard Errors in Two-Sample 2sls

This appendix derives the ts2sls asymptotic standard error when the first and second stage residuals are not necessarily independent. The notation departs completely from the notation in the main text in order to (roughly) follow [Murphy and Topel \(1985\)](#).

Notation. We assume two possibly interdependent samples of size N_1 and N_2 drawn from the same population where the subscripts 1 and 2 define the samples. We are interested in the following two stage model of the observed data:

$$\text{Structural equation:} \quad Y_j = F_j\gamma + X_j\beta + \eta_j, \quad j = 2, \quad (\text{A.1})$$

$$\text{First stage:} \quad F_j = W_j\pi_W + X_j\pi_X + e_j, \quad j = 1, \quad (\text{A.2})$$

$$\text{Second stage:} \quad Y_j = H_j\pi\gamma + X_j\beta + u_j, \quad j = 2, \quad (\text{A.3})$$

where $Y_j \sim N_j \times 1$ denotes a vector of observations of the outcome variable in sample j , $X_j \sim N_j \times K$ is a matrix of included instruments, $F_j \sim N_j \times M$ is a matrix of endogenous variables, $W_j \sim N_j \times L$ is a matrix of excluded instruments where $L \geq M$, $H_j = \begin{pmatrix} X_j & W_j \end{pmatrix} \sim N_j \times (K + L)$ is the matrix of first stage regressors, $\eta_j \sim N_j \times 1$ is the vector of structural residuals, $e_j \sim N_j \times M$ is the matrix of first stage residuals, $u_j \sim N_j \times 1$ is the vector of second stage residuals, $\beta, \gamma, \pi_X, \pi_W$ are conforming matrices of parameters, and $\pi = \begin{pmatrix} \pi_X & \pi_W \end{pmatrix}' \sim (K + L) \times M$. Let $\hat{\pi} = (H_1' H_1)^{-1} H_1' F_1$ denote the fitted coefficients from the first stage regression and $Z_2 = \begin{pmatrix} X_2 & H_2 \hat{\pi} \end{pmatrix} \sim N_2 \times (K + M)$ denote the matrix of regressors in the second stage.

Assumptions.

$$E \left[Z_j' Z_j \right] = Q \sim (K + M) \times (K + M), \quad (\text{A.4})$$

$$E \left[H_j' H_j \right] = R \sim (K + L) \times (K + L), \quad (\text{A.5})$$

$$E \left[Z_j' H_j \right] = S \sim (K + M) \times (K + L), \quad (\text{A.6})$$

$$E \left[Z_j' u_j u_j' Z_j \right] = \Omega_{Zu} \sim (K + M) \times (K + M), \quad (\text{A.7})$$

$$E \left[H_j' e_j \gamma \gamma' e_j' H_j \right] = \Omega_{H(e\gamma)} \sim (K + L) \times (K + L), \quad (\text{A.8})$$

$$E \left[Z_j' e_j \gamma \gamma' e_j' Z_j \right] = \Omega_{Z(e\gamma)} \sim (K + M) \times (K + M), \quad (\text{A.9})$$

$$E \left[Z_j' u_j \gamma' e_j H_j \right] = \Omega_{Zu(e\gamma)H} \sim (K + M) \times (K + M), \quad (\text{A.10})$$

$$E \left[Z_j' u_j \gamma' e_j Z_j \right] = \Omega_{Zu(e\gamma)Z} \sim (K + M) \times (K + M), \quad (\text{A.11})$$

$$\lim_{N_1, N_2 \rightarrow \infty} N_2/N_1 = \alpha > 0. \quad (\text{A.12})$$

Note that in Equations (A.4)–(A.11), the moment conditions hold for any sample, $j = 1, 2$.

Derivation. Rewriting Equation (A.3) as $Y_2 = X_2\beta + H_2\hat{\pi}\gamma - H_2(\hat{\pi} - \pi)\gamma + u_2$, one can derive an expression for the sampling error in the least squares estimator $(\hat{\beta} \ \hat{\gamma})'$:

$$\begin{aligned} \sqrt{N_2} \begin{pmatrix} \hat{\beta} - \beta \\ \hat{\gamma} - \gamma \end{pmatrix} &= \left(\frac{1}{N_2} Z_2' Z_2 \right)^{-1} \left(\frac{1}{\sqrt{N_2}} Z_2' u_2 \right) - \left(\frac{1}{N_2} Z_2' Z_2 \right)^{-1} \frac{1}{\sqrt{N_2}} Z_2' H_2 (\hat{\pi} - \pi) \gamma \\ &= \left(\frac{1}{N_2} Z_2' Z_2 \right)^{-1} \left(\frac{1}{\sqrt{N_2}} Z_2' u_2 \right) - \sqrt{\frac{N_2}{N_1}} \left(\frac{1}{N_2} Z_2' Z_2 \right)^{-1} \left(\frac{1}{N_2} Z_2' H_2 \right) \left(\frac{1}{N_1} H_1' H_1 \right)^{-1} \left(\frac{1}{\sqrt{N_1}} H_1' e_1 \right) \end{aligned}$$

where the last line substitutes the first stage relationship $\sqrt{N_1}(\hat{\pi} - \pi) = \left(\frac{1}{N_1} H_1' H_1 \right)^{-1} \left(\frac{1}{\sqrt{N_1}} H_1' e_1 \right)$.

Assuming sufficient regularity conditions to invoke a law of large numbers to substitute using (A.4)–(A.6) and the central limit theorem to use (A.7), (A.8) and (A.10), we have:

$$\begin{aligned} \sqrt{N_2} \begin{pmatrix} \hat{\beta} - \beta \\ \hat{\gamma} - \gamma \end{pmatrix} &\rightarrow N(0, \Sigma), \\ \Sigma &= Q^{-1} \left(\Omega_{Zu} + \alpha S R^{-1} \Omega_{H(e\gamma)} R^{-1} S' - \sqrt{\alpha} \left(\Omega_{Zu(e\gamma)H} R^{-1} S' + S R^{-1} \Omega'_{Zu(e\gamma)H} \right) \right) Q^{-1}. \end{aligned}$$

Lemma 1

$$H(H'H)^{-1}H'Z = Z.$$

Proof: Substitute $Z = \begin{pmatrix} X & H\hat{\pi} \end{pmatrix}$, $H = \begin{pmatrix} X & W \end{pmatrix}$ and note that Z is in the subspace of H . Thus the projection of Z onto H yields Z .

Using Lemma 1, $S R^{-1} \Omega_{H(e\gamma)} R^{-1} S' = \Omega_{Z(e\gamma)}$, $\Omega_{Zu(e\gamma)H} R^{-1} S' = \Omega_{Zu(e\gamma)Z}$, and

$$\Sigma = Q^{-1} \left(\Omega_{Zu} + \alpha \Omega_{Z(e\gamma)} - \sqrt{\alpha} \left(\Omega_{Zu(e\gamma)Z} + \Omega'_{Zu(e\gamma)Z} \right) \right) Q^{-1}. \quad (\text{A.13})$$

With independent samples and homoskedastic residuals, $\Omega_{Zu(e\gamma)Z} = 0$ and Equation (A.13) reduces to equation (16) in [Inoue and Solon \(2010\)](#).³³ When the two samples fully coincide, one can show using $u = e\gamma + \eta$ and $\alpha = 1$ that $\Sigma = Q^{-1} \Omega_{Z\eta} Q^{-1}$, the standard expression for the 2sls variance matrix. A feasible estimator of Σ is:

$$\hat{\Sigma} = (Z_2' Z_2)^{-1} \left(\Omega_{Z_2 u_2} + \alpha \Omega_{Z_1(e_1 \hat{\gamma})} - \sqrt{\alpha} \left(\Omega_{Z_{1\cap 2} u_{1\cap 2}(e_{1\cap 2} \hat{\gamma}) Z_{1\cap 2}} + \Omega'_{Z_{1\cap 2} u_{1\cap 2}(e_{1\cap 2} \hat{\gamma}) Z_{1\cap 2}} \right) \right) (Z_2' Z_2)^{-1},$$

³³[Khawand and Lin \(2015\)](#) show that our ts2sls estimator is equivalent to a weighted average of the 2sls estimator using the overlapping sample and a split-sample 2sls estimator which uses in the second stage only observations not in the first stage sample. Equation (A.13) is more general than their proposition 6 in that it allows for an arbitrary residual structure. Moreover, their proposition is incorrect because they assume independence of the 2sls and ss2sls estimators despite the shared first stage and because of several typos.

where the subscript $1 \cap 2$ denotes the intersection of the samples. The functional form of the cross-product matrices $\Omega_{Z_2 u_2}, \Omega_{Z_1(e_1 \hat{\gamma})}, \Omega_{Z_{1 \cap 2} u_{1 \cap 2}(e_{1 \cap 2} \hat{\gamma})_{Z_{1 \cap 2}}$ depends on the assumed covariance structure of the residuals (homoskedastic, heteroskedastic, clustered, etc.).

References

- Aaronson, Daniel, Ellen Rissman, and Daniel Sullivan, “Can Sectoral Reallocation Explain the Jobless Recovery?,” *Federal Reserve Bank of Chicago Economic Perspectives*, 2004, (2Q), 36–49.
- Abraham, Katharine and Lawrence F Katz, “Cyclical Unemployment: Sectoral Shifts or Aggregate Disturbances?,” *Journal of Political Economy*, 1986, 94.
- Adão, Rodrigo, Michal Kolesár, and Eduardo Morales, “Shift-Share Designs: Theory and Inference,” Working Paper 24944, National Bureau of Economic Research August 2018.
- Ahn, Hie Joo and James D Hamilton, “Heterogeneity and Unemployment Dynamics,” 2014.
- Alvarez, Fernando and Robert Shimer, “Search and Rest Unemployment,” *Econometrica*, 2011, 79 (1), 75–122.
- Angrist, Joshua and Alan Krueger, “The Effect of Age at School Entry on Educational Attainment: An Application of Instrumental Variables With Moments From Two Samples,” *Journal of the American Statistical Association*, 1992, pp. 328–336.
- Artuç, Erhan, Shubham Chaudhuri, and John McLaren, “Trade Shocks and Labor Adjustment: A Structural Empirical Approach,” *American Economic Review*, 2010, 100 (3), 1008–45.
- Autor, David H., David Dorn, and Gordon H. Hanson, “The China Syndrome: Local Labor Market Effects of Import Competition in the United States,” *American Economic Review*, 2013, 103 (6), 2121–68.
- Barnichon, Regis and Andrew Figura, “Labor Market Heterogeneity and the Aggregate Matching Function,” *American Economic Journal: Macroeconomics*, October 2015, 7 (4), 222–49.
- Bartik, Timothy J., *Who Benefits from State and Local Development Policies?*, W.E. Upjohn Institute for Employment Research, 1991.
- Berger, David, “Countercyclical Restructuring and Jobless Recoveries,” 2014.
- Borusyak, Kirill, Peter Hull, and Xavier Jaravel, “Quasi-Experimental Shift-Share Research Designs,” Working Paper 24997, National Bureau of Economic Research September 2018.
- Brainard, S. Lael and David M. Cutler, “Sectorial Shifts and Cyclical Unemployment Reconsidered,” *The Quarterly Journal of Economics*, 1993, 108 (1), pp. 219–243.
- Card, David and Dean Hyslop, “Does Inflation Grease the Wheels of the Labor Market?,” in Christina D. Romer and David H. Romer, eds., *Reducing Inflation: Motivation and Strategy*, University of Chicago Press, 1997, pp. 71 – 122.
- Charles, Kerwin, Erik Hurst, and Matt Notowidigdo, “Masking and Aggregate Employment Changes: Housing Booms and Manufacturing Decline During the 2000s,” 2014.
- Chodorow-Reich, Gabriel and Loukas Karabarbounis, “The Cyclical Cost of the Opportunity Cost of Employment,” *Journal of Political Economy*, 2016, 124 (6), 1563–1618.
- Christiano, Lawrence, Martin Eichenbaum, and Mathias Trabandt, “Unemployment and Business Cycles,” *Econometrica*, 2016, 84 (4), 1523–1569.
- Daly, Mary C. and Bart Hobijn, “Downward nominal wage rigidities bend the Phillips curve,” *Journal of Money, Credit and Banking*, 2014, 46 (S2), 51–93.
- Davis, Steven J. and John C. Haltiwanger, “Labor Market Fluidity and Economic Performance,”

2014. Jackson Hole Economic Policy Symposium.
- and John Haltiwanger, “Gross Job Creation, Gross Job Destruction, and Employment Reallocation,” *The Quarterly Journal of Economics*, 1992, *107* (3), pp. 819–863.
- , R. Jason Faberman, and John C. Haltiwanger, “The Establishment-Level Behavior of Vacancies and Hiring,” *The Quarterly Journal of Economics*, 2013, *128* (2), 581–622.
- , —, and John Haltiwanger, “Labor market flows in the cross section and over time,” *Journal of Monetary Economics*, 2012, *59* (1), 1 – 18. Carnegie-NYU-Rochester Conference Series on Public Policy at New York University on April 15-16, 2011.
- DeLong, J. Bradford, “Identifying Cyclical vs. Structural Unemployment,” Blog post August 2010.
- and Lawrence H. Summers, “How Does Macroeconomic Policy Affect Output?,” *Brookings Papers on Economic Activity*, 1988, *1988* (2), pp. 433–494.
- Dickens, William T., Lorenz Goette, Erica L. Groshen, Steinar Holden, Julian Messina, Mark E. Schweitzer, Jarkko Turunen, and Melanie E. Ward, “How Wages Change: Micro Evidence from the International Wage Flexibility Project,” *Journal of Economic Perspectives*, June 2007, *21* (2), 195–214.
- Dvorkin, Maximiliano, “Sectoral Shocks, Reallocation and Unemployment in Competitive Labor Markets,” 2014. Unpublished manuscript.
- Farmer, Tracy and Michael Searson, “Use of Administrative Records in the Bureau of Labor Statistics’ Covered Employment and Wage (ES-202) Program,” Technical Report, Bureau of the Census Annual Research Conference 1995.
- Foster, Lucia, Cheryl Grim, and John Haltiwanger, “Reallocation in the Great Recession: Cleansing or Not?,” *Journal of Labor Economics*, 2016, *34* (S1), S293–S331.
- Fujita, Shigeru and Giuseppe Moscarini, “Recall Unemployment,” 2013.
- Garin, Julio, Mike Pries, and Eric Sims, “Reallocation and the Changing Nature of Economic Fluctuations,” 2013.
- Gertler, Mark, Chris Huckfeldt, and Antonella Trigari, “Unemployment Fluctuations, Match Quality, and the Wage Cyclicity of New Hires,” 2015.
- Glaeser, Edward L., “Reinventing Boston: 1630i_c½2003,” *Journal of Economic Geography*, 2005, *5* (2), 119–153.
- Goette, Lorenz, Uwe Sunde, and Thomas Bauer, “Wage Rigidity: Measurement, Causes and Consequences,” *The Economic Journal*, 2007, *117* (524), F499–F507.
- Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, “Bartik Instruments: What, When, Why, and How,” Technical Report, National Bureau of Economic Research 2018.
- Groshen, Erica and Simon Potter, “Has structural change contributed to a jobless recovery?,” *Current Issues in Economics and Finance*, 2003, *9* (8).
- Hall, Robert, “Employment Fluctuations with Equilibrium Wage Stickiness,” *American Economic Review*, 2005, *95* (1), 50–65.
- and Sam Schulhofer-Wohl, “Measuring Job-Finding Rates and Matching Efficiency with Heterogeneous Jobseekers,” 2015. NBER Working Paper No. 20939.
- Hosios, Arthur J., “Unemployment and Vacancies with Sectoral Shifts,” *The American Economic Review*, 1994, *84* (1), 124–144.
- Inoue, Atsushi and Gary Solon, “Two-Sample Instrumental Variables Estimators,” *The Review of Economics and Statistics*, 2010, *92* (3), 557–561.
- Jackman, Richard and Stephen Roper, “Structural Unemployment,” *Oxford Bulletin of Economics and Statistics*, 1987, *49* (1), 9–36.

- Jaimovich, Nir and Henry Siu, “The Trend is the Cycle: Job Polarization and Jobless Recoveries,” 2014.
- Kahn, Shulamit, “Evidence of Nominal Wage Stickiness from Microdata,” *The American Economic Review*, 1997, 87 (5), pp. 993–1008.
- Kennan, John and James R. Walker, “The Effect of Expected Income on Individual Migration Decisions,” *Econometrica*, 2011, 79 (1), 211–251.
- Khawand, Christopher and Wei Lin, “Finite Sample Properties and Empirical Applicability of Two-Sample Two-Stage Least Squares,” 2015.
- Kline, Patrick, “Understanding Sectoral Labor Market Dynamics: An Equilibrium Analysis of the Oil and Gas Field Services Industry,” 2008. Unpublished manuscript.
- Koenders, Kathryn and Richard Rogerson, “Organizational dynamics over the business cycle: a view on jobless recoveries,” *Review*, 2005, (Jul), 555–580.
- Krugman, Paul, “Jobs and Skills and Zombies,” Blog post March 2014.
- Lilien, David M, “Sectoral shifts and cyclical unemployment,” *The Journal of Political Economy*, 1982, pp. 777–793.
- Mehrotra, Neil R and Dmitriy Sergeyev, “Sectoral Shocks, the Beveridge Curve and Monetary Policy,” *mimeo*, 2012.
- Molloy, Raven, Christopher L. Smith, Riccardo Trezzi, and Abigail Wozniak, “Understanding Declining Fluidity in the U.S. Labor Market,” *Brookings Papers on Economic Activity*, 2016, Spring.
- Murphy, Kevin and Robert Topel, “The Evolution of Unemployment in the United States: 1968-1985,” in Stanley Fischer, ed., *NBER Macroeconomics Annual 1987*, Vol. 2 The MIT Press 1987, pp. 11–68.
- Murphy, Kevin M. and Robert H. Topel, “Estimation and Inference in Two-Step Econometric Models,” *Journal of Business & Economic Statistics*, 1985, 3 (4), 370–379.
- Notowidigdo, Matthew J., “The Incidence of Local Labor Demand Shocks,” June 2011.
- Pacini, David and Frank Windmeijer, “Robust inference for the Two-Sample 2SLS estimator,” *Economics Letters*, 2016, 146, 50 – 54.
- Pilosoph, Laura, “Sectoral Shocks and Move Unemployment,” 2014. Unpublished manuscript.
- Pissarides, Christopher A., “The Unemployment Volatility Puzzle: Is Wage Stickiness the Answer?,” *Econometrica*, 2009, 77 (5), 1339–69.
- Sahin, Aysegül, Joseph Song, Giorgio Topa, and Giovanni L. Violante, “Mismatch Unemployment,” *American Economic Review*, 2014, 104 (11), 3529–64.
- Schmitt-Grohé, Stephanie and Martin Uribe, “Downward Nominal Wage Rigidity, Currency Pegs, and Involuntary Unemployment,” *Journal of Political Economy*, 2016, 124 (5), 1466–1514.
- Schumpeter, Joseph A., *Capitalism, Socialism, and Democracy* 1942.
- Shimer, Robert, “Mismatch,” *American Economic Review*, September 2007, 97 (4), 1074–1101.
- , “Reassessing the Ins and Outs of Unemployment,” *Review of Economic Dynamics*, 2012, 15, 127–48.
- Staiger, Douglas and James H. Stock, “Instrumental Variables Regression with Weak Instruments,” *Econometrica*, 1997, 65 (3), 557–586.
- Walsh, Carl E, “Labor Market Search, Sticky Prices, and Interest Rate Policies,” *Review of Economic Dynamics*, 2005, 8 (4), 829–849.