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 in affecting business cycle outcomes. Yet, the issue remains one of great debate.

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 when the reallocation coincides with a recession, but roughly neutral effects when it occurs coincident with 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, 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 reallocation shocks, i.e. 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 the pattern of industry reallocation 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 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 result in higher unemployment if it occurs 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 expan-
sions 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. 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 from this literature in its focus on business cycles outcomes. As such, we construct a measure that does not rely on a specific source of variation in sectoral reallocation. Our findings complement recent 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 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

\footnote{See e.g. Groshen and Potter (2003); Koenders and Rogerson (2005); Berger (2014); Garin, Pries, and Sinus (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 sees 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.}
small. Moreover, it is precisely when this wage differential is small that the unemployment response to 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.


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 across industries based on the dispersion in industry employment growth rates as in Lilien (1982). The economy consists of \( A \) distinct 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, \( g_{a,i,t,t+j} \equiv \frac{e_{a,i,t+j}}{e_{a,i,t}} - 1 \) the area-industry employment growth rate, and \( g_{a,t,t+j} \equiv \frac{e_{a,t+j}}{e_{a,t}} - 1 \) total local area employment growth. Our reallocation index for area \( a \) between months \( t \) and \( t+j \) is:

\[
R_{a,t,t+j} = \frac{12}{j} \sum_{i} s_{a,i,t} \left| \frac{1 + g_{a,i,t,t+j}}{1 + g_{a,t,t+j}} - 1 \right|. \tag{1}
\]

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 a monthly flow expressed at an annual rate, such that \( R_{a,t,t+j} \subseteq [0, 12/j] \).

2.2. Econometric Approach

We organize our discussion around a system of equations for unemployment \( u \) and reallocation in area \( a \):

\[
\Delta u_{a,t,t+j} = \beta_j R_{a,t,t,k} + \Gamma^u X_{a,t,t+j} + \varepsilon_{a,t,t+j}, \tag{2}
\]

\(^2\)A previous version of the paper defined \( R_a \) using an equivalent representation in terms of changes in industry employment shares, \( R_{a,t,t+j} = \left( \frac{12}{j} \right) \left( \frac{1}{2} \sum_{i=1}^{I} |s_{a,i,t+j} - s_{a,i,t}| \right) \). Our reallocation measure differs slightly from Lilien (1982). First, Lilien measures reallocation only period-by-period, corresponding to \( R_{a,t,t+1} \). Second, Lilien sums the squares of industry growth rate dispersion whereas we sum absolute values to reduce sensitivity to outliers. The variable \( R_{a,t,t+1} \) also equals the Davis and Haltiwanger (1992) cross-industry job reallocation rate if total employment remains unchanged between the two periods. Appendix A contains additional details.
\[ R_{a,t,t+k} = g(u_{a,t}, u_{a,t+1}, \ldots, u_{a,t+k}) + \Gamma^{R_{a,t,t+k}} + \nu_{a,t,t+k}, \]  

where \( \Delta u_{a,t,t+j} = u_{a,t+j} - u_{a,t} \). Equation (2) allows unemployment \( u \) in region \( a \) to evolve as a function of observable characteristics \( X_{a,t,t+j} \), reallocation over some (potentially longer) period \( R_{a,t,t+k} \), and unobserved area-specific determinants \( \varepsilon_{a,t,t+j} \). Our object of interest is \( \beta_j \).

Equation (3) acknowledges that reallocation is an endogenous outcome jointly determined with the path of unemployment. The prior literature has emphasized two sources of causality running from unemployment to reallocation. First, a low opportunity cost of restructuring during periods of weak demand may make high unemployment a cause of greater reallocation (Schumpeter, 1942; Berger, 2014). Second, if industries differ in their cyclical sensitivities, then a demand-induced recession will cause cyclical reallocation across industries (Abraham and Katz, 1986). More generally, both unemployment and reallocation may depend on common determinants. For example, an area with a large manufacturing base in 1980 may have experienced both substantial reallocation over the past few decades and had high unemployment directly as a result of concentrating in industries which had negative labor demand shocks. Taken together, \( \beta_j \) in equation (2) cannot be consistently estimated by OLS.

We introduce a “double Bartik” strategy to estimate \( \beta_j \). Following Bartik (1991) and a large subsequent literature, we define Bartik predicted employment growth as the employment growth which would obtain 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,

\[ g^b_{a,t,t+j} = \frac{12}{j} \sum_{i=1}^{I} s_{a,i,t} \frac{g_{a,i,t,t+j} - 1}{1 + g^b_{a,t,t+j} - 1}, \]  

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 “elsewhere” employment growth rate for industry \( i \). Substituting \( g_{a,i,t,t+j} \) and \( g^b_{a,t,t,j} \) 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,

\[ R^b_{a,t,t+j} = \left( \frac{12}{j} \right) \left( \frac{1}{2} \sum_{i=1}^{I} s_{a,i,t} \left| \frac{1 + g_{a,i,t,t+j} - 1}{1 + g^b_{a,t,t,j} - 1} \right| \right). \]  

We believe this second Bartik measure is original.\(^3\)

We use Bartik predicted reallocation \( R^b_{a,t,t+k} \) as an excluded instrument for \( R_{a,t,t+k} \) and we designate Bartik predicted employment growth as a control (i.e., included instrument). The

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\(^3\)The 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. While we motivate equation (5) by directly substituting \( g_{a,i,t,t+j} \) and \( g^b_{a,t,t,j} \) into equation (1), the same expression follows from the more primitive assumption that the growth rate of all industries in an area is identical to the national industry growth rate.
relevance condition, $\text{Cov}(R_{a,t,t+k}, R^\delta_{a,t,t+k} | X_{a,t,t+j}) > 0$, will hold if growth rates of the same industry in different local areas have a common component. The exclusion restriction requires $\text{Cov}(\varepsilon_{a,t,t+j}, R^\delta_{a,t,t+k} | X_{a,t,t+j}) = 0$. Whereas actual reallocation may depend on the trajectory of local unemployment, Bartik predicted reallocation is pre-determined as of time $t$ with respect to local outcomes. Thus, predicted reallocation solves the problem of feedback from local unemployment ($g(u_{a,t}, u_{a,t+1}, \ldots, u_{a,t+k})$) to reallocation. Including $g^\delta_{a,t,t+j}$ in $X_{a,t,t+j}$ controls for both the area’s industrial cyclical sensitivity to the national business cycle 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.

2.3. Specification Details

Timing of measuring reallocation. We measure 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.

Two issues motivate measuring reallocation which survives over multiple periods rather than following the standard approach in the literature of measuring reallocation period-by-period. First, period-by-period measures partly reflect reallocation which occurs because industries differ in their cyclical sensitivities. We refer to our measure as secular reallocation because it filters out temporary, cyclically-induced labor reallocation. Second, the Bartik predicted reallocation instrument depends on realized employment changes at the national level. How quickly national labor reallocation occurs following a change in, say, the distribution of industry productivities may depend on the presence of labor market frictions which also affect the unemployment response to the reallocation. Using a long horizon helps to ensure that such frictions do no not materially affect realized reallocation nationally.

We define a national labor market recession as the period between a private sector employment peak and lasting until the employment trough. We define a recovery as the period from the trough until the economy regains its previous peak level. For example, the peak in U.S. national private sector employment prior to the Great Recession occurs in January 2008, the trough occurs in February 2010, and the recovery lasts until the private sector regains its previous peak level in March 2014. We define an expansion as the period between 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 January 2008 and reallocation during the 2008-14 recession-recovery using the growth rates of industry employment between January 2008 and March 2014. 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.4

We apply the same national timing to all local areas to compute predicted reallocation and growth. Using local business cycle timing instead could induce a feedback from local demand/supply shocks to predicted reallocation through the length of the local cycle and thus reintroduce reverse causality. Because national and local cycles are highly correlated in our sample, our partitioning captures much of the variation in local business cycles.5 Applying this national timing and including a time fixed effect in $X_{a,t}$ then allows for the interpretation of our regressions as pooled cross-sections.

By construction, national secular reallocation during a national recession-recovery cycle is mean-preserving in overall employment. Measuring reallocation between two periods when total employment remains unchanged facilitates a natural economic interpretation, since:

$$R_{a,t,t+T}|e_{a,t}=e_{a,t+T} = \frac{12}{T} \sum_{i=1}^{T} \left| \frac{e_{a,i,t+T} - e_{a,i,t}}{e_{a,t}} \right|.$$  

Equation (6) rewrites $R_{a,t,t+T}$ as the minimum fraction of total period $t$ employment that

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4 We 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 $R^{b}_{a,t,t+j}$ 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.

5 Applying the same recession-recovery/expansion partition to local areas, we find a monthly average of 75% of local areas in a local recession-recovery cycle when the national economy is in a recession-recovery cycle and 68% of local areas in a local expansion when the national economy is in an expansion.
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 $R^b_{a,t,t+T}$ 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.

**Asymmetry by state of business cycle.** 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 $\beta$ across business cycle phases are informative about the underlying economic mechanisms.

**Impulse response functions.** Varying the horizon of the unemployment response holding fixed the horizon over which reallocation occurs traces out the impulse response of unemployment to reallocation. 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 will estimate:

$$\Delta u_{a,t,t+j} = \beta_{j,c} R_{a,t,t+T} + \Gamma_{j,c} X_{a,t,t+j} + \varepsilon_{a,t,t+j}, \quad (7)$$

where $c \in \{\text{Recession-recovery, Expansion}\}$.

**2.4. Discussion**

The Bartik research design has the advantage of not requiring the researcher to take a stand on the deep determinants of reallocation in any given period, 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 the consequences for average labor demand, 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. Nonetheless, our results shed light on a long-running debate about whether the reallocation of labor exerts an independent impact on unemployment and the labor market 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 would complicate the interpretation of \( \beta \) 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 also relates to both of these issues by providing a concrete example of a set of primitive shocks which give rise to our measure of reallocation.

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 prevent the release of identifying information regarding single establishments.\(^6\) 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.\(^7\) 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

\(^6\)Even 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.

\(^7\)See http://www.bls.gov/cew/cewbultncur.htm#Coverage.
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. 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. 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 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

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8 We 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.

9 The 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.
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. 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 of the March 1990-April 1993 recession-recovery cycle and the April 1993-December 2000 expansion cycle appear roughly comparable across these definitions, facilitating comparison across time and classification.

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

---

10 We 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.

11 Alternatively, 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.
Table 1 – Reallocation by Episode and Industry Detail

<table>
<thead>
<tr>
<th>Episode</th>
<th>Months Expansion</th>
<th>Industry definition</th>
<th>SIC 1.5</th>
<th>NAICS 2</th>
<th>SIC 2</th>
<th>NAICS 3</th>
<th>SIC 4</th>
<th>NAICS 4</th>
<th>SIC 6</th>
<th>NAICS 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mar80-Oct83</td>
<td>43</td>
<td>No</td>
<td>1.14</td>
<td>1.29</td>
<td>1.68</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oct83-Mar90</td>
<td>77</td>
<td>Yes</td>
<td>0.71</td>
<td>0.93</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mar90-Apr93</td>
<td>37</td>
<td>No</td>
<td>0.82</td>
<td>1.04</td>
<td>0.97</td>
<td>1.15</td>
<td>1.32</td>
<td>1.34</td>
<td>1.56</td>
<td></td>
</tr>
<tr>
<td>Apr93-Dec00</td>
<td>92</td>
<td>Yes</td>
<td>0.42</td>
<td>0.60</td>
<td>0.85</td>
<td>0.77</td>
<td>0.95</td>
<td>1.14</td>
<td>1.13</td>
<td></td>
</tr>
<tr>
<td>Dec00-May05</td>
<td>53</td>
<td>No</td>
<td>0.80</td>
<td>0.97</td>
<td>1.25</td>
<td></td>
<td></td>
<td></td>
<td>1.42</td>
<td></td>
</tr>
<tr>
<td>May05-Jan08</td>
<td>32</td>
<td>Yes</td>
<td>0.60</td>
<td>0.73</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td>1.20</td>
<td></td>
</tr>
<tr>
<td>Jan08-Mar14</td>
<td>74</td>
<td>No</td>
<td>0.64</td>
<td>0.71</td>
<td>0.87</td>
<td></td>
<td></td>
<td></td>
<td>1.03</td>
<td></td>
</tr>
</tbody>
</table>

\[
R^2 : \frac{1}{j} | \Delta s_{i,t+j} | = \alpha_i + \varepsilon_{i,t+j}
\]

Industry count

| 18 | 20 | 73 | 92 | 305 | 963 | 1028 |

Notes: The table reports values of \( R_{us,t+j} \) 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.

(Davis, Faberman, and Haltiwanger, 2012; Molloy, Smith, Trezzi, and Wozniak, 2016), the rate of reallocation has trended down. For example, 4.6% (1.29*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 for recession-recoveries is monotonic. 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 Recession period (see also Foster, Grim, and Haltiwanger, 2016).

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, 0.4 p.p. movement within 2 digit but across 3 digit industries, 1.0 p.p. movement within 4 digit but across 3 digit industries, and 0.9 p.p. movement within 4 digit but across 6 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
3.3. Local Reallocation

Figure 2 shows a map of the variation in predicted reallocation during the 2008-2014 recession-recovery cycle.\textsuperscript{12} 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.

Table 2 reports the pairwise correlations in predicted local reallocation across each national recession-recovery and expansion. Bartik predicted reallocation has a positive correlation across some national recession-recoveries and a negative correlation across others. These patterns inform our analysis in three ways. First, in some specifications we will exploit the absence of perfect serial correlation by isolating changes in predicted reallocation within an area over time. Second, we will always cluster all standard errors by CSA/MSA to account for arbitrary correlation within an area over time. Third, in interpreting our findings and in the model in

\textsuperscript{12}For 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.
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 excluded 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 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.
Table 3 – First Stage Regressions

<table>
<thead>
<tr>
<th></th>
<th>Recession-recovery cycles</th>
<th>Expansion cycles</th>
<th>Pooled</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(4)</td>
<td></td>
</tr>
<tr>
<td>Right hand side variables:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predicted reallocation</td>
<td>0.98** (0.25)</td>
<td>0.21 (0.24)</td>
<td>0.66** (0.22)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.80** (0.18)</td>
</tr>
<tr>
<td>Episodes</td>
<td>Ex. 1990-93</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>National cycle FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Predicted growth</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.38</td>
<td>0.08</td>
<td>0.22</td>
</tr>
<tr>
<td>CSA-MSA clusters</td>
<td>217</td>
<td>218</td>
<td>218</td>
</tr>
<tr>
<td>Observations</td>
<td>534</td>
<td>748</td>
<td>557</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1091</td>
</tr>
</tbody>
</table>

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

Before proceeding, we briefly discuss clustered standard errors in the ts2sls framework. Our setup differs from the typical ts2sls design in which the first and second stage samples contain entirely separate observations and the regression residuals are assumed to have a homoskedastic or heteroskedastic structure, implying independence of the residuals across the two samples. Appendix A derives the asymptotic variance matrix of the second stage coefficients when such independence does not hold. The expression we derive is to our knowledge original and nests the 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:

Second stage:  
$$u_{a,t+j} - u_{a,t} = \beta [\hat{\pi}_1 R_{a,t+T}^b] + \Gamma' X_{a,t} + \alpha_t + \varepsilon_{a,t,t+j}, \quad (9)$$

First stage:  
$$R_{a,t+T} = \pi_1 R_{a,t+T}^b + \pi_2 X_{a,t} + \alpha_t + \eta_{a,t+T}, \quad (10)$$

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 expansion. The 30 month horizon corresponds to the mean peak-to-trough length in our sample. The endogenous variable $R_{a,t+T}$ and excluded instrument $R_{a,t+T}^b$ 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 focus our analysis at this horizon. We will shortly report the impulse response function for recession-recoveries at various horizons.

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 B: 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. 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 effect of reallocation 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, and all coefficients exactly equal those from estimating regressions during recession-recovery and expansion phases separately. Reallocation during a recession-recovery increases unemployment by an economically large and statistically significant amount. Across columns, the data reject a 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 a zero effect of reallocation on unemployment during expansions, with the point estimates slightly negative. The data therefore also

---

13We further describe the construction of these variables and report the coefficients and standard errors on the control variables in appendix B.
Table 4 – Homogenous Effects over Cycle

<table>
<thead>
<tr>
<th>Right hand side variables:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reallocation</td>
<td>0.44⁺</td>
<td>0.39⁺</td>
<td>0.60**</td>
</tr>
<tr>
<td>(0.25)</td>
<td>(0.15)</td>
<td>(0.18)</td>
<td></td>
</tr>
<tr>
<td>National cycle FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Predicted growth</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>First stage coefficient</td>
<td>0.80</td>
<td>1.18</td>
<td>1.11</td>
</tr>
<tr>
<td>First stage F stat.</td>
<td>18.8</td>
<td>67.7</td>
<td>29.5</td>
</tr>
<tr>
<td>CSA-MSA clusters</td>
<td>220</td>
<td>220</td>
<td>220</td>
</tr>
<tr>
<td>First stage observations</td>
<td>1,091</td>
<td>1,091</td>
<td>1,091</td>
</tr>
<tr>
<td>Second stage observations</td>
<td>1,305</td>
<td>1,305</td>
<td>1,305</td>
</tr>
</tbody>
</table>

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, respectively.

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 $\beta_j$ from a local projection of the change in the unemployment rate on reallocation, that is, the coefficients $\beta_j$ from estimating equations (9) and (10) 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 the coefficient and standard error from a separate regression estimated in the recession-recovery sample, with the dependent variable the change in the unemployment rate from the national
Table 5 – Heterogeneous Effects over Cycle

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

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. ** indicates significance at the 1% level.

peak to trough. For brevity, we report results controlling for the predicted growth variables and time effects. Thus, the first row, labeled “Baseline”, reproduces the coefficient in the third row of 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 increase slightly in each of these specifications.

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
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.

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 7-9 assess sensitivity to excluding areas with large employment shares in particular industries which have figured prominently in recent periods of reallocation: specialty trade contractors, manufacturing, and health care. Each row reports the results after removing from the sample areas with a beginning-of-cycle employment share above the 75th percentile in the indicated industry. The coefficients from each of these exercises remain close to the baseline. Row 10 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. Thus, the variation in row 7 comes only from industries experiencing

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14 We associate specialty trade contractors with SIC code 0C17 or NAICS code 238; manufacturing with SIC codes 0D20-39 and NAICS codes 311-339; and health care with SIC code 0I80 and NAICS codes 621-624.

15 More specifically, we exclude a NAICS (SIC) industry if national employment expands or contracts during each cycle in which NAICS (SIC) employment is reported. These industries are: 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).
### Table 6 – Robustness

<table>
<thead>
<tr>
<th>Specification</th>
<th>$\beta$</th>
<th>s.e.</th>
<th>CSAs</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Baseline</td>
<td>0.87**</td>
<td>0.26</td>
<td>218</td>
<td>748</td>
</tr>
<tr>
<td>2. Bartik growth vigintiles</td>
<td>0.98**</td>
<td>0.30</td>
<td>218</td>
<td>748</td>
</tr>
<tr>
<td>3. Control for age shares</td>
<td>1.10**</td>
<td>0.23</td>
<td>218</td>
<td>748</td>
</tr>
<tr>
<td>4. Predicted growth by period</td>
<td>0.94**</td>
<td>0.26</td>
<td>218</td>
<td>748</td>
</tr>
<tr>
<td>5. Predicted growth by region</td>
<td>0.99**</td>
<td>0.30</td>
<td>218</td>
<td>748</td>
</tr>
<tr>
<td>6. Drop if area has large industry</td>
<td>0.86**</td>
<td>0.29</td>
<td>202</td>
<td>641</td>
</tr>
<tr>
<td>7. Drop if high manufacturing share</td>
<td>1.25**</td>
<td>0.45</td>
<td>188</td>
<td>556</td>
</tr>
<tr>
<td>8. Drop if high construction share</td>
<td>1.11**</td>
<td>0.27</td>
<td>197</td>
<td>559</td>
</tr>
<tr>
<td>9. Drop if high health care share</td>
<td>0.70*</td>
<td>0.33</td>
<td>195</td>
<td>557</td>
</tr>
<tr>
<td>10. Drop persistent industries</td>
<td>1.47**</td>
<td>0.37</td>
<td>218</td>
<td>748</td>
</tr>
<tr>
<td>11. Drop 1990-93</td>
<td>0.86**</td>
<td>0.31</td>
<td>217</td>
<td>534</td>
</tr>
<tr>
<td>12. Drop 2008-14</td>
<td>1.10**</td>
<td>0.32</td>
<td>216</td>
<td>544</td>
</tr>
<tr>
<td>13. HP filter dating</td>
<td>0.88**</td>
<td>0.28</td>
<td>217</td>
<td>741</td>
</tr>
<tr>
<td>14. NAIRU dating</td>
<td>1.15*</td>
<td>0.58</td>
<td>218</td>
<td>727</td>
</tr>
<tr>
<td>15. Expand window ± 3 months</td>
<td>0.71*</td>
<td>0.28</td>
<td>217</td>
<td>686</td>
</tr>
<tr>
<td>16. Peak-to-peak reallocation</td>
<td>0.82*</td>
<td>0.41</td>
<td>218</td>
<td>748</td>
</tr>
</tbody>
</table>

Notes: Each row of the table reports the coefficient and standard error of reallocation from a separate regression estimated in the recession-recovery sample, with the dependent variable the change in the unemployment rate from the national employment peak to trough. Each regression also includes predicted growth from the national peak to trough, predicted growth over the full recession-recovery cycle, and cycle fixed effects. The first row, labeled “Baseline”, reproduces the second row of 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 7-9 exclude observations in the cycle’s top quartile of employment share in the industry indicated. Row 10 excludes the construct of predicted reallocation any industry which either expands or contracts nationally in every cycle in our data. Row 11 drops the 1990-93 cycle. Row 12 drops the 2008-14 cycle. In row 13, a recovery ends when the cyclical component of an HP filter of national employment (smoothing parameter 129,600) equals zero. In row 14, a recovery ends when the national unemployment rate first equals the CBO’s estimate of the NAIRU. In row 15, the recession-recovery window is extended by 3 months on each side. Row 16 constructs predicted reallocation on a peak-to-peak basis. **, *, + denote significance at the 1%, 5%, or 10% level, respectively.

persistent but not permanent expansions or contractions.

Row 11 excludes the 1990-93 cycle from the second sample and reports the coefficient from a conventional 2sls regression. Row 12 shows that excluding the Great Recession has a small effect on the results.

Rows 13 to 16 explore robustness to the precise timing definition. Row 13 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 14, 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 15 expands the
recession-recovery window symmetrically by 3 months on each side. Finally, row 16 redefines the reallocation timing to measure reallocation between two national employment peaks. The basic pattern 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.

5.1. Setup

Time is discrete. The economy consists of $A$ islands, each of which has $I$ industries.

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 $\sum_{a=1}^{A} \sum_{i=1}^{I} l_{a,i,t} = 1$.

The firm vacancy posting condition and matching process are standard. Firms post $v_{a,i,t}$ vacancies in industry $i$ at cost $\kappa$ per vacancy. A free entry condition drives the expected value of a vacancy to zero. The matching function takes the Cobb-Douglas form $n_{a,i,t} = Mv_{a,i,t}^{1-\alpha}x_{a,i,t}^{\alpha}$. 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 $q_{a,i,t} = M\theta_{a,i,t}^{-\alpha}$.

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, 2016). For the 2008-14 cycle, we measure reallocation between the peak in January 2008 and December 2016.
Specifically, at the end of period $t$, employed workers transition into unemployment in their same industry at rate $\delta_t - \lambda^I_{t}$. Both unemployed and employed workers receive an industry reallocation shock at exogenous rate $\lambda^I_{t}$. An industry reallocation shock consists of an immediate job separation if previously employed, $I$ time-invariant area and sector-specific taste parameters $\psi_{aj}$, and a draw of $I$ idiosyncratic taste shocks $\varepsilon_{jt}$ from a distribution $F^I(\varepsilon)$. These taste parameters and shocks enter additively into the worker’s value function for searching in each sector $j = 1, \ldots, I$ in the worker’s initial area $a$. We parameterize $F^I(\varepsilon)$ as Type I EV($-\rho^I \tilde{\gamma}, \rho^I$), where $\tilde{\gamma}$ is Euler’s constant. We parameterize the fixed utilities $\psi_{aj}$ such that the steady-state allocation of labor is efficient.

The parameter $\lambda^I$ determines the share of unemployed re-optimizing their industry search market. Equivalently, $\lambda^I$ has the interpretation of a stochastic death or retirement shock, with a new generation of workers of mass $\lambda^I$ 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 $\psi_j$ parameters can be interpreted as permanent preferences to work in particular sectors. The $\varepsilon_j$ 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 $\lambda^I$ and the volatility of the process generating $\varepsilon_j$ together govern the magnitude of gross flows and the directness of search across industries.

We abstract from geographical mobility. In appendix C.9, 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.

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

$$x_{a,i,t} = \delta_t e_{a,i,t-1} + u_{a,i,t-1} - \lambda^I_{t-1} I_{a,i,t-1} + \lambda^I_{a,i,t-1} I_{a,t-1},$$

The assumption of time dependent, stochastic $\lambda^I$ shocks 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.
\[ e_{a,i,t} = (1 - \delta_{t-1})e_{a,i,t-1} + f_{a,i,t}x_{a,i,t}, \]
\[ u_{a,i,t} = (1 - f_{a,i,t})x_{a,i,t}. \]

We assume no aggregate uncertainty and perfect consumption insurance within (but not across) islands. Thus, workers and firms in an area both evaluate the future with the discount factor \( m_{a,t,t+1} \). Let \( p_{a,i,t} \) denote the real marginal product of a match, \( w_{a,i,t} \) the real wage payment to the worker, \( z \) the worker’s flow opportunity cost of employment, \( J_{a,i,t} \) the value of a filled job to a firm, \( W_{a,i,t} \) the value of a filled job to a worker, \( U_{a,i,t} \) the value of unemployment in industry \( i \) of area \( a \) to a worker, and \( E \) the expectations operator. The following three Bellman equations and the free entry condition summarize the labor market block of the model:

\[
J_{a,i,t} = (p_{a,i,t} - w_{a,i,t}) + (1 - \delta_t)m_{a,t,t+1}J_{a,i,t+1},
\]
\[
W_{a,i,t} = w_{a,i,t} + m_{a,t,t+1}\left\{ \left[ (1 - \delta_t) + \left( \delta_t - \lambda_t^I \right) f_{a,i,t+1} \right] W_{a,i,t+1} + \left( \delta_t - \lambda_t^I \right) (1 - f_{a,i,t+1})U_{a,i,t+1} \right\}
+ m_{a,t,t+1}\lambda_{a,t} \left( E \max_j \left\{ (1 - f_{a,j,t+1})U_{a,j,t+1} + f_{a,j,t+1}W_{a,j,t+1} + \psi_j + \varepsilon_{jt} \right\} \right),
\]
\[
U_{a,i,t} = z + m_{a,t,t+1}\left\{ (1 - \lambda_t^I) [ f_{a,i,t+1}W_{a,i,t+1} + (1 - f_{a,i,t+1})U_{a,i,t+1} ] \right\}
+ m_{a,t,t+1}\lambda_{a,t} \left( E \max_j \left\{ (1 - f_{a,j,t+1})U_{a,j,t+1} + f_{a,j,t+1}W_{a,j,t+1} + \psi_j + \varepsilon_{jt} \right\} \right),
\]
\[
\kappa = q_{a,i,t}J_{a,i,t}.
\]

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

\[ w_{a,i,t} = \max\left\{ w_{a,i,t}^*, (1 - \chi^w) w_{a,i,t-1}/\Pi_{a,t} \right\}, \]

where \( w_{a,i,t}^* \) is the Nash bargained real wage, \( \Pi_{a,t} \) is gross producer price inflation, and \( \chi^w \) 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).\(^{18}\)

\(^{18}\)Still, 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.
5.1.2. General equilibrium  We embed the industry structure in a demand framework. Output of industry $i$ in area $a$ is

$$Q_{a,i,t} = \eta_{i,t} e_{a,i,t},$$

(16)

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 $P^Q_{a,i,t}$ to a wholesaler. The wholesaler combines local industry output into an area-specific good $Q_{a,t}$ using the technology

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

(17)

giving rise to a downward sloping industry-level demand curve $Q_{a,i,t} = \tau_{a,i,t} \left( \frac{P^Q_{a,i,t}}{P^Q_{a,t}} \right)^{-\zeta} Q_{a,t}$, and where $\zeta \geq 1$ and $P^Q_{a,t} = \left[ \sum_i \tau_{a,i,t} (P^Q_{a,i,t})^{1-\zeta} \right]^{\frac{1}{1-\zeta}}$. 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 (11) is the product of industry productivity and the real price of industry $i$’s good:

$$p_{a,i,t} = \eta_{i,t} P^Q_{a,i,t}.$$  

(18)

With downward sloping demand, the decline in output engendered by a decline in $\eta_{i,t}$ induces a rise in the real price $P^Q_{a,i,t}$, 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.

Closing the model requires specifying the determination of the set of real industry prices $P^Q_{a,i,t}$, 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 $\mu_t$ 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 C.

5.2. Calibration

We calibrate a version of the model with two areas and ten industries, $A = 2$ and $I = 10$, 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
Table 7 – Calibrated Labor Market Parameters

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f$</td>
<td>Job finding rate</td>
<td>0.5</td>
<td>Shimer (2012)</td>
</tr>
<tr>
<td>$q$</td>
<td>Job filling rate</td>
<td>0.75</td>
<td>Davis et al. (2013)</td>
</tr>
<tr>
<td>$\delta$</td>
<td>Separation rate</td>
<td>0.066</td>
<td>Matched monthly CPS</td>
</tr>
<tr>
<td>$\lambda^I$</td>
<td>Industry reallocation</td>
<td>0.043</td>
<td>Matched monthly CPS</td>
</tr>
<tr>
<td>$\rho^I$</td>
<td>Industry reallocation noise</td>
<td>0.95</td>
<td>Peak unemployment effect in recessions</td>
</tr>
<tr>
<td>$D$</td>
<td>Discount factor</td>
<td>0.997</td>
<td>4% annual rate</td>
</tr>
<tr>
<td>$\beta$</td>
<td>Bargaining power</td>
<td>0.6</td>
<td></td>
</tr>
<tr>
<td>$\chi^w$</td>
<td>Downward-wage rigidity</td>
<td>0.0035</td>
<td>Average monthly nominal wage growth</td>
</tr>
<tr>
<td>$z$</td>
<td>Opportunity cost</td>
<td>0.55</td>
<td>Chodorow-Reich and Karabarbounis (2016)</td>
</tr>
</tbody>
</table>

and ensuring that national industry trends are representative of local industry trends.\(^{19}\)

We briefly describe the calibration of the labor market block of the model, shown in table 7. Appendix C 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 $\lambda^I$. Given that our model has neither aggregate productivity growth nor trend inflation, we set the downward wage rigidity parameter $\chi^w$ 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. The parameter governing the directedness of search $\rho^I$ 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 a wide range of estimates. We therefore infer $\rho^I$ together with the shocks, as we describe in the following section. This yields $\rho^I = 0.95$.

5.3. Quantitative Exercise

We conduct a just-identified indirect inference to recover $\rho^I$ and the reallocation and recession shocks such that the model matches the following empirical targets over a full recession-

\(^{19}\)Recall our first-stage coefficient of roughly 1 in table 3. With $I = 2$ 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 $I \geq 10$ largely eliminates such cases.
recovery cycle: (1) the average employment share changes,\(^{20}\) (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 \(I = 10\) 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 these perfect-foresight paths. (We order the industries in decreasing order of productivity change.) The productivity 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 \(\mu_t\) 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). While not directly targeted, the national unemployment peak occurs after 24 months, close to the 30 months in the data.

We simulate the model 200 times for different initial employment share in the small area.\(^{21}\) 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.\(^{22}\)

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

\(^{20}\)We 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.

\(^{21}\)Since the small area is infinitesimal, the solution for the large area is identical in each simulation.

\(^{22}\)Allowing for a longer time before reversal has little effect on our results.
Figure 4 – Productivity Paths and Local Predicted Growth and Reallocation

Panel A: Industry productivity paths

Panel B: Predicted Reallocation and Predicted Growth

Notes: Panel A displays the perfect-foresight productivity paths $\eta_i$ of each of the $i = 1, \ldots, 4$ 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.

Figure 5 – Model Impulse Response Function and Marginal Effect

Panel A: Cross-section at National Unemployment Peak

Panel B: IRF of Marginal Unemployment Effects

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.

(residualized) instrumented reallocation in a recession, whereas there is no economically significant relationship in an expansion.

The right panel of figure 5 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 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 2.77 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.23 In expansions the wage constraint does not bind, so real wages rise in the 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.24 The decline in total vacancies causes unemployment to increase.25

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23Our 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. Hall and Schulhofer-Wöhl, 2015; Ahn and Hamilton, 2014). Pilossof (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.

24Throughout 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.

25The 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
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 et al., 2014; Barnichon and Figura, 2015).\textsuperscript{26}

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

\textsuperscript{26}Constant 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).
Figure 7 – Marginal Effect of Reallocation in Alternative Model Specifications

Panel A: No downward wage rigidity
Recession: Baseline
Expansion: Baseline
Recession: Nash Bargaining
Expansion: Nash Bargaining

Panel B: Low reallocation frictions
Recession: Baseline
Expansion: Baseline
Recession: Low Frictions
Expansion: Low Frictions

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.

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 $\varepsilon_j$ 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 10 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 a

27We kept the baseline $\rho^f$ in the experiment with Nash Bargaining, since raising $\rho^f$ 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 9 displays the comparison with a higher $\rho^f = 4$, 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 horizon.
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 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 expression applies in our setting where a subset of observations are shared across samples or more generally with clustered standard errors and common clusters across the two samples. 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:

\[
Y_j = F_j \gamma + X_j \beta + \eta_j, \quad j = 2, \quad (A.1)
\]
Let $\hat{W}_X \beta, \gamma, \pi$ is the matrix of first stage regressors, $N_Y$ where the last line substitutes the first stage relationship

\[
\sqrt{\sum_{j} \left( \hat{W}_X \beta, \gamma, \pi \right)^2} = \hat{W}_X \beta, \gamma, \pi \sim (K + L) \times M.
\]

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 $\pi = (\pi_X \pi_W)' \sim (K + L) \times M$. Let $\hat{\pi} = (H_1^t H_1)^{-1} H_1^t F_1$ denote the fitted coefficients from the first stage regression and $Z_2 = \left( X_2 \ H_2 \hat{\pi} \right) \sim N_2 \times (K + M)$ denote the matrix of regressors in the second stage.

**Assumptions.**

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

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

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

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

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

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

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

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

\[
\lim_{N_1, N_2 \to \infty} N_2 / N_1 = \alpha > 0. \quad (A.12)
\]

Note that in equations (A.4)–(A.11), the moment conditions hold for any sample.

**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 $(\hat{\beta} \hat{\gamma})'$:

\[
\sqrt{N_2} \left( \hat{\beta} - \beta \right) = \left( \frac{1}{N_2} Z_2' Z_2 \right)^{-1} \left( \frac{1}{\sqrt{N_2}} Z_2' u_2 \right) - \left( \frac{1}{N_2} Z_2' Z_2 \right)^{-1} \frac{1}{\sqrt{N_2}} Z_2' H_2 (\hat{\pi} - \pi) \gamma
\]

\[
= \left( \frac{1}{N_2} Z_2' Z_2 \right)^{-1} \left( \frac{1}{\sqrt{N_2}} Z_2' u_2 \right) - \sqrt{\alpha} \left( \frac{1}{N_2} Z_2' Z_2 \right)^{-1} \left( \frac{1}{N_2} Z_2' H_2 \right) \left( \frac{1}{N_1} H_1' H_1 \right)^{-1} \left( \frac{1}{\sqrt{N_1}} H_1' \epsilon_1 \right) \gamma
\]

where the last line substitutes the first stage relationship $\sqrt{N_1} (\hat{\pi} - \pi) = \left( \frac{1}{N_1} H_1' H_1 \right)^{-1} \left( \frac{1}{\sqrt{N_1}} H_1' \epsilon_1 \right)$. 

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:

$$\sqrt{N_2} \left( \hat{\beta} - \beta, \hat{\gamma} - \gamma \right) \rightarrow N(0, \Sigma),$$

where:

$$\Sigma = Q^{-1} \left( \Omega_{Zu} + \alpha SR^{-1} \Omega_{H(e_\gamma)} R^{-1} S' - \sqrt{\alpha} \left( \Omega_{Zu(e_\gamma)} H R^{-1} S' + SR^{-1} \Omega_{Zu(e_\gamma)H} \right) \right) Q^{-1}.$$

**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:

$$SR^{-1} \Omega_{H(e_\gamma)} R^{-1} S' = \Omega_{Z(e_\gamma)},$$

$$\Omega_{Zu(e_\gamma)} H R^{-1} S' = \Omega_{Zu(e_\gamma)} Z,$$

and:

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

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). When the two samples fully coincide, one can show using $u = e_\gamma + \eta$ and $\alpha = 1$ that $\Sigma = Q^{-1} \Omega_{Zu} Q^{-1}$, the standard expression for the 2sls variance matrix.

A feasible estimator of $\Sigma$ is:

$$\hat{\Sigma} = (Z'_2Z_2)^{-1} \left( \Omega_{Zu2} + \alpha \Omega_{Z1(e_1\hat{\gamma})} - \sqrt{\alpha} \left( \Omega_{Z1\cap2u1\cap2(e_1\cap2\hat{\gamma})Z1\cap2} + \Omega'_{Z1\cap2u1\cap2(e_1\cap2\hat{\gamma})Z1\cap2} \right) \right) (Z'_2Z_2)^{-1},$$

where the subscript $1 \cap 2$ denotes the intersection of the samples. The functional form of the cross-product matrices $\Omega_{Zu2}, \Omega_{Z1(e_1\hat{\gamma})}, \Omega_{Z1\cap2u1\cap2(e_1\cap2\hat{\gamma})Z1\cap2}$ depends on the assumed covariance structure of the residuals (homoskedastic, heteroskedastic, clustered, etc.)

**References**


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