Aggregate Effects and Measuring Regional Dynamics

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Abstract

Empirical models of regional adjustment often control for aggregate effects when estimating the impact of regional shocks. It is, however, difficult to filter out the effects of aggregate shocks—such as national recessions—because the incidence of these shocks varies across space and time. We argue that an approximate factor structure is better suited to controlling for this form of spatiotemporal heterogeneity than existing methods. Applying the method to US states, we find that region-specific labor demand shocks are primarily absorbed through changes in participation; that the migration response to these shocks is limited; and that recoveries are highly protracted.

Keywords: Labor mobility, migration, aggregate shocks, factor model, spatiotemporal heterogeneity

JEL classification codes: J61, R23, R30, C33

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1 Introduction

Empirical models of regional adjustment are often used to measure household and firm responses to local economic conditions. For example, vector autoregressions (VARs) in the tradition of Blanchard and Katz (1992) continue to be a popular method for decomposing the incidence of regional labor markets shocks on the unemployment, labor force and migration channels (recent examples include Beyer and Smets, 2015; Greenaway-McGrevy and Hood, 2016; and Dao, Furceri and Loungani, 2017). These models are also commonly used to examine the effects of policy interventions, such as local development programs (Kline and Moretti, 2011), education policies (Bartik, 2009) and local regulation changes (Greenstone, 2001), as well as the effects of specific shocks on local labor markets, such as foreign immigration (Borjas, 2006).

In these models it is common to condition on the state of the macroeconomy in order to help isolate region-specific shocks in the data. We use the term "aggregate effects" to refer to these macroeconomic conditions, which can be conceptualized as the incidence and ongoing effects of economic shocks that have a pervasive effect across a large number of regions in the economy, such as a national recession. Often these aggregate effects are permitted to have an asymmetric or heterogenous effect on different regions—particularly when the models are applied to European regions. For example, when extending the seminal Blanchard and Katz (1992) model to the European Economic Community, Decressin and Fatás (1995) first regress regional employment growth, unemployment and participation rates on national averages, and then use the resultant panel of residuals in their empirical VAR. This approach simultaneously controls for aggregate effects and allows for heterogenous responses of each region to these effects. This "regression-based" (RB) approach to filtering out aggregate effects has proved popular and has been adopted by Tani (2003),[1] Pekkala and Kangasharju (2002) for Finland, Broersma and van Dijk for the Netherlands (2002), and Hauser (2014).[2]

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[2] Blanchard and Katz (1992) initially consider using a similar approach for their analysis based on US states (see p. 31-33). They ultimately reject the approach after finding that regional regression coefficients are sufficiently homogenous in their sample. Many other studies consider using the regression-based approach to filter out common shocks, but ultimately reject using the approach after finding that the regional regression coefficients are sufficiently homogenous.

The RB filter is in many ways more flexible than conventional methods that are used to filter out aggregate effects, such as including period fixed effects in the empirical specification or modelling variables relative to national aggregates (by, for example, subtracting national employment growth from regional employment growth). This is because the RB approach allows for cross-sectional heterogeneity in regional responses to aggregate effects. Nonetheless, it is a relatively rigid method for filtering out business cycle fluctuations, as it models a single source of covariation—national aggregates—with the sensitivity of each region to the national aggregate governed by a fixed parameter. As we demonstrate below in more detail, these restrictions impair the filter's ability to effectively remove aggregate shocks from regional data.

In this paper we present and apply a new, more flexible, and straightforward method for filtering out aggregate effects when estimating models of regional adjustment. The method is based around the latent common factor structure, which, when applied to regional data, permits heterogenous regional responses to several sources of common variation. While the factor model maintains the intuition of the RB approach, it has three distinct advantages when used to filter out aggregate effects. First, it can accommodate *spatiotemporal heterogeneity* in the impact of aggregate shocks on regional economies. This heterogeneity is a salient feature of regional economic time series, and is immediately apparent from the fact that different national recessions tend to have a different geographic incidence. We illustrate this empirical finding in Section 3.1 below. The factor model can accommodate this kind of heterogeneity because it permits several sources of common variation. Second, the common factors are latent and extracted from the endogenous variables in the model, meaning that the researcher does not need to select an observable variable to approximate the source of covariation between regions. Thus, while an external oil supply shock may precipitate a national downturn, we do not need to include oil prices or other exogenous variables in the empirical model in order to control for the downturn. Finally, because the factor model can nest a lower-dimensional dynamic factor structure (Amengual and Watson, 2007), it can also accommodate differences in the timing of aggregate effects on different regions. The method does, however, have drawbacks. The main drawback of the factor model is that estimators require both large n (number of cross sections) and T (number of time series) in order to consistently estimate the components of the model under standard conditions (Bai, 2003). This makes the factor structure well-suited to the large regional panels based on US states, EU NUTS regions, or metropolitan areas.

Our proposed method is to use the estimated factor loadings from the fitted factor structure to control for aggregate effects in the empirical model. This is straightforwardly achieved by augmenting the empirical model with the estimated factor loadings, which serve as time-invariant regressors in the model. The parameters associated with the loadings (the common factors) are permitted to vary over time, thereby controlling for aggregate effects. See (3) below for the precise empirical specification employed.

We demonstrate the efficacy of method by applying it to a set of US state labor market data (employment, labor force, and working-age population). First, to motivate the use of the factor structure, we show that the geographic incidence of national recessions on employment, labor force and working-age population tends to be different for each recession over the past four decades. For example, the Great Recession of 2007-2009 hit Florida, the Rust Belt and Southwest hardest; the recession of the early 1990s primarily affected the Northeast; and the recessions of the early 1980s hit the Rust Belt. Meanwhile, energy-producing states tend to perform well during national downturns. The RB approach is too rigid to effectively filter out this form of spatiotemporal heterogeneity in national recessions. We then demonstrate that the factor structure (with a handful of common factors) does a better job of filtering out the incidence of these recessions.

We then augment an empirical model of regional adjustment in the tradition of Blanchard and Katz (1992) with the estimated factor loadings in order to filter out aggregate effects. We employ a vector error correction model (VECM) to describe variation in regional employment, labor force and population growth. Because regional unemployment rates serve as cointegrating errors in the model, the VECM nests the VAR more commonly used to model regional employment growth and unemployment rates, but it offers some particular advantages when it comes to filtering out common sources of variation. Specifically, because employment, labor force and population growth rates exhibit much less persistency than regional unemployment rates, the factor structure in the growth variables is estimated with more precision than the factor structure in the more persistent unemployment rates (Greenaway-McGrevy, Han and Sul, 2012a).

We find that the initial incidence of a region-specific labor demand shock falls primarily on participation rates, with secondary effects on unemployment and out-migration. Recoveries in unemployment and participation are thereafter highly protracted, taking in excess of twenty years. The out-migration generated by the economic shock is comparatively limited, meaning that state unemployment rates are the primary channel through which shocks are mediated over the long-run. These results are consistent with a broader literature that suggests that migration responses to local economic conditions are muted and that economic shocks can have persistent effects on local unemployment rates (Partridge *et al.*, 2015).

The primary contribution of this paper is to propose and implement a methodology that controls for aggregate effects that exhibit spatiotemporal heterogeneity—thereby allowing the practitioner to focus exclusively on the effects of region-specific shocks. We remain agnostic as to whether aggregate shocks *should* be filtered out when estimating models of regional adjustment—after all, national recessions generate regional disparities to which firms and workers respond. However, much of the empirical literature suggests that both household migration and job restructuring are different in response to a national recession, suggesting that researchers interested in studying the effects of region-specific shocks should consider effective methods to filter out aggregate shocks from the data. For example, Molloy and Wozniak (2011) show that gross household migration in the US is strongly pro-cyclical, and Dao *et al.* (2017) show that migration responses vary considerably over the business cycle. Meanwhile Caballero and Hammour (2005), Davis *et al.* (2011) and Fallick and Fleischman (2004) show that job churning slows significantly in the wake of a national recessions. In fact, Molly and Wozniak (2011) show that migration falls after recessions despite the fact that dispersion in local labor market indicators either increases (e.g., unemployment) or remains flat (e.g., de-trended employment levels). Through the lens of the model, these two empirical findings (i.e., increases in disparities among regional labor markets followed by slow-downs in geographic reallocation of resources) will be interpreted as serial dependence in the demand shock—which makes it difficult to measure the size of the migration response relative to the size of the original shock (see Greenaway-McGrevy and Hood, 2016).

The remainder of the paper is organized as follows. In section two we discuss the relevant literature. In section three we outline our approach to filtering out aggregate effects from state-level labor market data, and compare it to the existing RB approach. Section four contains a description of the empirical models of regional adjustment and application to our state-level dataset. We conclude in section five.

2 Related literature

This paper is based around an empirical model of regional adjustment. The Blanchard and Katz (1992) model serves as the canonical conceptual framework for regional labor market adjustment. Blanchard and Katz (1992) use a structural VAR to decompose variation in regional employment, unemployment and participation rates into labor supply and demand shocks and the responses thereto. That basic idea has since been applied in many other countries and collections of geographic regions: Jimeno and Bentotila (1998) adapt the methodology to study Spanish regions; Fredriksson (1999) looks at Swedish regions; and Bertola (2000) and Tani (2003) at European regions. Fidrmuc (2004), Gács and Huber (2005), and Bornhorst and Commander (2006) focus on regions in Central and Eastern Europe. In recent work, Sala and Trivín (2014) study Spanish regions. In addition, this model is extended to build geographic models of mobility in other contexts (Borjas *et al.*, 1997; Borjas, 1999, 2006; Kline, 2008). Finally, similar regional panel VAR analysis is also used to study to local housing markets and migration (Glaeser and Gyourko, 2005; Glaeser *et al.*, 2005; Saiz, 2010; Saks, 2008; and Zabel, 2012).

Our paper also relates to a broader literature that has focussed on modelling the regional sensitivities to national business cycles. Carlino and Sill (2001) look for common trends and cycles in regional output and find strong evidence that some regions respond more strongly to aggregate business cycle fluctuations than others. In an earlier paper, Sill (1997) finds that employment in geographic regions does not tend to move synchronously with aggregate conditions, but that some regions lead and others lag the national cycle, while Hamilton and Owyang (2012) document a similar phenomenon using quarterly state gross output data. Other papers have focussed on modelling the channels that generate these forms of spatiotemporal heterogeneity in national business cycles. Structural models of covariation such as those used by Carlino, DeFina and Sill (2001), Clark (1998), and Coulson (1999) specify sectoral composition as a channel generating regional covariation, finding that industry-level shocks account for much of the variation in MSAs (Coulson, 1999; Carlino, DeFina and Sill, 2001) but not census regions (Clark, 1998). In contrast to these structural models of covariation, our factor structure directly models covariation between different regions: Identification is based on correlation structures in the data and therefore does not rely on *ex ante* selection of specific channels that generate covariation (such as sectoral composition). While we offer a limited interpretation of the estimated factors and loadings we extract from the data (see Section 3.3.1 below), in contrast to Carlino, DeFina and Sill (2001), Clark (1998) and Coulson (1999), our primary concern is not to ascertain the precise channels that generate covariation—our concern is simply to remove the variation.

This paper is related to a growing literature that employs factor model to decompose subaggregates into common and idiosyncratic components. These include Forni and Reichlin (1998), Foerster *et al.* (2011), and Garin *et al.* (2018). To our knowledge, however, this literature has focussed on decompositions of national aggregates by industry, rather than by geography, and has focussed on interpretation of aggregate components rather than on removing aggregate effects.

Our empirical methodology also draws on a large body of work that has established the econometric theory for approximate factor models of cross-sectional dependence. Bai and Ng (2002) provide selection criteria for choosing the number of common factors in the model, while Bai (2003) provides asymptotic theory for the principal component estimator of the factor structure. Pesaran (2006), Bai (2009) and Greenaway-McGrevy, Han and Sul (2012b) study various estimators of panel regression models with a factor error structure. Our method is related to these approaches in that the common factors are treated as latent omitted variables that must be controlled for when estimating the regression model.

3 Aggregate Effects and the Factor Structure

In economics the conventional use of "aggregate" refers to the sum of all components of the economy. These components could represent disaggregations by region—as in the present application—or by sector or industry, for example. At a fine enough level of disaggregation (so that the number of components is arbitrarily large), unforeseen changes in the aggregate (i.e., aggregate shocks) can only be brought about by pervasive changes in the components of the aggregate. This is to say that when shocks appear in an aggregate time series, they must also be manifest most of the disaggregated time series as well (provided that the weighted aggregation is not dominated by a few time series). However, they do not need to manifest *equally* in all of the disaggregated sub-components. For example, external oil shocks need not affect Texas, Massachusetts and Michigan in the same way.

In this section we demonstrate that the factor model is effective at filtering out aggregate effects from regional economic time series. This is because the model can accommodate what we refer to as spatiotemporal heterogeneity in the regional incidence of aggregate shocks. First, we present evidence of this spatiotemporal heterogeneity by tabulating the regional incidence of national recessions on state-level employment growth over the 1976-2015 period. From this exercise we identify three groups of states that exemplify spatiotemporal heterogeneity. Next, we show that the regression-based approach leaves business-cycle fluctuations in the filtered time series. Finally, we introduce the factor model, and demonstrate that it is more effective at filtering out these aggregate-level effects compared to the regression-based approach. We focus on state-level employment growth to illustrate these points because it is one of the three endogenous variables in the empirical model (along with labor force and working-age population—see Section 4), and because spatiotemporal heterogeneity in national recessions are clearly manifest in the time series.[3] Details on these data can be found in Section 4.1.

[3]The unemployment rate would also be a natural variable to focus on for this analysis. However, because we do not model the explicitly unemployment rate in the empirical model, the exercise would not inform the ultimate empirical specification.

3.1 Spatiotemporal Heterogeneity in the Regional Incidence of National Recessions

In this subsection we establish the following empirical regularities: (1) that national recessions have a differential regional impact; and (2) that national recessions at different points in time have affected locations differently. We collectively refer to these empirical regularities as spatiotemporal heterogeneity in national recessions.

To illustrate these empirical regularities we tabulate the percent change in state employment during National Bureau of Economic Research (NBER) contractions between 1976 and 2015 (see Table 1). For each of these contractionary periods, we order the states by the percent change in employment, which allows us to examine the regional incidence of each recession in turn.

Early Eighties Recessions We treat the 1980 and 1981-82 recessions as a single recession since most states did not experience a "double-dip" in employment over this period. These recessions were particularly severe for the states that comprise the Rust Belt, such as Michigan, Indiana, Ohio, West Virginia, Illinois, Wisconsin and Pennsylvania, as well as other states in the Midwest that were also severely affected by the 1980s "Farm Crisis," such as Iowa and South Dakota. States that also fared particularly badly include Idaho and Oregon—which experienced a rapid decline in manufacturing and forestry-related employment in the early 1980s—and the District of Columbia. Employment increased substantially in many states during this period—particularly in the energy-producing states of Alaska, Oklahoma, Texas, Louisiana, Wyoming and Colorado, as well as in the Sun Belt states of Arizona, Nevada, New Mexico and Florida. With the exception of Rhode Island, much of the Northeast also experienced an increase in employment during this period.

1990-91 Recession In contrast to the early eighties recessions, this downturn primarily affected the Northeast and the Mid Atlantic, including Pennsylvania, Maryland, Delaware, and Virginia. Much like the early eighties recessions, the energy-producing states are among those states that experienced an increase in employment during this period—along with many of the states further West, such as Arizona, Nevada, Utah, Idaho and Hawaii.

The 2001 Recession The least severe of the recessions, this downturn sees comparatively little variation in state employment growth rates, which range from –2.20% to 2.24%. This recession is also notable for the fact that the energy-producing states did not generally out-perform the rest of the economy.

Great Recession This is the most severe recession in the sample, with only six states experiencing growth in employment between 2008 and 2010. It was especially severe in the Sun Belt states of Arizona, Nevada and Florida, as well as the rust belt states of Michigan, Ohio, and Indiana. Employment in the energy-producing states of Alaska, Texas, Oklahoma, Louisiana and North Dakota increased between 2008 and 2010. The Northeast also fared comparatively well during the recession.

[Insert Table 1 about here]

In the analysis to follow we will focus on three groups of states that exemplify the spatiotemporal heterogeneity in national downturns over the past four decades. First, the Northeast (and some of the Mid-Atlantic states) fared comparatively well during the early 1980s recessions and the Great Recession, but was hit hard in the 1990-91 recession. We include Maine, Massachusetts, New Hampshire, Vermont, Rhode Island, Connecticut, New York, New Jersey, Maryland, Delaware and Virginia in this group. Second, the Rust Belt and some Midwest farming states, which by-and-large escaped the 1990-91 recession, were hit hard in 1980s recessions and the Great Recession. We include Michigan, Indiana, Ohio, Illinois, Wisconsin, West Virginia and Pennsylvania in this group. Finally, we consider the energy-producing states of Alaska, Texas, Oklahoma, Louisiana, North Dakota, Wyoming and Colorado as another group. These states appear less affected by national downturns and often experience a comparatively large increase in employment during national recessions.[4]

[4] Many of the states may be better thought of as spanning two or more groups. For example, Pennsylvania and New York span both the Rust Belt and Northeast regions, while West Virginia could equally be thought of as an energy producer. In any event, these classifications only serve to demonstrate the efficacy of the different filters – none of the filters require these groupings.

3.2 The Regression-Based approach to filtering out Aggregate Effects

Following Blanchard and Katz (1992), Decressin and Fatás (1995) use regression-based methods to remove aggregate effects in their panel of European labor market data. They run preliminary regressions of each time series on a national-level variable, and retain the residual for their model of regional adjustment. The basic model is as follows

$$y_{i,t} = \alpha_i + \beta_i x_t + y^0_{i,t}, \tag{1}$$

where $y_{i,t}$ denotes a labor market variable of interest (either employment growth, unemployment rate or participation rate) at time t for region i; and x_t denotes the aggregate counterpart of the variable across the whole economy (either aggregate employment growth, the aggregate unemployment rate, or the aggregate participation rate) at time t. Having estimated (1) by OLS for each endogenous variable in the VAR, Decressin and Fatás (1995) retain the residuals for their VAR analysis.

By conditioning on national-level averages, the RB approach attenuates the effects of aggregate shocks in the panel. Nevertheless, it is unlikely to filter out all of the variation attributable to these aggregate effects. As we have demonstrated above in Table 1, the regional incidence of national recessions tends to change from recession to recession—but the RB approach imposes a single parameter β_i on the national factor x_t. The problem is likely to become more acute in longer samples because the number of recessions in the sample increases.

We illustrate this point in Figures 1 through 3 below for the three groups of states introduced in the previous subsection—the Northeast, the Rust Belt and the Energy-producers. Each figure plots state-level employment growth alongside the residuals from OLS estimation of the regression (1). For each state we also display the fitted coefficient $\hat{\beta}_i$ on the graph to indicate how sensitive the state is to national employment growth.

The Northeast Figure 1 depicts the filtered time series for the Northeast states. These states tend to have a slope coefficient very close to one, meaning that the regression based approach undercorrects for the recessions that states experience relatively severely (such as the 1990-91 recession), and over-corrects for recessions that they experience relatively mildly (such as the Great Recession). The regression-based filter evidently does a poor job of controlling for the 1990-91 recession. Although the decline in the filtered series is attenuated after conditioning on the national growth rate, there is still a substantial decline in employment over the recessionary period—particularly in Connecticut, Maine, Rhode Island, New Hampshire and Massachusetts. The flipside of this result is that the regression based approach also over-corrects for the Great Recession, which was comparatively mild in the Northeast: Note the small "spikes" in the filtered time series during the great recession period in most of these graphs.

[Insert Figure 1 here]

Rust Belt Figure 2 depicts the RB filtered growth rates for the rust belt states, which were hit particularly hard in the early eighties recessions. The regression-based approach consequently does not do a good job of controlling for that recession. In fact, for Illinois, Indiana, Michigan and West Virginia the approach does not attenuate the initial fall in employment at all. For Ohio, Wisconsin and Pennsylvania, the effects of the early eighties recessions are still clearly evident in the filtered time series.

[Insert Figure 2 here]

Energy Producers Figure 3 exhibits the employment growth rates and filtered time series for the energy-producing states. There is clear covariation in (the unfiltered) employment growth rates between these states that appears only weakly related to national employment growth. For example, these states experience a contraction in employment during the mid 1980s while the national economy is in expansion. This period coincides with a decline in global oil prices. But these regions are not wholly independent of the national economy and are periodically subject to national recessions—particularly the Great Recession. We can also see that Texas, Oklahoma, Louisiana and Wyoming are also affected by the second 1981-82 recession in the early eighties. Unsurprisingly, regression-based filter does not remove much variation from employment growth for these states—the filtered time series look very similar to the unfiltered growth rates. Because the approach conditions on a single time series, regions that are driven by other factors (such as energy prices) will not have much of their variation removed. States such as Oklahoma, Louisiana and Wyoming appear severely affected by 1981-82 recession, but because of a lack of covariation with national growth during other time periods, the regression-based approach does not properly control for it.

[Insert Figure 3 here]

3.3 Using the Factor Model to filter out Aggregate Effects

To adequately capture the spatiotemporal heterogeneity in national recessions illustrated in Table 1 we require a more flexible functional form than that offered by the regression model (1). Like the regression-based filter, the adopted model should allow for aggregate effects to have heterogenous regional incidence, since national recessions have a differential regional impact. But unlike the regression-based filter, it should also permit temporal heterogeneity in how these aggregate effects manifest themselves—so that different recessions are permitted to have different regional impacts.

To this end, we propose that the approximate factor structure as a model for filtering out aggregate effects. For an arbitrary scalar $y_{i,t}$ the standard linear factor model is of the form

$$y_{i,t} = f_t' \lambda_i + z_{i,t}. \tag{2}$$

Here $y_{i,t}$ is some variable of interest (such as employment growth, population growth, or labor force growth in our application), f_t is an $r \times 1$ vector of *common factors* (in a given time period), λ_i is a

$r \times 1$ vector of *factor loadings*. The *common component* of the panel is $\lambda_i' f_t$, while the *idiosyncratic component* is $z_{i,t}$. The common factors and loadings are not directly observed. Intuitively, the common factors capture the sources of pervasive covariation in the panel $y_{i,t}$, such as the aggregate shocks, while λ_i represents the responsiveness of the cross section to the factors, thus permitting the cross-sectional heterogeneity to aggregate shocks. The model allows for a finite set of r different factors. Because the factor model permits r different sources of covariation, it can also account for the changes in the regional incidence of different recessions by fitting a different factor for recessions with substantially different geographic incidences. Moreover, (2) is observationally equivalent to a dynamic factor model in which both current and lagged factors are pervasive sources of covariation (see, among others, Bai and Ng, 2007; Amengual and Watson, 2007; and Hallin and Liska, 2007), so we can permit some or all of the cross sections to exhibit lagged responses to aggregate shocks.

To estimate the factors $\{f_t\}_{t=1}^T$ and loadings $\{\lambda_i\}_{i=1}^n$ we use the standard principal component method, which estimates the column space of the factors and loadings under the restrictions that the estimated factors are orthogonal, and that the loadings are orthogonal with unit variance (for details see Bai, 2003). The factors are identified based on the cross-sectional correlation between the n different time series. Estimation of the aggregate effects via this dependence structure of the data obviates the need for a priori assumptions regarding exogenous sources of variation in the aggregate economy—such as oil shocks or sectoral composition (cf. Clark, 1998; Coulson, 1999; Carlino and Sill, 2001; Carlino, DeFina and Sill, 2001), and also does not require that all locations respond to aggregate shocks in the same way. To determine the factor number r we use the Hallin and Liska (2007) cross validation of the Bai and Ng (2002) model selection criteria (see the Appendix for details).

In the following subsections we apply the factor model to the panel of state-level employment growth spanning 1976 to 2015. First, we present the estimated factors alongside a variance decomposition in order to demonstrate how the factor structure accounts for spatiotemporal heterogeneity in national recessions. We then demonstrate that the estimated factor model is more effective at filtering out the effects of national recessions from the time series than the RB approach.

3.3.1 Fitting the Factor Model to State Employment Growth

In this section we provide an overview of the estimated factor structure applied to state level employment growth. The Hallin and Liska (2007) method selects three factors for employment growth (see the Appendix for details). The three estimated factors are exhibited in figures 5, 7 and 9. Meanwhile, figures 4, 6 and 8 depict of the proportion of variation in employment growth explained by each factor (this information is also tabulated in Table A.2 in the Appendix). These maps also contain information on the relative size of the factor loadings. We discuss each of the factors in turn.

[Insert Figures 4 and 5 here]

Figure 5 demonstrates that the first factor mimics the national trend in the business cycle–it falls during contractions and is positive for prolonged periods during expansions. As shown in Figure 4, it also explains substantial variation for a large number of states, particularly in the northern Midwest, West, and South. In fact, the first factor explains at least 60% of the variation in employment growth for thirty of the states (see Table A.2 in the Appendix).

Yet despite the importance of the first factor for many states, there are notable exceptions. The most obvious are energy-producing states, including Oklahoma, Louisiana, Wyoming, and North Dakota, for which the first factor explains less than 20% of the variation in employment growth. It also explains less than 35% of the variation in Texas. As shown in Table 1, these energy-producing states often do well during national recessions. In addition, we can see that the first factor explains less than 60% of the variation in many of the states in the Northeast and Mid Atlantic (such as Massachusetts, Connecticut, New Hampshire, Rhode Island, Delaware) as well as South Dakota, Montana, Iowa and Idaho. It explains only about 43% of the variation in New York, which, like Texas, has a large economy—indicating that the first factor is not picking-up variation in some of the largest states in the Union. The Northeast is notable as it was hit hard in the 1990-91 recession, but performed well during the early 1980s recessions, as shown in Table 1. For these groups of states that do not follow national trends as closely as the other states, either the second or third factors (or a combination thereof) substantially improve our ability to filter out aggregate effects.

[Insert Figures 6 and 7 here]

The second factor captures the effects of the early nineties recession for both the energy-producing states and the Northeast states. The latter experienced an increase in employment during the recession, while the former were hit particularly hard. Figure 6 shows that the second factor explains much of the variation in these two groups. The factor accounts for at least 24% of the variation in Texas, North Dakota, Oklahoma, Louisiana, Montana and Wyoming, and at least 13% of the variation in Massachusetts, Connecticut, New York, Idaho, Colorado, West Virginia, New Hampshire, Virginia, New Jersey, DC, Delaware, Maine, Maryland and Rhode Island. But whereas the energy-producing states load positively onto the second factor, the Northeast loads negatively onto it, reflecting the opposite effects of the 1990-91 recession on these two groups of states (note that the estimated factor in Figure 7 is positive during the 1990-91 recession, so that the negative loadings of the Northeast states are consistent with the severe impact of the recession in these states).

It is also interesting to note that the second factor is significantly negative during the mid-1980s. This is during the "Massachusetts miracle" (when the Northeast was performing well) and oil prices were at record lows. Again, these patterns correspond to the signs of the loadings of each group of states.

[Insert Figures 8 and 9 here]

The third factor captures the experience of the energy-producing states and the Northeast during the early eighties recessions. In contrast to the early nineties recession, both groups of states performed relatively well during this national downturn (as shown in Table 1). The factor explains at least 11% of the variation in New Jersey, West Virginia, Louisiana, New Hampshire, Massachusetts, Colorado, Wyoming, Connecticut, Texas, Oklahoma and South Dakota. As shown in figure Figure 8, these states load negatively onto the factor – which is significantly negative during the early 1980s (see Figure 9). This reflects the fact that these states were doing well during the early eighties recession.

The third factor also accounts for some additional variation in the Rust Belt as well as other states that were hit particularly hard in the 1980s recessions. For example, it accounts for at least 8% of the variation in Rust Belt states such as Indiana, Ohio, and Michigan, and it accounts for 18% of the variation in Iowa and 32% of the variation in South Dakota—both of which were hit hard in the "Farm Crisis" of the early 1980s. These states correspondingly load positively onto the factor. The factor also accounts for 12% of the variation in Florida–which loads negatively onto the factor and experienced an increase in employment during the early 1980s recessions.

Finally, we briefly examine the estimated common factors to population growth and labor force growth. These are depicted in the Appendix, where figures A.1, A.2, A.3 and A.4 plot the first, second, third and fourth factors for the three labor market variables. The factors to employment and labor force growth are highly correlated (i.e., the first factors to employment and labor force growth are highly correlated; the second factors to employment and labor force growth are highly correlated, etc.). Meanwhile, the first factor to population growth exhibits much more independent behavior. There are sustained declines in the factor after the early 1980s and the Great Recessions. Compared to the employment and labor force growth factor, the population factor exhibits much less variation around the 1991 and 2001 recessions, perhaps indicating that the more severe early 1980s and Great Recession generated a much greater migration response that the less severe recessions in the sample. The second and third factors to population growth exhibit substantial covariation with the second and third factors to employment and labor force growth.

3.3.2 Using the factor model to filter out aggregate effects from state-level employment growth

In this subsection, we revisit the state groups introduced above in Section 3.1 to consider whether the factor model does a better job at removing national recessions.

The Northeast Recall that the 1990-91 recession was particularly severe in the Northeastern states, and that the regression-based filter did not do an effective job of removing the fall in employment growth over the recessionary period (see Figure 1 above). The factor model is a more effective filter. As shown in Figure 10, there is no significant decline in the filtered time series during the 1991 recession in any of the states. Over-correction for the great recession does not appear to occur either, as was evident with the RB filter in Figure 1 above. While some states may experience peaks or troughs around recessions, there is no longer a pattern that is common across states.

[Insert Figure 10 here]

The Rust Belt Recall that rust belt states fared especially poorly in the early 1980s, and that the regression-based filter only mildly attenuated the early 1980s recession from time series (see Figure 2). The factor model is more effective at filtering out the effects of the recessions. As shown in Figure 11, after application of the factor model much of the variation over this period in removed from the time series.

[Insert Figure 11 here]

Energy producers Recall that for energy-producing states, the regression-based filter has almost no effect on the time series (see Figure 3). The factor model filter, however, does appear to pick up substantial common variation in these states, suggesting that while energy states do experience substantial aggregate variation, they do not follow the national trend. See Figure 12.

[Insert Figure 12 here]

4 Empirical Model of Regional Adjustment

In this section we incorporate the factor structure into an empirical model of regional adjustment in the spirit of Blanchard and Katz (1992, hereafter the "BK model"). We first show how the model is augmented with a factor structure in order to filter out aggregate effects in estimation. We then describe our data before estimating the model in order to measure the effects of region-specific labor demand shocks on employment, labor force and population. Finally, we compare these results to those obtained from the RB filter as well as those based on simple deviations from national averages—as per the main empirical specification used in Blanchard and Katz (1992). Throughout we use $e_{i,t}$ to denote log employment in state i at time t; $l_{i,t}$ denotes the log labor force; and $p_{i,t}$ denotes the log working age population.

We specify the canonical BK model as a structural VECM, wherein the log employment and participation rates ($e_{i,t} - l_{i,t}$ and $l_{i,t} - p_{i,t}$, respectively) enter into the model as cointegrating errors. The VECM structure nests the more commonly-used VAR in employment growth ($\Delta e_{i,t}$), unemployment ($l_{i,t} - e_{i,t}$) and participation (cf. Blanchard and Katz, 1992; Decressin and Fatás, 1995; Dao *et al.*, 2017). There is therefore no loss in terms of descriptive capability in adopting the VECM.

The VECM does, however, offer some advantages over the VAR when it comes to using the factor structure to filter out aggregate effects. As we demonstrate below, we augment the empirical model with the estimated factors loadings of the endogenous variables in the system of equations. The VECM describes the growth rates in employment, labor force and population, which are serially correlated but far less persistent than the unemployment and participation rates. Serial dependence in the idiosyncratic component of the panel impedes the precision of the principal components estimator (Greenaway-McGrevy, Han and Sul, 2012a). In particular, the fitted common factors can incorrectly attenuate the persistence in the fitted idiosyncratic components—which could consequently lead to misleading results in a multivariate analysis of the serial dependence structures in these components.

The general set of panel data VECMs are as follows:

$$\Delta Y_{i,t} = \boldsymbol{\alpha}_i + \boldsymbol{\delta}_t + \boldsymbol{\beta} Z_{i,t-1} + \sum_{s=1}^{p} \mathbf{B}_s \Delta Y_{i,t-s} + \mathbf{F}_t' \hat{\boldsymbol{\Lambda}}_i + v_{i,t},\ \ v_{i,t} = \boldsymbol{\Gamma} \varepsilon_{i,t}, \tag{3}$$

where $Y_{i,t} = (e_{i,t}, p_{i,t}, l_{i,t})'$ and $Z_{i,t} = (e_{i,t} - l_{i,t}, l_{i,t} - p_{i,t})'$ is a 2×1 vector consisting of the stationary cointegrating errors. The matrix $\boldsymbol{\beta}$ thus describes how employment, population and labor force respond to the local employment and participation rates. Through the lens of the Blanchard and Katz (1992) economic model, the population response embodies the household migration responses to the local economic conditions while the employment response embodies the job creation (or destruction) response to local conditions. For example, after an economic downturn, the Blanchard and Katz (1992) model predicts that workers will out-migrate is search of employment, leading to a reduction in population, while firms may locate new jobs in the locality, attracted by the surplus of labor and lower wages, which would generate a recovery in employment.

The salient feature of the empirical model is the inclusion of the estimated factor loadings $\hat{\boldsymbol{\Lambda}}_i$. This is an $3r \times 1$ vector consisting of the stacked loadings for each of the three variables in the system of equations (employment growth, population growth, and labor force growth).[5] The $3r \times 3$ matrix $\mathbf{F}_t$ is a matrix of associated common factors, the elements of which are treated as parameters in estimation. The component $\mathbf{F}_t' \hat{\boldsymbol{\Lambda}}_i$ therefore controls for aggregate effects in the regression. We augment the model with the estimated loadings rather than the factors for model parsimony. Including the factors would lead to an additional $3r\,(p+1)$ parameters in each equation, where r is the number of factors and p is the lag order. In contrast, including the loadings results in an additional $3r$ coefficients.

An alternative (albeit related) way to motivate (3) is to incorporate a factor error structure into the structural errors of the Blanchard and Katz (1992) model. This "factor error" structure serves to capture aggregate labor market shocks that have a heterogenous regional incidence via the factor loadings. The loadings can then be estimated from the first-differenced panel of variables

[5] By the Frisch-Waugh theorem, estimating (3) by OLS is equivalent to (i) running a regression of each variable in the VECM on $\hat{\boldsymbol{\Lambda}}_i$ and retaining the residuals; and (ii) estimating a VECM using the residuals from step (i). In this way, the VECM described in (3) is similar to the regression based approach used by Decressin and Fatas (1995).

(i.e., $\Delta Y_{i,t}$) and included in the VECM to filter out the aggregate shocks. See section 5 in the Appendix.

The vector of reduced-form errors $v_{i,t}$ is assumed to be *iid* and maps back into a vector of structural shocks $\varepsilon_{i,t}$ through the 3×3 matrix $\mathbf{\Gamma}$. Labor demand shocks are identified by assuming that all unforecastable changes in employment reflect changes in labor demand. This corresponds to a recursive VAR identification strategy (Stock and Watson, 2001), in which the first variable in the appropriately ordered 3×1 vector of variables $Y_{i,t}$ is employment. Structural employment shocks are allowed to have a contemporaneous effect on the other variables but not vice versa, inducing all of the correlation between the reduced-form residuals to be attributed to the structural labor demand shock. We can then trace out the effects of a single labor demand shock using a Cholesky decomposition of the reduced-form error covariance matrix and the reduced-form VAR.

The assumption that covariation between reduced-form residuals is attributable to the structural labor demand shock corresponds to a situation in which labor demand is highly inelastic in the short run, there is negligible unanticipated short-run variation in labor supply, or a combination of both, which Blanchard and Katz (1992) describe as being "highly plausible" (p. 24). Blanchard and Katz (1992) explore whether recursive identification holds by exploiting exogenous heterogeneity in immigration rates between states, and conclude that the recursive method identifies demand shocks well. The validity of the recursive identification assumption is not a function of the method used for filtering out the effects of aggregate shocks. The factor method will simply tend to filter out a higher portion of variation than do the other methods, leaving a subset of the same variation used by the other methods to identify the labor demand shocks. Below, we find that no matter what method is used for controlling aggregate effects, employment and participation rates decrease as a result of a negative shock, suggesting that a labor demand shock is being identified. In addition, we estimate the model with wage growth included as an endogenous variable, finding that wages also decrease in our factor-filtered specification in response to a negative labor demand shock. Results are contained in the Appendix.

4.1 Data

In order to estimate the BK model described in Section 4 we require state level employment, labor force, and working age population. We obtain employment and wages from the Annual State Personal Income and Employment published by the Bureau of Economic Analysis (BEA) (https://www.bea.gov/regional). Labor force is the sum of employment and unemployment. The latter is obtained from the Local Area Unemployment Statistics (LAUS) published by the Bureau of Labor Statistics (BLS) (http://www.bls.gov/lau/).[6] The LAUS data contain monthly state-wide unemployment counts for which simple arithmetic averages provide annual values. We use BEA employment data rather than LAUS employment data because the BEA data are (i) based on establishment surveys (largely the QCEW, which is based on state unemployment insurance, or UI, data); (ii) adjusted to account for employment that is not covered by the UI system; and (iii) adjusted for misreporting as well as for missing industry classifications. Working age population is obtained from the Intercensal and Postcensal Population published by the Census Bureau (https://www.census.gov/programs-surveys/popest.html). The entire data set is available beginning in 1976 and ending in 2015.

4.2 Empirical Results

Impulse responses from the fitted VECM are used to measure the effect of labor demand shocks on employment, labor force and population over the short and long run. The steps involved in estimation of the system (3) are as follows:

1. Fit a factor model to each variable ($\Delta e_{i,t}$, $\Delta p_{i,t}$ and $\Delta l_{i,t}$) separately using principal components. We select the appropriate number of factors using the Hallin-Liska method (see the

[6] Note that these are not the same data that BK use. The LAUS data are subject to state-space filtering, while the unemployment and employment data that BK used were not. See www.bls.gov/lau/laumthd.htm. However, while BK used employment counts from the establishment-based QCEW, the only official state-level panel of unemployment rates available was the *Geographic Profile of Employment and Unemployment*, which is based on the current population survey (CPS). There are a number of reasons to avoid using the *Geographic Profile* data. First of all, because these data are based on the CPS, sample sizes by state are likely to be so small as to yield significant measurement error. Additionally, BK imputed the values they used for 1970-1976, raising yet more concerns about reliability and measurement error. Rowthorn and Glyn (2006) discuss the implications of measurement error for BK's results. We show below that by omitting these data and using only employment and population, results are quantitatively the same.

Appendix for details). We retain the estimated factor loadings for step 2.

2. Estimate (3) by OLS, stacking the factor loadings from step 1 in $\hat{\mathbf{\Lambda}}_i$. We use the Lee and Phillips (2015) panel data Schwarz criterion for selecting the lag order. A single lag is selected.

3. Apply a Cholesky factorization of the reduced-form residual variance-covariance matrices to identify the labor demand shocks.

4. Compute the impulse response functions to a –1% labor demand shock.

5. Apply the bootstrap method to obtain 95% confidence intervals. The bootstrap is based on Efron's (1981) centered percentile bootstrap. See the Appendix for details. Impulse responses at selected horizons are tabulated in Table A.1 in the Appendix.

Impulse responses for employment, working age population and labor force are illustrated in Figure 13. We also present impulse responses for the unemployment rates (i.e., the employment and participation rates) in Figure 14.

The initial -1% shock to employment is absorbed through a 0.70% reduction in the participation rate, a 0.21% reduction in the employment rate, and out-migration of 0.09%. Thus the participation rate is the primary channel through which the shock is initially absorbed.

Following the shock, there is an additional 0.13 percentage point fall in employment between year one and year two, but thereafter employment slowly recovers. After twenty years, employment is 0.74% below its pre-shock level. After forty years, the model implies that employment is 0.57% below its pre-shock level (see Table A.1).

Working-age population continues to decline steadily in the first five years after the shock, falling by an additional 0.3 percentage points between years one and five. Out-migration in the first five years after the shock therefore generates a cumulative decline in population of 0.39%. From year five onwards out-migration is limited. After twenty years, population has declined by 0.42% compared to its pre-shock level, implying a out-migration of an additional 0.03 percentage points over the fifteen year period between year 5 and 20.

The recovery in the participation and employment rates is highly protracted. The model implies that twenty years after the shock, the participation rate is 0.29% below its pre-shock level, while the employment rate is 0.03% below its pre-shock level. Forty years after the shock these rates are 0.12% and 0.1% below their pre-shock levels, respectively (see Table A.1).

In summary, over the long run the out-migration response is rather limited (especially when compared to the results from the RB model below)—meaning that the participation and employment rates account for most of the mediation of the shock over the long-run.

[Insert Figures 13 and 14 here]

4.3 Regional Adjustment using conventional methods to filter out Aggregate Effects

We compare the results based on the model (3) to those obtained from conventional approaches for filtering our aggregate effects. First, we consider a VECM that is based on RB filtered time series (as in Decressin and Fatás, 1995). Second, we consider a VECM that is fitted to variables expressed as deviations from national averages (as in the original Blanchard and Katz paper). We finish this section with a comparison of the three different approaches.

4.3.1 The Regression-Based Filter

The general set of VECMs is as follows:

$$\Delta Y_{i,t}^{0} = \boldsymbol{\alpha}_i + \boldsymbol{\beta} Z_{i,t-1}^{0} + \textstyle\sum_{s=1}^{p} \mathbf{B}_s \Delta Y_{i,t-s}^{0} + v_{i,t}^{0},\ v_{i,t}^{0} = \boldsymbol{\Gamma}\varepsilon_{i,t}, \tag{4}$$

where the '0' superscript indicates that the variables in the vector are residuals from a regression of the form given in (1). For example, $\Delta Y_{i,t}^{0} = \left(\Delta e_{i,t}^{0}, \Delta p_{i,t}^{0}, \Delta l_{i,t}^{0}\right)$, for $\Delta e_{i,t}^{0} := e_{i,t} - \hat{\alpha}_i^{(\Delta e)} - \hat{\beta}_i^{(\Delta e)} \Delta e_t^{(ag)}$, where $\Delta e_t^{(ag)}$ denotes national employment growth, and $\hat{\alpha}_i^{(\Delta e)}$ and $\hat{\beta}_i^{(\Delta e)}$ denote OLS coefficients from a regression of the time series on the nation aggregate. Impulse responses and bootstrapped confidence bands are then computed based on the OLS estimates. As above, we use Efron's (1981) centered percentile bootstrap. The Lee and Phillips (2015) Schwarz criterion selects one lag.

[Insert Figures 15 and 16 here].

Impulse responses are illustrated in Figures 15 and 16. The initial -1% shock to employment is absorbed through a 0.60% reduction in the participation rate, a 0.27% reduction in the employment rate, and out-migration of 0.13%. The participation rate is therefore the primary channel through which the shock is initially absorbed.

Following the shock, there is a continued decline in employment for five years, reaching a nadir of -2.12% in period 7. Thereafter employment recovers. After 20 years it remains 1.94% below its pre-shock level. Meanwhile population has declined by 1.23% after twenty years—implying a very large out-migration response to the initial 1% fall in employment. Compared to the factor model filter, the RB approach implies that regional downturns generate a significant amount of out-migration.

The recoveries in the participation and employment rates from the initial shock are extremely protracted. After 20 years, the model implies that the participation rate is 0.61% below its pre-shock level, while the employment rate is 0.1% below its pre-shock level. After forty years, these rates are 0.44% and 0.04% below their pre-shock levels.

4.3.2 Deviations from National Averages

In this model the variables are expressed as relative to national averages, which is equivalent to the RB method with $\alpha_i^{(j)} = 0$ and $\beta_i^{(j)} = 1$ in (1). The general set of VECMs is as follows:

$$\Delta Y_{i,t}^0 = \boldsymbol{\alpha}_i + \boldsymbol{\beta} Z_{i,t-1}^0 + \textstyle\sum_{s=1}^p \mathbf{B}_s \Delta Y_{i,t-s}^0 + v_{i,t}^0,\ v_{i,t}^0 = \boldsymbol{\Gamma}\varepsilon_{i,t}, \tag{5}$$

where the '0' superscript now indicates that the variables in the vector are expressed relative to national averages. For example, $\Delta e_{i,t}^0 := e_{i,t} - \Delta e_t^{(ag)}$, where $\Delta e_t^{(ag)}$ denotes national employment growth. Impulse responses and bootstrapped confidence bands are then computed based on the OLS estimates. As above, we use Efron's (1981) centered percentile bootstrap. The Lee and Phillips (2015) Schwarz criterion selects one lag.

Impulse responses are illustrated in Figures 17 and 18. The initial -1% shock to employment is absorbed through a 0.55% reduction in the participation rate, a 0.3% reduction in the employment rate, and out-migration of 0.15%. The participation rate is therefore the primary channel through which the shock is initially absorbed.

Following the shock, there is a continued drop in employment for 5 periods, reaching a nadir of -2.21% in year 6. Thereafter employment recovers. After twenty years it is 1.74% below its pre-shock level. There is also a significant out-migration response—much like the RB approach–with working-age population declining by 1.49% after 20 years.

The recovery in the unemployment rates is somewhat protracted. After 20 years, the participation rate is 0.12% below its pre-shock level, while the employment rate is 0.13% below its pre-shock level. After forty years, the participation rate is 0.01% below its pre-shock level, but the employment rate is still 0.09% below its pre-shock level, indicating that the shock has a much more persistent effect on the employment rate than on the participation rate in this model.

[Insert Figures 17 and 18 here]

4.4 Discussion

Our findings suggest that the participation rate is the primary margin through which the state absorbs and adjusts to a region-specific shock once heterogenous aggregate effects are properly controlled for. Migration plays a limited role in adjustment over the long term, and the recovery process is highly protracted. The latter result is consistent with a broader literature that suggests that economic shocks can have long-lasting effects on regional labor markets (see the discussion in Partridge *et al.*, 2015). Meanwhile, the limited out-migration response is consistent with the broader literature that concludes that migration plays a relatively small role in equilibrating regional unemployment rates (see, e.g., Greenaway-McGrevy and Hood, 2016 and references therein). Greenaway-McGrevy and Hood (2016) find most of a labor demand shock is initially absorbed by unemployment and participation (93% of the shock to employment), and employment growth makes up only about 27% of the recovery in two decades. We find here that about 90% of the initial shock is absorbed by participation and unemployment, with a somewhat larger effect on population in 20 years (42%).

These findings contrast markedly with the results from both the RB and national-averages approaches. Although these models also show that the shock is initially absorbed through a fall in labor market participation, the long-run adjustment to the shock entails a substantive out-migration of workers that generates a reduction in working-age population that is larger than the original shock to labor demand itself.

The similarities between the RB approach and national averages approach are notable—especially in contrast to results from the factor model approach. The RB results look quite different from the factor model results, even though the regression-based approach is similar to a factor model with a single factor (as discussed above, the first factor looks quite similar to the national average employment growth rate). The similarity between the RB approach and the national averages approach suggests that the regression-based filter is not filtering aggregate effects more effectively than the national averages approach, and that more than one source of aggregate variation is at work. It is also notable that the RB results in a substantially longer recovery process in state unemployment rates compared to national averages. This may be due to the RB filter over-correcting for the effect of recessions (see the discussion in Section 3.2), thereby spuriously magnifying the effect of the initial shock the data.

Our results also contrast markedly with the original findings of Blanchard and Katz (1992), who conclude that migration is the main channel through which shocks are absorbed, and suggest the employment rate is relatively more important than participation in absorbing the short-run incidence of the shock. They find that after 8 years, only 15-17% of the unemployment and participation rate responses to a labor demand shock remain, and that 65% of the initial shock is accommodated by migration. After filtering out heterogenous aggregate shocks, we find larger effects on the labor market after 8 years (23% unemployment rate, 70% participation rate), indicating a substantially slower recovery; and we find a significantly more muted initial population response—only 9.2% of the initial shock is accommodated through migration. Bartik (1993) argues that Blanchard and Katz's (1992) method biases their results toward finding a faster recovery. Using a different method, Bartik (1993) finds that 25% of the initial effect on the participation rate remains after 17 years. We find an even larger effect on participation—47%—after 17 years. Our results are similar to those of Decressin and Fatas (1995), find that shocks are absorbed mostly by participation in Euro-area regions, a finding that mirrors our results. Notably, these authors use the RB approach to control for heterogenous aggregate effects.

Finally, it is notable that the recovery in employment begins only one period after the initial shock when using the factor method to identify region-specific shocks. This suggests that there is not much serial dependence in labor demand shocks once we filter out aggregate effects using the factor structure. As pointed out by Hall (1992), Greenaway-McGrevy and Hood (2016), and Amior and Manning (2018), labor demand shocks must be serially uncorrelated if we are to measure the contribution of the endogenous response of labor demand based on the employment impulse responses function. By using the factor structure we obtain an employment response that is consistent with very little serial dependence in the labor demand shock—although it is clear that there is some still present. Notably, there is much less serial dependence in the shock compared to the RB approach.

5 Conclusion

In this paper we apply a new method for filtering out the effects of aggregate shocks from models of regional adjustment. Our approach uses a factor structure to describe aggregate effects in regional labor market data. We argue that the filter is well-suited to removing aggregate effects because it permits spatiotemporal heterogeneity in the manifestation of national recessions on different locations. This form of flexibility is critical because the geographic incidence of national recessions has changed with each recession.

Once we properly filter out aggregate effects, the empirical model describes the incidence and recovery from region-specific shocks. Our fitted model suggests that exogenous changes in labor demand are primarily moderated through the participation rate and (to a lesser degree) the employment rate—migration therefore plays a secondary role. This result is very different to that obtained using the more common regression-based approach to filtering out aggregate effects (Decressin and Fatás, 1995), which, when applied to US data, suggests that migration is the primary moderator of shocks to labor demand. We reconcile these findings by suggesting that (i) the factor model does a better job of filtering out aggregate effects, and (ii) at the aggregate level, labor demand shocks are far more persistent, which makes it difficult to accurately measure the contribution of migration to the recovery process (see the discussion in Greenaway-McGrevy and Hood, 2016; and Hall, 1992).

Appendices

Blanchard and Katz model with factor errors

The Blanchard and Katz (1992) model reduces to a structural VECM of the form

$$\Delta Y_{i,t} = \boldsymbol{\gamma} Y_{i,t-1} + \boldsymbol{\Gamma} \varepsilon_{i,t}$$

where $\varepsilon_{i,t}$ is a vector of structural labor demand and supply shocks, $\boldsymbol{\gamma}$ is rank deficient under cointegration, and $\boldsymbol{\Gamma}$ maps the shocks to the reduced form errors (see eq. (4) in Greenaway-McGrevy and Hood, 2016). (Note that additional lags may be included in the VECM to account for serial dependence in the structural shocks when estimating the model.) We suppose that the structural errors follow a factor structure $\varepsilon_{i,t} = f_t' \Lambda_i + \varepsilon_{i,t}^0$, where the matrix of common factors f_t represent aggregate structural shocks, and the loadings Λ_i capture the regional incidence of these shocks on location i. Here we show that we can recover estimates of Λ_i from the first-differenced variables $\Delta Y_{i,t}$, which can then be included in the VECM to filter out the aggregate shocks f_t.

Defining $\boldsymbol{\Phi} = \boldsymbol{\gamma} + I$ and rearranging the VECM we have $Y_{i,t} = \boldsymbol{\Phi} Y_{i,t-1} + \boldsymbol{\Gamma} \varepsilon_{i,t}$, so that by back-substitution we can express

$$Y_{i,t} = \textstyle\sum_{s=0}^{t-1} \boldsymbol{\Phi}^s \varepsilon_{i,t-s} + Y_{i,0}.$$

for some initialization $Y_{i,0}$. Substituting the factor-error structure into this expression, we get

$$Y_{i,t} = \underbrace{\textstyle\sum_{s=0}^{t-1} \boldsymbol{\Phi}^s f_{t-s}'}_{=:F_t'} \Lambda_i + \underbrace{\textstyle\sum_{s=0}^{t-1} \boldsymbol{\Phi}^s \varepsilon_{i,t-s}^0}_{=:Y_{i,t}^0} + Y_{i,0} = F_t' \Lambda_i + Y_{i,t}^0 + Y_{i,0}.$$

Thus $Y_{i,t}$ follows a non-stationary factor structure in which F_t and $Y_{i,t}^0$ are $I(1)$ vectors (although note that a linear combination of these vectors is $I(0)$ under the assumption of cointegration). We can recover estimates of Λ_i by applying principal components to first-differences $\Delta Y_{i,t}$, as suggested by Bai and Ng (2004) for $I(1)$ panels that exhibit a factor structure. We augment the

Table A.1: Factor Number Estimation: State Data (1977-2015)

	$\mathrm{IC}_{p1}(k)$	$\mathrm{IC}_{p2}(k)$	$\mathrm{IC}_{p3}(k)$
employment growth	3	3	3
labor force growth	4	4	4
working-age population growth	4	4	4

Factor numbers estimated using Hallin-Liska cross validation of Bai-Ng criteria

original VECM with these estimates in order to filter out the common shocks f_t.

Factor number estimation

Bai and Ng (2002) show that the factor number can be consistently estimated as both n (cross sections) and T (time series) approach infinity. Both the n and T dimensions of the the sample is rather limited here, so the Bai and Ng (2002) criteria may have difficulty pinning down the factor number if the signal-to-noise ratio is weak or if the idiosyncratic components exhibit dependence or heteroskedasticity. Indeed, the Bai-Ng selection criteria chose the maximum number of factors for both employment growth and population growth in our sample. To mitigate these effects, we use the Hallin-Liska (2007) cross validation of the Bai-Ng $\mathrm{IC}_p(k)$ criteria to estimate the factor number. We select from between zero to 6 factors. The upper bound (6 factors) reflects the relatively small time series dimension of the sample ($T = 39$).We initialize the Hallin-Liska cross validation procedure with an initial window size of 17 cross sections ($\simeq \frac{1}{3}n$) and increase the number of states incrementally. We use the following penalties on model dimensionality: 0.01, 0.02, 0.03,..., 4.99, 5. See Hallin and Liska (2007) for details on the procedure.

Table A.1 exhibits the results. Either 3 or 4 factors are selected for all variables. Because the unobserved factors are presented in all three labor market variables, there should be the same number of factors in each panel. We therefore use four factors, since under-specification of the model dimension will lead to inconsistency, but over-specifying the dimension only leads to an efficiency loss (see, e.g., Moon and Weidner, 2010).

Bootstrap Procedure

Our bootstrap procedure is as follows. We use 1000 replications.

1. Estimate the reduced-form VECM given in (3) and obtain reduced-form residuals. We employ five lags when estimating the models since the ensuant efficiency losses are outweighed by the potential costs of a more parsimonious but misspecified model (Berkowitz and Kilian, 2000).

2. We re-sample the residuals with replacement, maintaining cross-sectional and cross-equation correlation in the re-sampled panels by re-sampling only in the time series dimension. We do this in order to preserve any weak-form correlation in the residual that would otherwise cause us to underestimate the variance of the estimator. For example, it is likely that shocks are correlated across locations both according to geography as well as according to industry mix. We reconstruct the panels net of the common component $\mathbf{F}_t'\hat{\boldsymbol{\Lambda}}$ using the reduced-form estimates of $\boldsymbol{\alpha}_i$, $\boldsymbol{\delta}_t$, $\boldsymbol{\beta}$ and $\{\mathbf{B}_s\}_{s=1}^{p}$ obtained in step 1.

3. Re-estimate the VECM for each replication sample and compute the impulse response functions of employment, population and labor force growth, and employment rates and participation rates, to a -1% labor demand shock.

4. Reported 95% confidence intervals for the impulse response functions are based on bootstrapped estimates of the standard errors (see Efron, 1981, pp. 139-140). Let $\hat{\sigma}_h$ denote the bootstrapped standard error of the IRF $\hat{\psi}_h$. Then the confidence interval around $\hat{\psi}_h$ is given by $\left[\hat{\psi}_h - 1.96\hat{\sigma}_h, \hat{\psi}_h + 1.96\hat{\sigma}_h\right]$.

Results from model with wages

This table shows impulse responses for the model that includes wage growth as an additional variable in the VECM. Wages are computed as annual wage an salary income divided by annual wage and salary employment.

[Insert Table A.3 here]

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References

[1] Amengual, D. and M. W. Watson (2007), "Consistent estimation of the number of dynamic factors in a large N and T panel," Journal of Business and Economic Statistics, 25, 91-96.

[2] Amior, Michael and Alan Manning (2018), "The persistence of local joblessness," American Economic Review, 108(7), 1942-1970.

[3] Bai, J. (2003), "Inferential Theory for Factor Models of Large Dimensions," Econometrica, 71, 135-171.

[4] ——— (2009), "Panel Data Models with Interactive Fixed Effects," Econometrica, 77, 1229-1279.

[5] Bai, J., and S. Ng (2002), "Determining the number of factors in approximate factor models," Econometrica, 70, 191-221.

[6] ——— (2007), "Determining the Number of Primitive Shocks in Factor Models, Journal of Business and Economic Statistics," 25, 52-60.

[7] Bartik, Timothy J. (2009), "What Proportion of Children Stay in the Same Location as Adults, and How Does This Vary Across Location and Groups?" Upjohn Institute Working Paper No. 09-145, Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

[8] Bertola, G. (2000), "Labor Markets in the European Union," ifo-Studien, 46(1), 99-122.

[9] Beyer, Robert C. M. and Frank Smets (2015), "Labour market adjustments in Europe and the US: How different?" Economic Policy 30(84), 643–682

[10] Blanchard, Olivier J. and Lawrence F. Katz (1992), "Regional Evolutions," Brookings Papers on Economic Activity, 23(1), 1-76.

[11] Borjas, George J. (1999), "The Economic Analysis from Immigration," in Orley Ashenfelter and David Card (eds.), Handbook of Labor Economics, Elsevier, ed. 1, vol. 3, no. 3.

[12] ———— (2006), "Native Internal Migration and the Labor Market Impact of Immigration," Journal of Human Resources, 41(2), 221-258.

[13] Borjas, G. J., R. B. Freeman, L. F. Katz, J. Dinardo and J. M. Abowd (1997), "How Much Do Immigration and Trade Affect Labor Market Outcomes?" Brookings Papers on Economic Activity, 1997(1), 1-90.

[14] Bornhorst, F. and S. Commander (2006), "Regional Unemployment and its Persistence in Transition Countries," Economics of Transition, 14(2), 269-288.

[15] Broersma, Lourens and van Dijk, Jouke (2002), "How do Dutch Regional Labour Markets Adjust to Demand Shocks?," Research Report 02D07, University of Groningen, Research Institute SOM (Systems, Organisations and Management).

[16] Caballero, R. and M. Hammour (2005), "The Cost of Recessions Revisited: A Reverse Liquidationist View, Review of Economic Studies," 72, 313-341.

[17] Carlino, G. A., and K. Sill (2001), "Regional Income Fluctuations: Common Trends and Common Cycles," The Review of Economics and Statistics, 83(3), 446-456.

[18] Carlino, G. A., R. H. DeFina, and K. Sill (2001), "Sectoral Shocks and Metropolitan Employment Growth," Journal of Urban Economics, 50(3), 396-417.

[19] Chudik, A., M. H. Pesaran, and E. Tosetti (2011), "Weak and Strong Cross Section Dependence and Estimation of Large Panels," Econometrics Journal, 14, C45-C90.

[20] Clark, T. E. (1998), "Employment Fluctuations in the U.S. Regions and Industries: The Roles of National, Region-Specific, and Industry-Specific Shocks," Journal of Labor Economics, 16, 202-229.

[21] Clark, T. E. and K. Shin (1999), "The Sources of Fluctuations within and across Countries," in G. Hess and E. van Wincoop (Eds.), Intranational Macroeconomics, Cambridge University Press, Cambridge, pp. 187-217.

[22] Coulson, N. E. (1999), "Sectoral Sources of Metropolitan Growth," Regional Science and Urban Economics, 29(6), 723-743.

[23] Dao, Mai, Davide Furceri and Prakash Loungani (2017), "Regional Labor Market Adjustment in the United States: Trend and Cycle," Review of Economics and Statistics, 99(2), 243-257.

[24] Davis, S. J., J. Faberman and J. C. Halitwanger (2011), "Labor Market Flows in the Cross Section and Over Time," NBER working paper 17294.

[25] Decressin, J.and A. Fatás (1995), "Regional Labor Market Dynamics in Europe," European Economic Review, 39(9), 1627-1655.

[26] Efron, Bradley (1981), "Nonparametric Standard Errors and Confidence Intervals," The Canadian Journal of Statistics, 9(2), 139-158.

[27] Fallick, B. and C. Fleischman (2004), "Employer-to-Employer Flows in the US Labor Market: The Complete Picture of Gross Worker Flows," Board of Governors of the Federal Reserve System, Finance and Economics Discussion Series 2004-34.

[28] Fidrmuc, J. (2004), "Migration and Regional Adjustment to Asymmetric Shocks in Transition Economies, "Journal of Comparative Economics, 32(2), 230-247.

[29] Foerster, Andrew T., Pierre-Daniel G. Sarte, Mark W. Watson (2011), "Sectoral versus Aggregate Shocks: A Structural Factor Analysis of Industrial Production," Journal of Political Economy, 119(1), 1-38.

[30] Forni, Mario and Lucrezia Reichlin (1998), "Let's Get Real: A Factor Analytical Approach to Disaggregated Business Cycle Dynamics," The Review of Economic Studies, 65(3), 453-473.

[31] Fredriksson, P. (1999), "The Dynamics of Regional Labour Markets and Active Labour Market Policy: Swedish Evidence," Oxford Economic Papers, 51(4), 623-648.

[32] Gács, V. and P. Huber (2005), "Quantity Adjustments in the Regional Labour Markets of EU Candidate Countries," Papers in Regional Science, 84(4), 553-574.

[33] Garin, Julio, Michael J. Pries and Eric R. Sims (2018), "The Relative Importance of Aggregate and Sectoral Shocks and the Chaning Nature of Economic Fluctuations," American Economic Journal: Macroeconomics, 10(1), 119-148.

[34] Glaeser, Edward L. and Joseph Gyourko (2005), "Urban Decline and Durable Housing," Journal of Political Economy, 113(2), 345-375.

[35] Glaeser, Edward L., Joseph Gyourko and Raven Saks (2005), "Why Is Manhattan So Expensive? Regulation and the Rise in House Prices," Journal of Law and Economics, 48(2), 331-369.

[36] Greenaway-McGrevy, R., C. Han and D. Sul (2012a), "Estimating the Number of Common Factors in Serially Dependent Factor Models." Economic Letters 116, 531-534.

[37] Greenaway-McGrevy, R., C. Han and D. Sul (2012b), "Asymptotic distribution of factor augmented estimators for panel regression." Journal of Econometrics 169, 48-53.

[38] Greenaway-McGrevy, R., and K. K. Hood (2016), "Worker Migration or Job Creation? Persistent Shocks and Regional Recoveries," Journal of Urban Economics, 96, 1-16.

[39] Greenstone, Michael (2001), "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures," NBER working paper 8484.

[40] Grobar, Lisa M. (1996), "Comparing the New England and Southern California Regional Recessions," Contemporary Economic Policy, 14(3), 71-84.

[41] Hall, Robert E. (1992), "Comments and Discussion," in Blanchard, Olivier J. and Lawrence F. Katz, "Regional Evolutions," Brookings Papers on Economic Activity, 23(1), 1-76.

[42] Hallin, M. and R. Liska (2007), "Determining the Number of Factors in the Generalized Dynamic Factor Model," Journal of the American Statistical Association, 102, 603-617.

[43] Hamilton, James D. and Michael T. Owyang (2012), "The Propagation of Regional Recessions," Review of Economics and Statistics, 94(4), 935-947.

[44] Hauser, Daniela (2014), "Technology Shocks, Labour Mobility, and Aggregate Fluctuations," Staff Working Paper, Bank of Canada, 2014-4.

[45] Jimeno, Juan F. and Samuel Bentolila (1998), "Regional Unemployment Persistence (Spain, 1976-1994)," Labour Economics, 5(1), 25-51.

[46] Berkowitz, Jeremy and Lutz Kilian (2000), "Recent developments in bootstrapping time series," Econometric Reviews, 19(1), 1-48.

[47] Kline, Patrick (2008), "Understanding Sectoral Labor Market Dynamics: An Equilibrium Analysis of the Oil and Gas Field Services Industry," working paper.

[48] Kline, Patrick and Enrico Moretti (2011), "Local Economic Development, Agglomeration Economies and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority," working paper.

[49] Lee, Yoonseok and Peter C. B. Phillips (2015), "Model selection in the presence of incidental parameters," Journal of Econometrics, 188(2), 474-489.

[50] Megna, Robert and Qiang Xu (2003), "Forecasting the New York State Economy: The Coincident and Leading Indicators Approach," International Journal of Forecasting, 19(4), 701-713.

[51] Molloy, Raven and Abigail Wozniak (2011), "Labor Reallocation over the Business Cycle: New Evidence from Internal Migration," Journal of Labor Economics, 29(4), 697-739.

[52] Moon, R., and M. Weidner (2010), "Linear Regression for Panel with Unknown Number of Factors as Interactive Fixed Effects," working paper, University College of London.

[53] Owyang, Michael T., Jeremy M. Piger & Howard J. Wall (2005), "The 2001 recession and the states of the Eighth Federal Reserve District," Regional Economic Development, Federal Reserve Bank of St. Louis, Nov., 3-16.

[54] Partridge, Mark D., Dan S. Rickman, M. Rose Olfert and Ying Tang (2015), "When Spatial Equilibrium Fails: Is Place-Based Policy Second Best?," Regional Studies. 49(8), 1303-1325.

[55] Pekkala, Sari and Aki Kangasharju (2002), "Adjustment to Regional Labour Market Shocks," Discussion Papers 274, Government Institute for Economic Research Finland (VATT).

[56] Pesaran, M. Hashem (2006), "Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure," Econometrica 76(4), 967-1012.

[57] Saiz, Albert (2010), "The Geographic Determinants of Housing Supply," Quarterly Journal of Economics, 125(3),1253-1296.

[58] Saks, Raven E. (2008), "Job Creation and Housing Construction: Constraints on Metropolitan Area Employment Growth," Journal of Urban Economics, 64(1), 178-195.

[59] Sala, H. and P. Trivín (2014), "Labour Market Dynamics in Spanish Regions: Evaluating Asymmetries in Troublesome Times," SERIEs, 5(2), 197-221.

[60] Sill, Keith (1997), "Regional Employment Dynamics," Working Papers 97-28, Federal Reserve Bank of Philadelphia.

[61] Stock, J.H. and M.W. Watson (2001), "Vector Autoregressions," Journal of Economic Perspectives, 15(4), 101-115.

[62] Tani, Massimiliano (2003), "Have Europeans Become More Mobile? A Note on Regional Evolutions in the EU: 1988-1997," Economic Letters, 80, 23-30.

[63] Yagan, Danny (2014), "Moving to Opportunity? Migratory Insurance over the Great Recession," Working Paper.

[64] Zabel, Jeffrey (2012), "Migration, Housing Market, and Labor Market Responses to Employment Shocks," Journal of Urban Economics, 72(2), 267-284.

Figures and Tables to Appear in Main Text

Table 1: Change in state-level employment during national recessions

1980-82 Recessions		1990-91 Recession		2001 Recession		Great Recession (2008-10)	
Michigan	-10.07%	Massachusetts	-7.25%	Mississippi	-2.20%	Nevada	-10.65%
Indiana	-7.12%	New Hampshire	-6.78%	Michigan	-1.75%	Arizona	-8.34%
West Virginia	-6.53%	Rhode Island	-6.73%	Indiana	-1.63%	Michigan	-8.07%
Ohio	-6.33%	Connecticut	-5.52%	South Carolina	-1.37%	Florida	-6.84%
Oregon	-6.12%	New Jersey	-4.20%	Kentucky	-1.35%	Idaho	-6.57%
Iowa	-5.49%	Maine	-3.49%	Alabama	-1.26%	California	-6.06%
DC	-4.59%	New York	-2.80%	Tennessee	-1.09%	Ohio	-5.54%
South Dakota	-4.28%	Vermont	-2.08%	Ohio	-1.06%	Alabama	-5.46%
Illinois	-4.23%	Maryland	-1.55%	Iowa	-1.03%	Oregon	-5.38%
Idaho	-3.72%	DC	-0.44%	North Carolina	-0.96%	Indiana	-5.24%
Wisconsin	-3.62%	Virginia	-0.37%	South Dakota	-0.79%	Tennessee	-5.22%
Pennsylvania	-3.41%	Delaware	-0.09%	Arkansas	-0.71%	Rhode Island	-5.03%
Mississippi	-3.21%	Pennsylvania	-0.07%	Delaware	-0.66%	Georgia	-4.68%
Kentucky	-3.02%	Missouri	0.11%	Wisconsin	-0.51%	South Carolina	-4.62%
Alabama	-2.83%	Michigan	0.26%	Illinois	-0.51%	Missouri	-4.59%
Tennessee	-2.74%	Georgia	0.38%	Missouri	-0.49%	North Carolina	-4.50%
Missouri	-2.34%	Ohio	0.69%	West Virginia	-0.30%	Hawaii	-4.23%
Arkansas	-2.02%	North Carolina	0.70%	Oregon	-0.29%	Wisconsin	-4.21%
Rhode Island	-1.80%	Illinois	1.19%	Louisiana	-0.13%	Illinois	-4.18%
Nebraska	-1.70%	South Carolina	1.49%	Washington	-0.08%	Maine	-4.15%
Montana	-1.36%	Tennessee	1.55%	Nebraska	-0.07%	New Hampshire	-4.02%
Minnesota	-1.15%	Florida	1.82%	Georgia	0.03%	Delaware	-3.99%
North Carolina	-0.14%	Mississippi	1.84%	Utah	0.13%	New Mexico	-3.72%
South Carolina	0.45%	California	1.95%	Pennsylvania	0.22%	Washington	-3.65%
Kansas	0.78%	Arizona	2.00%	North Dakota	0.25%	Minnesota	-3.57%
New York	1.07%	Indiana	2.02%	Oklahoma	0.34%	Kentucky	-3.35%
Maryland	1.16%	Kentucky	2.03%	New Mexico	0.44%	Mississippi	-3.24%
Delaware	1.50%	Kansas	2.40%	Minnesota	0.46%	New Jersey	-3.10%
Maine	1.55%	Alabama	2.64%	Texas	0.49%	Utah	-3.09%
North Dakota	1.71%	Oklahoma	2.77%	Rhode Island	0.50%	Connecticut	-2.98%
Washington	1.74%	West Virginia	2.82%	Colorado	0.51%	Montana	-2.84%
Hawaii	1.81%	Nebraska	2.83%	Connecticut	0.59%	Vermont	-2.54%
Virginia	2.02%	Minnesota	3.12%	New Jersey	0.61%	Maryland	-2.43%
Massachusetts	2.25%	North Dakota	3.20%	Idaho	0.61%	Arkansas	-2.35%
New Jersey	2.43%	Iowa	3.31%	Maine	0.63%	Virginia	-2.34%
Connecticut	3.11%	Arkansas	3.39%	Kansas	0.73%	Kansas	-2.04%
California	3.18%	Wisconsin	3.60%	New York	0.73%	Colorado	-2.04%
Georgia	3.38%	Oregon	3.81%	California	0.73%	Iowa	-1.98%
Vermont	3.91%	Louisiana	3.89%	Virginia	0.83%	Massachusetts	-1.86%
Utah	4.18%	Colorado	4.12%	Florida	0.85%	Pennsylvania	-1.78%
New Mexico	4.45%	Wyoming	4.32%	Vermont	0.92%	West Virginia	-1.48%
Nevada	5.43%	Texas	4.33%	Massachusetts	0.94%	Wyoming	-1.12%
Arizona	5.88%	Montana	4.61%	Montana	0.98%	Nebraska	-0.86%
New Hampshire	6.35%	New Mexico	4.66%	Arizona	0.99%	Oklahoma	-0.36%
Louisiana	6.43%	Alaska	5.48%	Hawaii	1.25%	New York	-0.33%
Wyoming	7.41%	Washington	5.69%	Maryland	1.33%	Alaska	1.02%
Colorado	9.97%	South Dakota	6.03%	New Hampshire	1.38%	South Dakota	1.25%
Florida	10.62%	Hawaii	6.81%	DC	1.48%	Louisiana	1.44%
Texas	11.26%	Utah	6.86%	Nevada	1.55%	Texas	1.92%
Oklahoma	12.19%	Idaho	7.53%	Wyoming	1.59%	DC	2.74%
Alaska	14.05%	Nevada	7.98%	Alaska	2.24%	North Dakota	4.45%

Source: BEA state personal income and employment

Percent changes (cumulative log differences) in annual employment levels over recessionary periods. We use the following years for each recession: 1980-82, 1990-91, 2001, and 2008-2010. These years are chosen to span the quarters of contraction in the national economy as specified by the National Bureau of Economic Research.

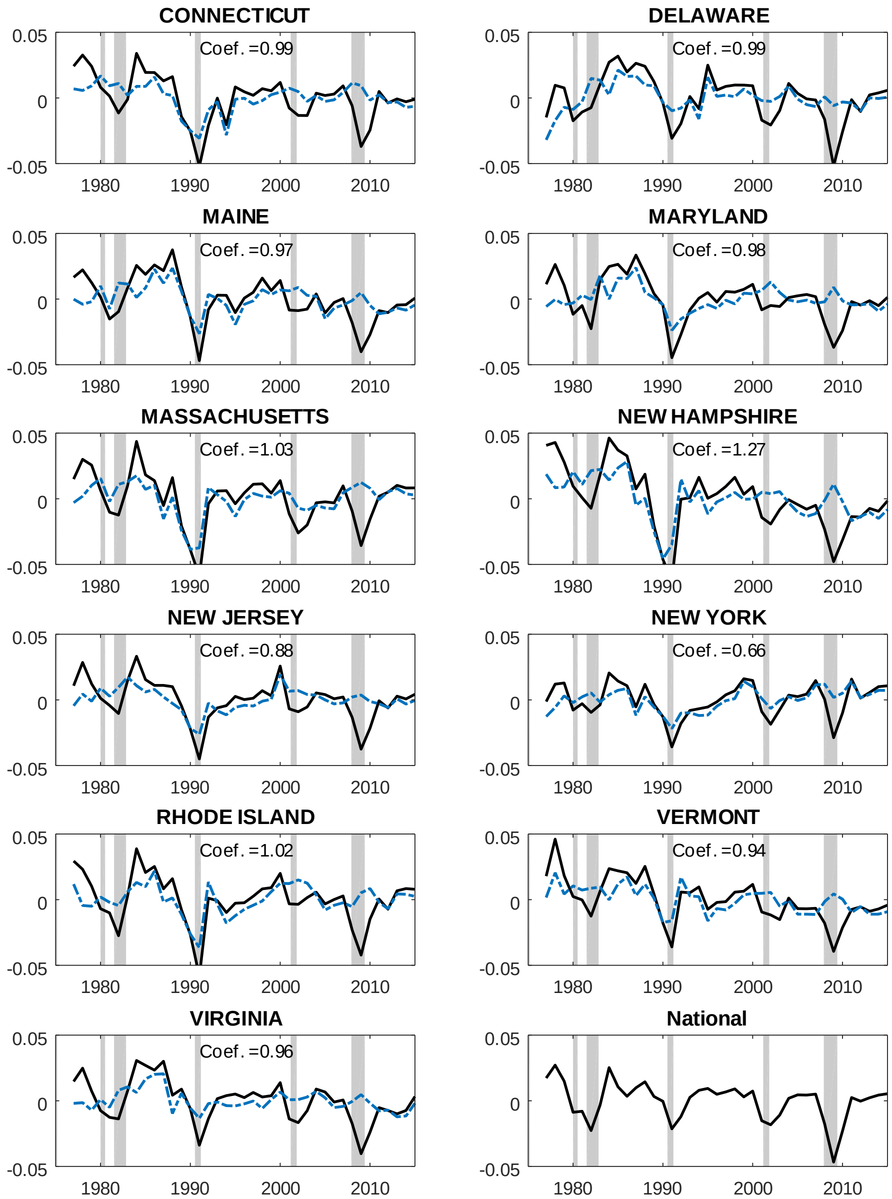

Figure 1: Northeast states, regression-based filter. Solid lines are state employment growth time series; Dashed lines are filtered time series.

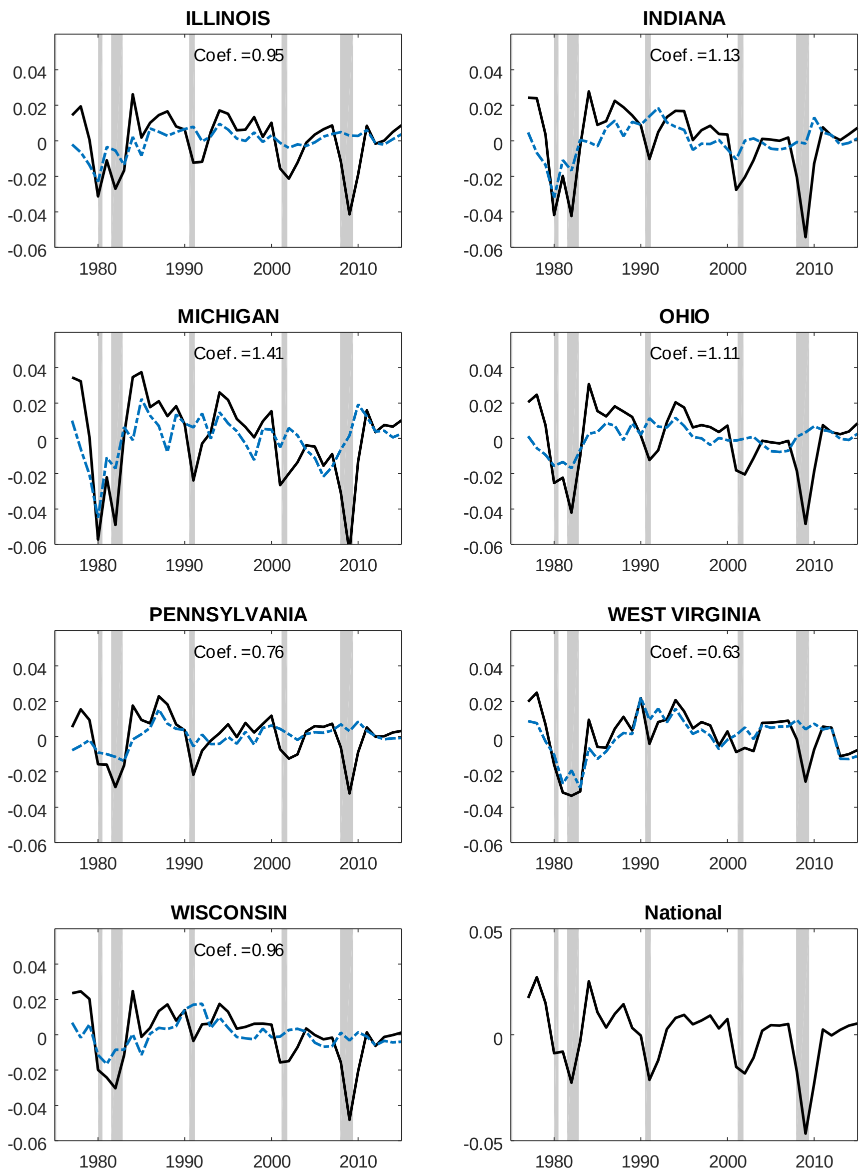

Figure 2: Rust-belt states, regression-based filter. Solid lines are state employment growth time series; Dashed lines are filtered time series.

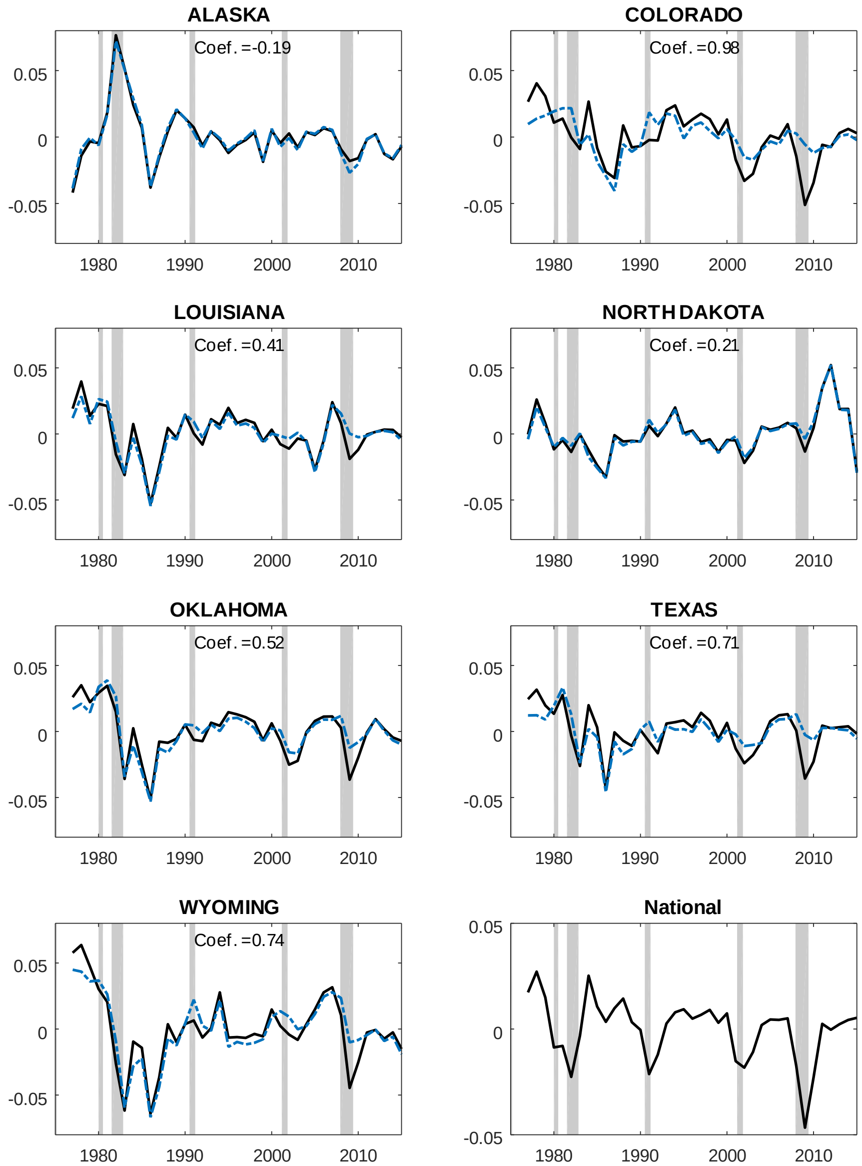

Figure 3: Energy-producing states, regression-based filter. Solid lines are state employment growth time series; Dashed lines are filtered time series.

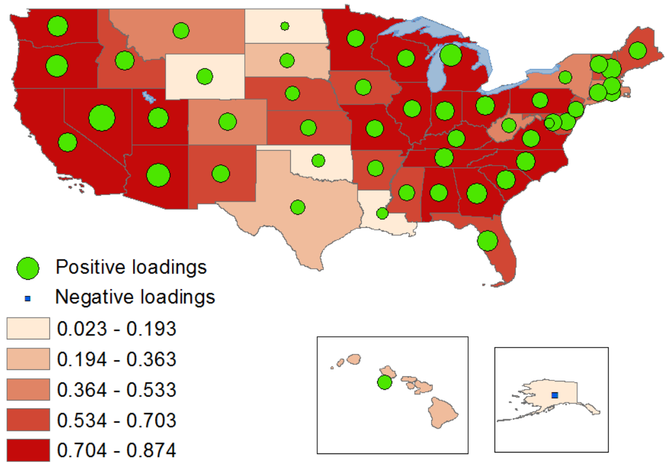

Figure 4: First factor to employment growth. Shading represents the proportion of variance explained by the factor in the state. Superimposed circles and squares are proportional to the magnitude of the factor loading for each state. Circles denote positive loadings; squares denote negative loadings.

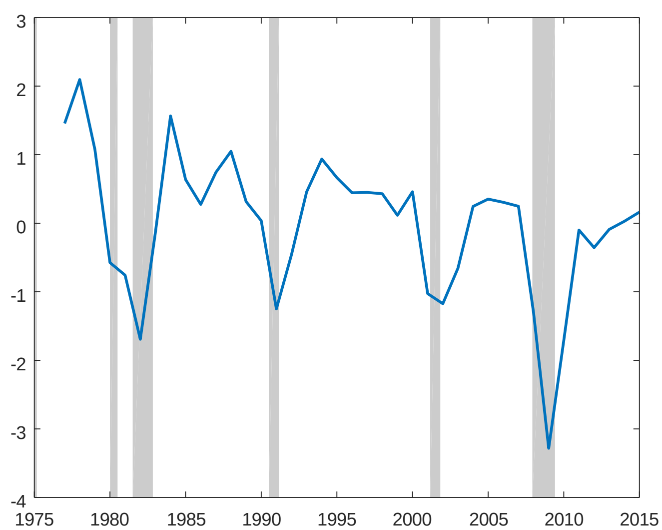

Figure 5: First estimated factor to employment growth

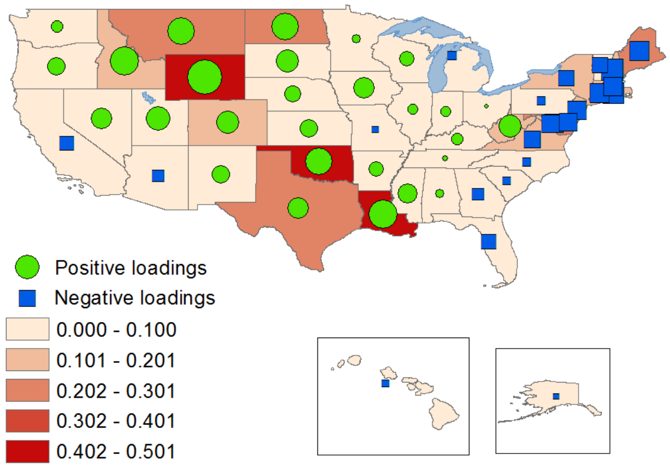

Figure 6: Second factor to employment growth. Shading represents the proportion of variance explained by the factor in the state. Superimposed circles and squares are proportional to the magnitude of the factor loading for each state. Circles denote positive loadings; squares denote negative loadings.

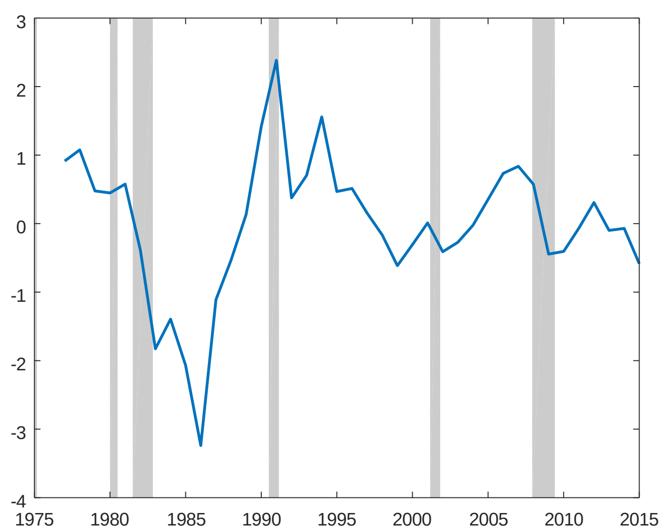

Figure 7: Second estimated factor to employment growth

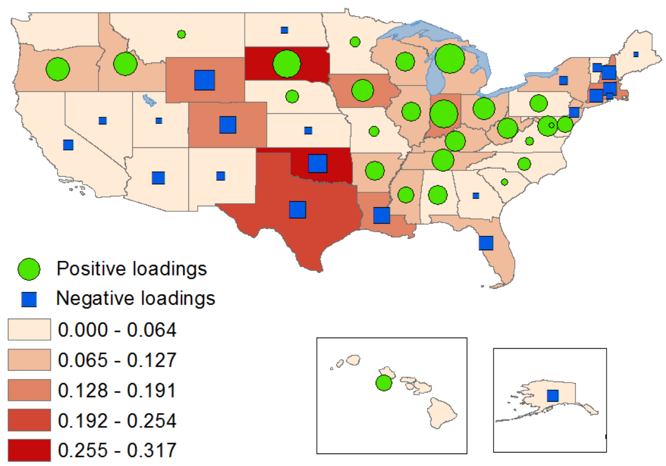

Figure 8: Third factor to employment growth. Shading represents the proportion of variance explained by the factor in the state. Superimposed circles and squares are proportional to the magnitude of the factor loading for each state. Circles denote positive loadings; squares denote negative loadings.

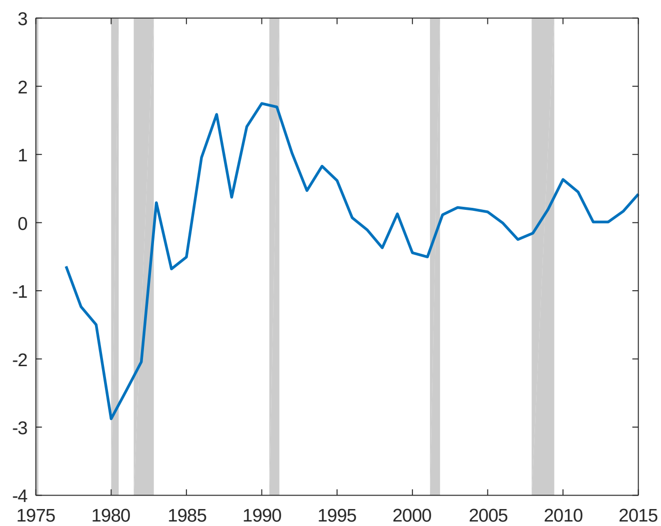

Figure 9: Third estimated factor to employment growth

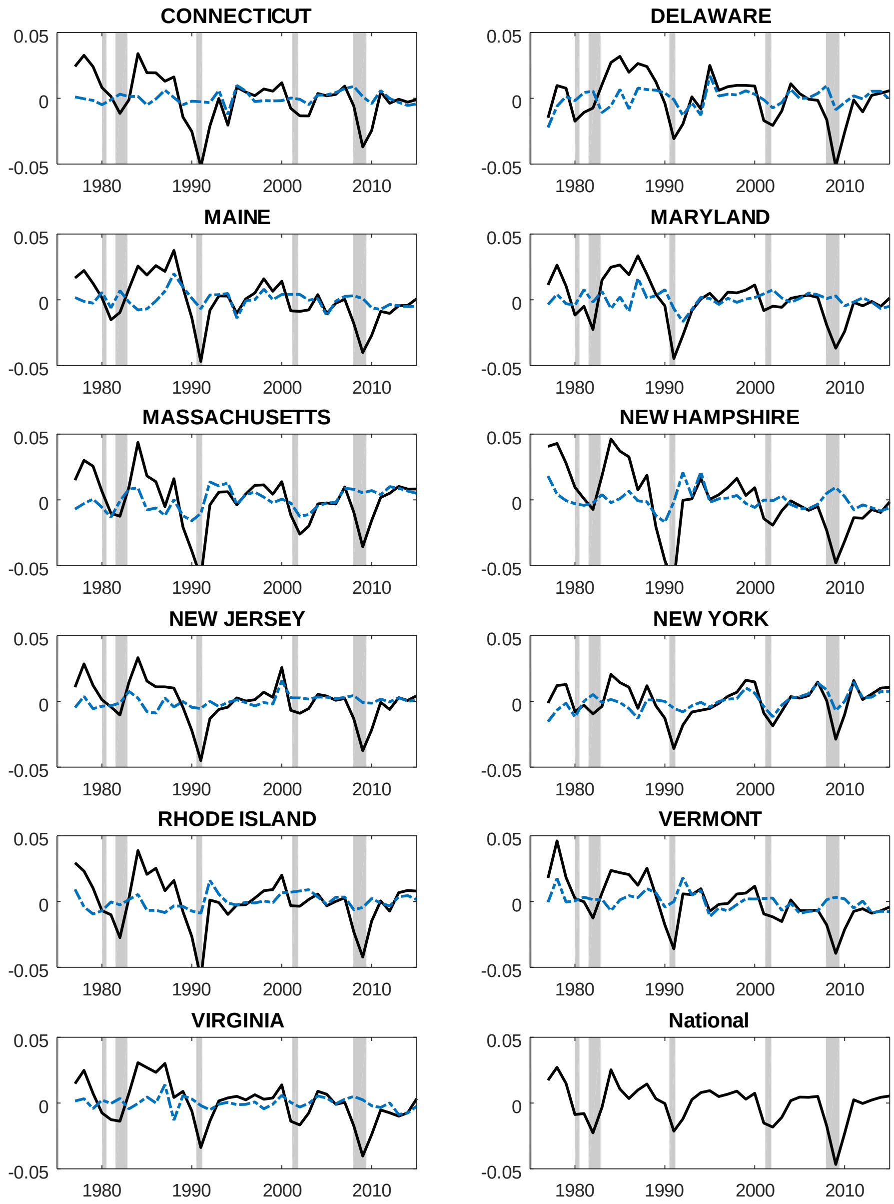

Figure 10: Northeast states, factor filter. Solid lines are state employment growth time series; Dashed lines are filtered time series.

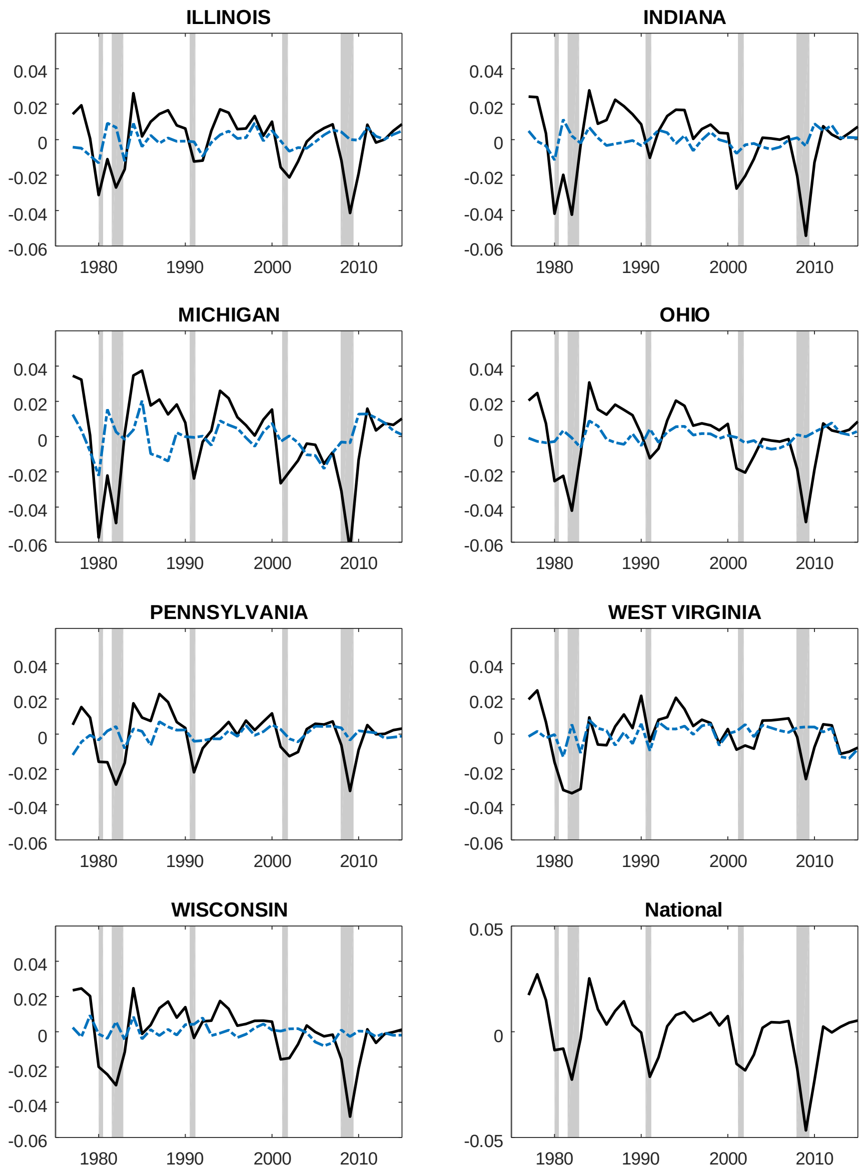

Figure 11: Rust-belt states, factor filter. Solid lines are state employment growth time series; Dashed lines are filtered time series.

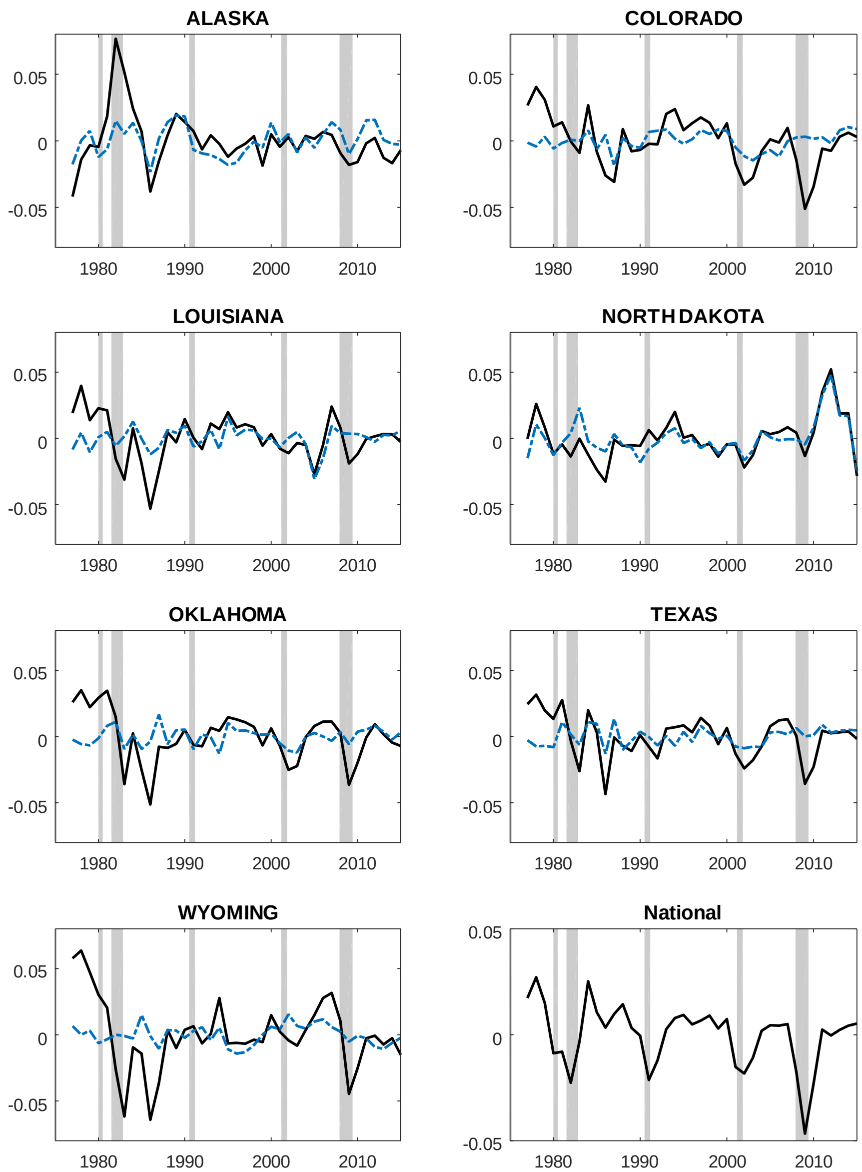

Figure 12: Energy-producing states, factor filter. Solid lines are state employment growth time series; Dashed lines are filtered time series.

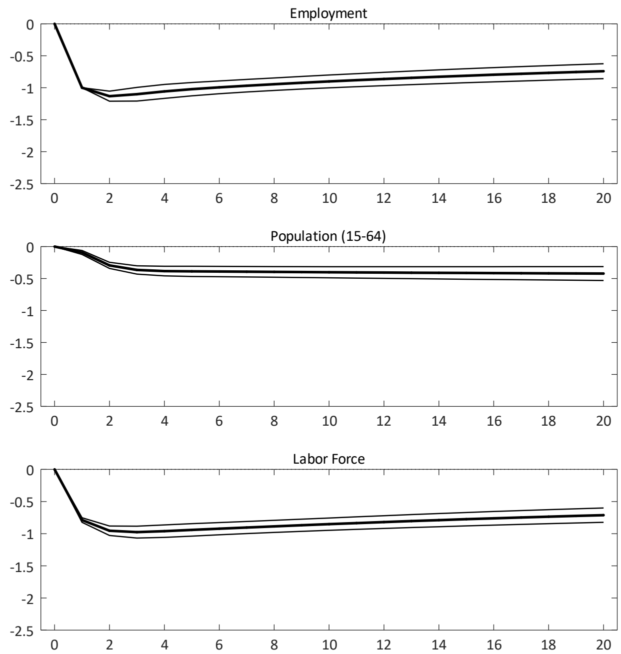

Figure 13: Impulse responses of employment, working-age population, and labor force. VECM augmented with factor loadings – see eq. (3).

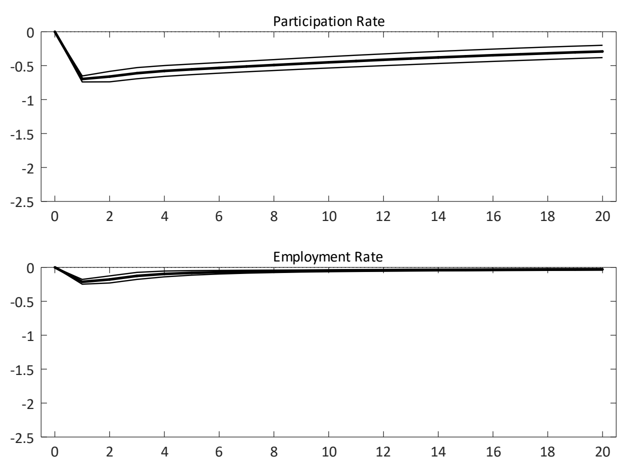

Figure 14: Impulse responses of employment and participation rates. VECM augmented with factor loadings – see eq. (3).

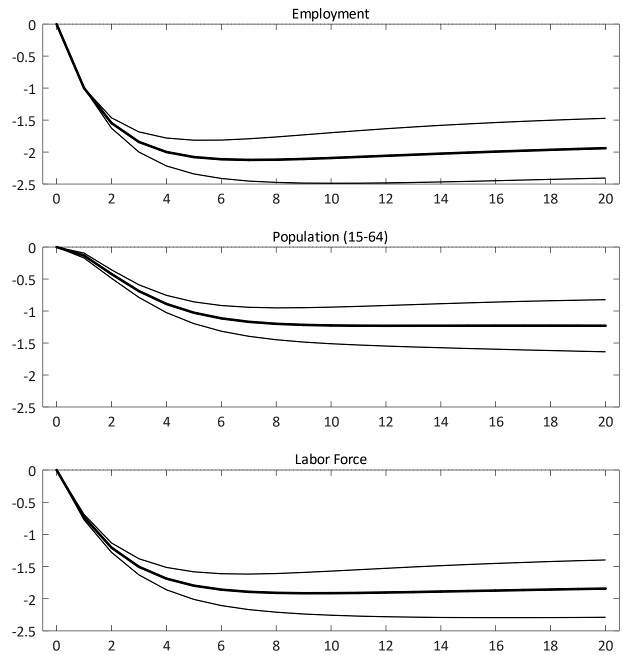

Figure 15: Impulse responses of employment, working-age population, and labor force. VECM based on Regression-Based Filter – see eq. (4).

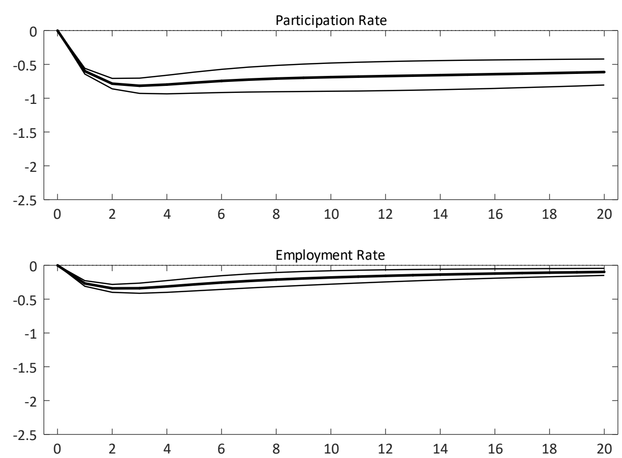

Figure 16: Impulse responses of employment and participation rates. VECM based on Regression-Based Filter – see eq. (4).

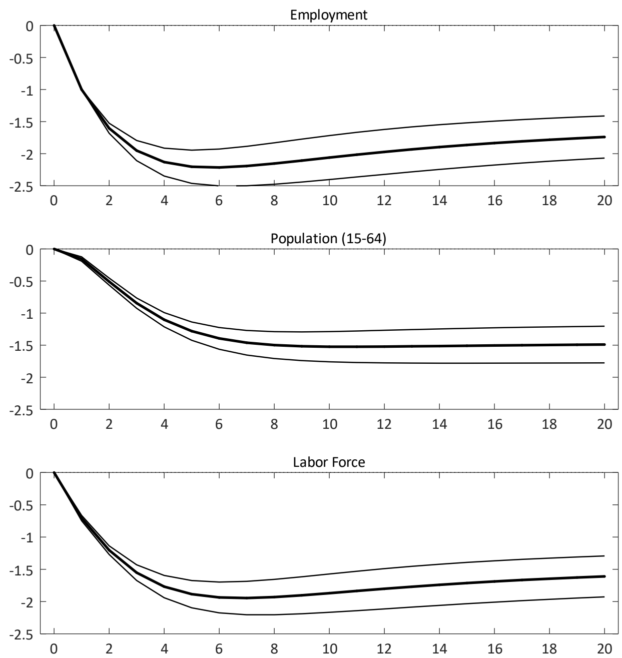

Figure 17: Impulse responses of employment, working-age population, and labor force. VECM based on deviations from national averages – see eq. (5).

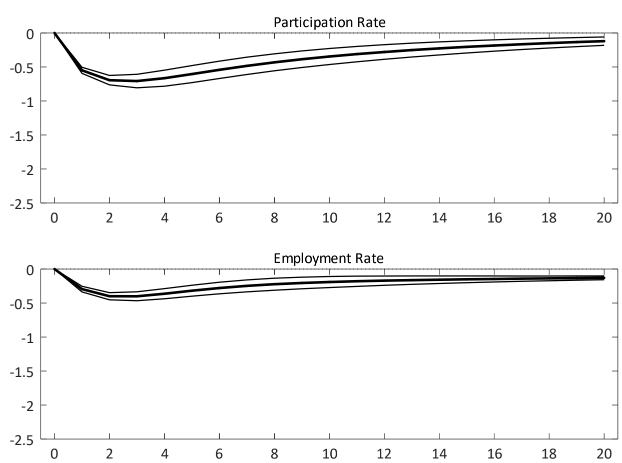

Figure 18: Impulse responses of employment and participation rates. VECM based on deviations from national averages – see eq. (5).

Additional Figures and Tables to Appear in Appendix

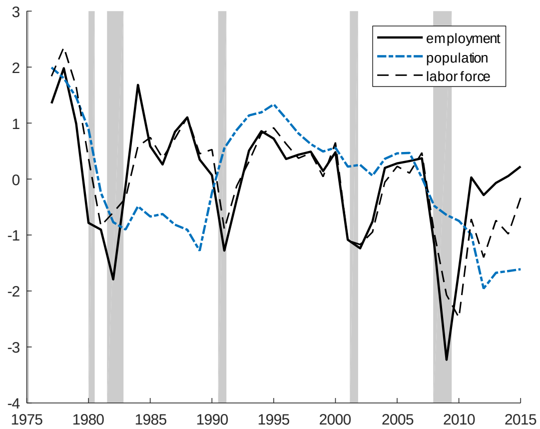

Figure A.1: The first estimated factors to employment, working-age population and labor force growth.

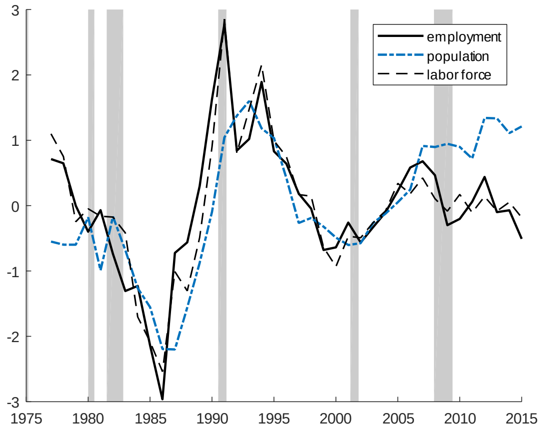

Figure A.2: The second estimated factors to employment, working-age population and labor force growth.

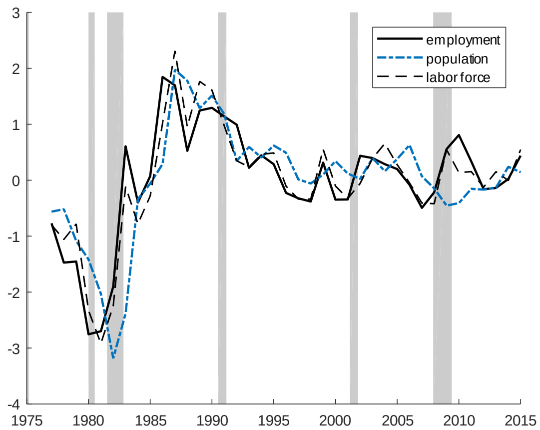

Figure A.3: The third estimated factors to employment, working-age population and labor force growth.

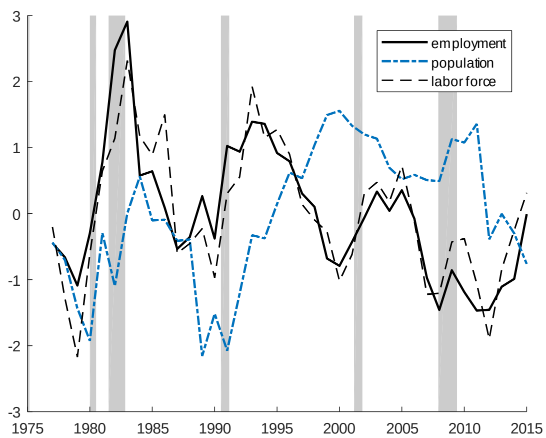

Figure A.4: The fourth estimated factors to employment, working-age population and labor force growth.

Table A.1: Impulse Responses

	Factor model filter			Regression-based filter			National Averages		
horizon	5% CI	Estimate	95% CI	5% CI	Estimate	95% CI	5% CI	Estimate	95% CI
				Employment					
1	-1.000	-1.000	-1.000	-1.000	-1.000	-1.000	-1.000	-1.000	-1.000
5	-0.918	-1.022	-1.127	-1.814	-2.078	-2.342	-1.945	-2.204	-2.462
10	-0.801	-0.901	-1.002	-1.697	-2.093	-2.488	-1.717	-2.060	-2.403
20	-0.625	-0.741	-0.857	-1.472	-1.939	-2.406	-1.411	-1.739	-2.068
30	-0.516	-0.639	-0.763	-1.366	-1.843	-2.321	-1.302	-1.612	-1.921
40	-0.447	-0.574	-0.701	-1.291	-1.780	-2.269	-1.254	-1.558	-1.863
				Working Age Population					
1	-0.061	-0.092	-0.122	-0.095	-0.132	-0.170	-0.123	-0.157	-0.191
5	-0.308	-0.387	-0.467	-0.857	-1.026	-1.196	-1.139	-1.281	-1.424
10	-0.315	-0.401	-0.488	-0.939	-1.225	-1.511	-1.288	-1.524	-1.759
20	-0.313	-0.422	-0.530	-0.823	-1.230	-1.636	-1.204	-1.490	-1.776
30	-0.311	-0.434	-0.558	-0.793	-1.255	-1.718	-1.174	-1.470	-1.766
40	-0.310	-0.443	-0.576	-0.805	-1.293	-1.782	-1.161	-1.461	-1.760
				Labor Force					
1	-0.752	-0.787	-0.823	-0.691	-0.732	-0.773	-0.664	-0.705	-0.747
5	-0.844	-0.941	-1.038	-1.582	-1.796	-2.010	-1.674	-1.885	-2.097
10	-0.756	-0.852	-0.947	-1.571	-1.914	-2.256	-1.572	-1.870	-2.167
20	-0.600	-0.712	-0.823	-1.397	-1.842	-2.288	-1.293	-1.610	-1.927
30	-0.501	-0.621	-0.741	-1.312	-1.783	-2.253	-1.199	-1.506	-1.813
40	-0.436	-0.562	-0.688	-1.251	-1.738	-2.224	-1.162	-1.465	-1.769
				Participation Rate					
1	-0.651	-0.696	-0.740	-0.558	-0.600	-0.642	-0.504	-0.549	-0.593
5	-0.475	-0.554	-0.632	-0.614	-0.770	-0.926	-0.479	-0.604	-0.730
10	-0.367	-0.450	-0.534	-0.479	-0.688	-0.897	-0.228	-0.346	-0.464
20	-0.199	-0.290	-0.381	-0.420	-0.613	-0.805	-0.059	-0.120	-0.181
30	-0.106	-0.186	-0.267	-0.394	-0.527	-0.660	-0.009	-0.036	-0.063
40	-0.056	-0.120	-0.184	-0.355	-0.444	-0.533	0.008	-0.005	-0.017
				Employment Rate					
1	-0.177	-0.213	-0.248	-0.227	-0.268	-0.309	-0.253	-0.295	-0.336
5	-0.048	-0.081	-0.115	-0.187	-0.282	-0.377	-0.238	-0.318	-0.399
10	-0.035	-0.050	-0.064	-0.080	-0.179	-0.278	-0.109	-0.191	-0.272
20	-0.018	-0.029	-0.041	-0.044	-0.097	-0.149	-0.102	-0.129	-0.157
30	-0.010	-0.019	-0.028	-0.036	-0.061	-0.086	-0.096	-0.105	-0.115
40	-0.005	-0.012	-0.019	-0.029	-0.042	-0.056	-0.089	-0.093	-0.097

Note: Impulse responses and bootstrapped confidence intervals at select horizons. CI denotes "confidence interval". Factor model filter refers to the VECM described in (3); Regression-based filter refers to the VECM described in (4); National averages refers to the VECM described in (5).

Table A.2: Factor Structure Variance Decomposition

state	employment growth				population growth				labor force growth			
	1st	2nd	3rd	4th	1st	2nd	3rd	4th	1st	2nd	3rd	4th
AL	0.82	0.00	0.06	0.01	0.66	0.01	0.01	0.00	0.45	0.00	0.00	0.02
AK	0.02	0.00	0.05	0.63	0.03	0.11	0.66	0.18	0.01	0.01	0.16	0.52
AZ	0.84	0.01	0.04	0.03	0.56	0.13	0.03	0.00	0.72	0.02	0.05	0.05
AR	0.68	0.01	0.07	0.03	0.73	0.00	0.05	0.01	0.51	0.01	0.04	0.06
CA	0.71	0.02	0.03	0.02	0.03	0.27	0.38	0.16	0.49	0.05	0.04	0.05
CO	0.52	0.16	0.16	0.03	0.65	0.13	0.00	0.00	0.51	0.20	0.17	0.01
CN	0.57	0.14	0.19	0.04	0.01	0.02	0.22	0.31	0.26	0.22	0.24	0.10
DE	0.59	0.20	0.00	0.03	0.06	0.19	0.11	0.14	0.28	0.36	0.01	0.03
DC	0.08	0.19	0.01	0.36	0.42	0.22	0.00	0.07	0.01	0.27	0.00	0.33
FL	0.70	0.02	0.12	0.03	0.35	0.17	0.25	0.02	0.57	0.03	0.16	0.03
GA	0.85	0.04	0.00	0.03	0.48	0.19	0.01	0.04	0.54	0.11	0.02	0.07
HI	0.25	0.00	0.01	0.01	0.17	0.04	0.13	0.00	0.16	0.05	0.08	0.01
ID	0.59	0.14	0.12	0.03	0.66	0.03	0.16	0.10	0.50	0.11	0.23	0.02
IL	0.79	0.00	0.07	0.01	0.52	0.00	0.18	0.00	0.52	0.00	0.02	0.01
IN	0.78	0.00	0.16	0.00	0.53	0.01	0.28	0.00	0.59	0.00	0.21	0.03
IA	0.56	0.09	0.18	0.01	0.27	0.12	0.44	0.00	0.40	0.06	0.21	0.01
KS	0.65	0.07	0.00	0.00	0.66	0.03	0.03	0.00	0.58	0.04	0.00	0.01
KY	0.79	0.00	0.08	0.00	0.76	0.01	0.02	0.00	0.60	0.01	0.02	0.00
LA	0.12	0.48	0.14	0.03	0.20	0.18	0.05	0.11	0.07	0.50	0.18	0.03
ME	0.64	0.21	0.02	0.00	0.14	0.45	0.13	0.05	0.42	0.33	0.01	0.00
MD	0.66	0.21	0.00	0.00	0.02	0.43	0.10	0.02	0.39	0.38	0.01	0.05
MA	0.52	0.13	0.16	0.01	0.00	0.00	0.06	0.33	0.21	0.15	0.29	0.05
MI	0.71	0.03	0.11	0.00	0.34	0.25	0.09	0.01	0.52	0.07	0.09	0.01
MN	0.87	0.00	0.01	0.00	0.64	0.08	0.07	0.01	0.71	0.01	0.03	0.00
MS	0.66	0.06	0.07	0.00	0.75	0.00	0.00	0.00	0.34	0.08	0.02	0.06
MO	0.87	0.02	0.01	0.02	0.51	0.06	0.08	0.00	0.67	0.04	0.00	0.04
MT	0.48	0.26	0.05	0.03	0.54	0.17	0.07	0.08	0.32	0.32	0.07	0.05
NE	0.68	0.06	0.06	0.00	0.40	0.14	0.24	0.01	0.54	0.02	0.09	0.00
NV	0.80	0.04	0.00	0.00	0.65	0.23	0.00	0.00	0.81	0.00	0.05	0.00
NH	0.57	0.16	0.16	0.00	0.14	0.36	0.18	0.13	0.51	0.15	0.26	0.00
NJ	0.62	0.18	0.11	0.00	0.13	0.00	0.13	0.08	0.20	0.29	0.22	0.01
NM	0.63	0.06	0.01	0.06	0.75	0.00	0.08	0.04	0.54	0.01	0.00	0.10
NY	0.43	0.14	0.07	0.07	0.02	0.02	0.05	0.00	0.00	0.14	0.12	0.11
NC	0.87	0.02	0.01	0.01	0.47	0.04	0.02	0.01	0.62	0.04	0.01	0.03
ND	0.03	0.25	0.00	0.03	0.00	0.70	0.02	0.02	0.00	0.33	0.00	0.07
OH	0.85	0.00	0.08	0.01	0.56	0.07	0.15	0.00	0.73	0.02	0.05	0.00
OK	0.15	0.43	0.29	0.00	0.36	0.38	0.11	0.01	0.13	0.46	0.23	0.00
OR	0.86	0.01	0.07	0.00	0.65	0.03	0.23	0.00	0.68	0.00	0.14	0.01
PA	0.73	0.02	0.04	0.09	0.19	0.01	0.10	0.03	0.29	0.02	0.06	0.15
RI	0.58	0.24	0.04	0.05	0.02	0.24	0.07	0.09	0.24	0.27	0.09	0.17
SC	0.85	0.01	0.00	0.00	0.49	0.04	0.00	0.06	0.53	0.03	0.00	0.00
SD	0.36	0.08	0.32	0.01	0.15	0.17	0.33	0.06	0.23	0.02	0.40	0.01
TN	0.87	0.00	0.07	0.00	0.78	0.03	0.08	0.00	0.70	0.00	0.06	0.01
TX	0.35	0.24	0.24	0.00	0.42	0.23	0.19	0.02	0.25	0.24	0.29	0.01
UT	0.78	0.10	0.00	0.04	0.73	0.06	0.05	0.08	0.71	0.06	0.03	0.05
VT	0.69	0.09	0.06	0.00	0.42	0.34	0.10	0.05	0.64	0.14	0.06	0.00
VA	0.75	0.16	0.00	0.00	0.20	0.24	0.11	0.01	0.50	0.29	0.01	0.00
WA	0.78	0.01	0.00	0.01	0.65	0.07	0.04	0.01	0.69	0.00	0.01	0.04
WV	0.48	0.16	0.12	0.06	0.68	0.13	0.01	0.02	0.09	0.37	0.07	0.00
WI	0.85	0.01	0.07	0.00	0.75	0.02	0.09	0.00	0.73	0.03	0.08	0.00
WY	0.18	0.50	0.17	0.08	0.57	0.27	0.00	0.09	0.26	0.46	0.08	0.12
Average	0.61	0.11	0.08	0.04	0.41	0.14	0.12	0.05	0.43	0.13	0.09	0.05

Note: Proportion of variance attributed to the 1st, 2nd, 3rd and 4th estimated factors. Factors are estimated by principal components applied to each labor market variable.

Table A.3: Impulse responses from model with wages

horizon (years)	5% CI	Estimate	95% CI
Employment			
1	-1.0000	-1.0000	-1.0000
5	-0.9157	-1.0217	-1.1277
10	-0.7546	-0.863	-0.9714
20	-0.5288	-0.6597	-0.7905
Working Age Population			
1	-0.0604	-0.0935	-0.1266
5	-0.2940	-0.3793	-0.4647
10	-0.2803	-0.3774	-0.4745
20	-0.2514	-0.3739	-0.4964
Labor Force			
1	-0.7538	-0.795	-0.8362
5	-0.8442	-0.9439	-1.0436
10	-0.7132	-0.8176	-0.9219
20	-0.5076	-0.6352	-0.7627
Wages			
1	-0.0310	-0.0963	-0.1617
5	-0.1304	-0.2544	-0.3785
10	-0.1084	-0.2515	-0.3947
20	-0.0591	-0.2416	-0.4241
Participation Rate			
1	-0.6509	-0.7015	-0.7521
5	-0.4905	-0.5646	-0.6386
10	-0.3645	-0.4402	-0.5159
20	-0.1870	-0.2613	-0.3356
Employment Rate			
1	-0.1638	-0.205	-0.2462
5	-0.0399	-0.0778	-0.1158
10	-0.0266	-0.0454	-0.0643
20	-0.0133	-0.0245	-0.0357