Aggregate Effects and Measuring Regional Dynamics

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Abstract

When a state experiences a labor demand shock, how does it recover? Do workers out-migrate to states with relatively higher wages, or do firms create jobs to absorb the unemployed and take advantage of low wages? Labor demand shocks can be either location-specific (i.e., independent of shocks in all other geographic regions) or aggregate (i.e. affecting several regions) in nature. While it is clear that location-specific shocks create disparities in labor markets to which firms and workers respond, aggregate shocks can likewise generate regional disparities in labor markets if different states exhibit different sensitivities to aggregate shocks. In this paper we adopt a model that is sufficiently flexible to permit different recovery paths in response to the two different types of shock. Specifically, we augment the conventional VAR toolkit with a factor model. Labor demand shocks are identified using the coventional recursive VAR assumptions, whilst the aggregate shocks are disentangled from the location-specific shocks using the factor model. We find stark differences between the responses to the two different types of shock. Recovery from an idiosyncratic shock occurs within 5-6 years, with job creation accounting for about 45% of the recovery, indicating that firm migration plays a more important role than previously thought. Conversely, the recovery from a common shock is highly protracted, with employment reaching its long-run level after no less than twelve years. Location-specific labor demand shocks exhibit far more variance than the aggregate labor demand shocks, meaning that while short-run variation in state-level labor markets is largely driven by location-specific events, much of the long-term variation is driven by aggregate events since the recovery time from the latter is much more protracted.

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1 Introduction

How do regions recover from employment shocks?[1] Do workers migrate out of slumping regions, repelled by a dearth of job openings, or are openings created as firms migrate in,[2] attracted by the surplus of labor? How long does this process take? These questions have been addressed in the previous literature, most notably in the US by Blanchard and Katz (1992, BK hereafter) using panel vector autoregression (VAR) modelling and identification.[3] Using this strategy, they conclude that regional employment shocks are (nearly) permanent, implying that worker migration is by far the most important mechanism through which regions recover. Such a recovery takes about 10 years to complete.

This methodology and set of results have had important ramifications in the subsequent literature. For example, Decressin and Fatás (1995) and Tani (2003) adopt the BK model to address similar questions in other economies. Shimer (2007), Borjas et al. (1997), Duranton (2007), and Kline (2008) each rely on BK's work in the development of models or empirical strategies, or in the establishment of "stylized facts."[4] Theoretical models of labor market mobility, such as Alvarez and Veracierto (1999, 2006) and Alvarez and Shimer (2008), rely on an implicit assumption that firm migration does not respond to policy changes. Obstfeld and Peri (1998) argue that the high worker mobility in the US has contributed to the success of the monetary union.

Because actual migration of both firms and workers cannot be observed directly, the relative mobility of firms and workers has been inferred using models that describe how local labor demand shocks affect observed labor market variables such as employment and wages. In these models firms and workers respond to the wage differential, specified as the wage in a given location less the average wage in all locations of the economy. Changes in local unemployment and participation rates that are not accounted for by changes in employment and population allow one to "back out"

[1] As is common in the literature, the terms "regional" and "local" will be used interchangeably; in this case, it will refer to the U.S. state.

[2] This does not necessarily mean that firms have to literally "move in" to local areas; Edmiston (2004), for example, suggests that plant expansions have much larger labor market impacts than do new plant openings, and thus are an important source of job creation.

[3] Kline (2008) refers to BK as the canonical model of regional labor market adjustment.

[4] Shimer (2007) argues that the slow response of workers to wage differentials justifies his assumption of random mobility. Borjas et al. (1997) cite BK to support their assumption that population changes reflect migration decisions. Duranton (2007) and Shimer (2007) cite BK to support the primacy of demand shocks when modeling differentials in local production.

worker migration, and so models that relate employment, wages, unemployment and participation are used to study firm and worker migration.

Wage differentials may initially arise from location-specific events, such as a change in state labor laws. However it is at least possible that aggregate shocks can create wage differentials between locations; for example, labor markets in energy-producing states are likely to be affected differently by an oil supply shock compared to labor markets in energy-consuming states. To illustrate this point in more detail we consider the historical experience of Massachusetts (MA). Figure 1 shows the MA unemployment rate, the national average unemployment rate, and the difference between the two series, which we can think of as the MA "unemployment differential."[5] In 1992 US unemployment reaches a peak of 7.5%, and at the same time the MA unemployment rate was over a percentage point *higher* at 8.8%. In each year during the subsequent decade the unemployment rate in both the US and Massachusetts dropped. However the rate of decline was faster in MA, so that by 2000 the MA rate is 2.7%, more the a percentage point *less* than the national rate of 4%. Over this time period, it appears that MA was excessively sensitive to the state of the aggregate economy. Similarly, when the US unemployment rates reaches troughs in 1988, 1979, and 2007, the MA rate is always lower than the national average. It appears that when the US is doing badly, the MA economy is, more often than not, doing particularly badly; and when the US is doing well, MA is doing particularly well. The MA unemployment differential will therefore reflect both aggregate and location-specific labor shocks: Indeed the correlation between the relative MA unemployment rate and the national unemployment is 0.53 over the entire sample.[6]

The conventional dynamic model of labor markets will attribute the decreases in the MA unemployment differential in both the 1976-1979 and 1991-2000 episodes to firm and worker migration. An alternate explanation that is consistent with these reductions in unemployment is that the MA economy is structured in such a way that it is particularly sensitive to macroeconomic activity, and that the macroeconomy experienced a sequence of negative and then positive shocks. Under this explanation, the relative recovery in MA was not due to migration or job creation, but rather was a consequence of a particular sequence of aggregate shocks experienced by the US economy as a whole. This alternate explanation does not preclude firms and workers responding to aggregate shocks, but it shows how a recovery can be generated by aggregate-level events regardless of

[5] The MA unemployment differential is equivalent to a common time effect (CTE) filtered rate. In practice the CTE filter is often used to obtain the wage differential from the cross-section of wages (e.g. Eberts and Stone,1990; Bartik, 1991; BK; and Decressin and Fatás, 1995).

[6] Evidence elsewhere in the extant literature suggests that more sophisticated filtering is needed to remove aggregate effects from the data in order to identify local shocks. 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. This suggests the phenomenon that is discussed above is a substantial concern, and that the rigidity of the CTE will contaminate the filtered data. 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 (2008) find a similar phenomenon using quarterly state gross output data. Because it lacks any form of dynamic structure, the CTE will not appropriately adjust for asynchronous local responses to aggregate shocks.

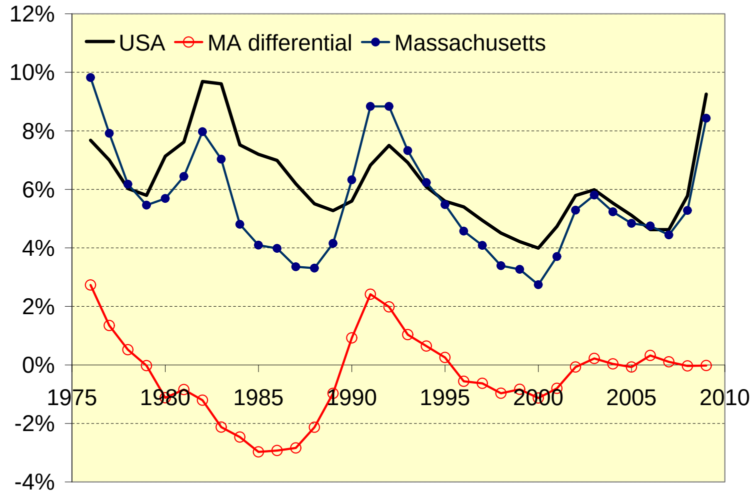

Figure 1: Unemployment in MA and the US. Source: BLS.

whether firms and workers respond. The example then highlights the importance of separating out aggregate and location-specific variation when measuring firm and worker mobility, since aggregate shocks may otherwise be mistaken for worker or firm migration.

When studying how firms and workers respond to wage (or unemployment) differentials we may wish to use a model that is sufficiently flexible to permit different recovery paths in response to aggregate and location-specific shocks. For example, we may wish to permit the degree of serial persistency to differ between aggregate and location-specific shocks. Yet how can we distinguish between the aggregate and the location-specific in the data? Inevitably, this involves placing more structure on the model, but first it is useful to be more specific in what we mean by "aggregate shocks." 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 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. These pervasive changes need not be identical for each member of the disaggregate group – nor do they even have to share the same sign. In statistical terms, these pervasive changes correspond to strong dependence between the components.[7] Thus we argue that aggregate shocks can be identified using standard linear models of strong-form dependence. A well-known example is the common time effect, whereby each cross section receives an identical shock. However, this is unnecessarily restrictive, and in particular precludes the heterogenous state-level sensitivity to the aggregate

[7] We contrast strong dependence against weak dependence, under which a law of large numbers holds.

discussed above.

In order to distinguish aggregate shocks, we adopt the approximate factor model (Chamberlain and Rothschild, 1983). Under this model a small number of unobserved components (common factors) interact linearly with state-specific parameters in order to produce the pervasive co-movement in state labor markets. The factor model has been used elsewhere for precisely this purpose. For example, factor models are used in (time-series) VAR analysis by Bernanke, Boivin and Eliasz (2005), where, as discussed by Stock and Watson (2005), the common factors to a wide range of economic variables are used span the space of unobserved structural shocks. The standard linear factor model is of the form

$$x_{it} = \sum_{j=1}^{r} \lambda_{j,i} F_{j,t} + e_{it} = \lambda_i' F_t + e_{it}. \tag{1}$$

Here x_{it} is some variable of interest (such as a labor demand shock), F_t is the vector of "common factors" (in a given time period), λ_i is a vector of "factor loadings," i indexes the regions in the sample, and t indexes the time series. The common component of the panel is $\lambda_i' F_t$, while the idiosyncratic component is e_{it}. The common factors and loadings are unobserved. Intuitively, the common factors ($F_{j,t}$) capture the sources of pervasive covariation in the panel x_{it}, such as the aggregate events, while $\lambda_{j,i}$ represents the responsiveness of region i to factor j. Because different types of national shocks may be present to which states are more or less responsive, the model allows for a finite set of r different factors. Moreover, (1) is observationally equivalent to a dynamic factor model in which both current and lagged factors are pervasive sources of covariation, so we permit lagged responses of some regions to aggregate shocks (see, among others, Amengual and Watson, 2007, Bai and Ng, 2002, and Hallin and Liska, 2007). Because the factor model is used to describe covariation in the panel, identification of the common and idiosyncratic component in (1) is based on the statistical properties of the panel (see, e.g., Bai, 2003).

By using (1) as a model for regional labor supply and demand shocks, variation in local labor markets can be decomposed into a common component, reflecting evolutions in response to aggregate shocks, and an idiosyncratic component, reflecting evolutions in response to location-specific shocks. We show that the dynamic paths of labor markets differ substantially depending on the type of labor demand shock. Responses to aggregate shocks exhibit longer recovery horizons of approximately 12-13 years, and more pronounced effects on employment and wages, whereas location-specific shocks are characterized by rapid recoveries of 5-6 years in duration. To relate this information back to mobility of firms and workers, we view the recoveries through the lens of a model that is based on the canonical BK model – our results suggest that while worker mobility still plays a major role in the post-shock recovery process, firm mobility has a more substantial role than previously thought. Moreover, while location-specific labor demand shocks exhibit approximately three times more variance than the aggregate labor demand shocks, aggregate labor demand shocks account for a greater proportion of the variance in labor market variables (for example, aggregate shocks account for 82% of the variation in regional unemployment rates). This is due to the fact that it takes much longer for labor markets to recover from an aggregate labor demand shock than a location-specific one. Thus, while short-run variation in local labor market conditions is largely driven by location-specific events, much of the long-term variation in state-level labor markets is driven by aggregate events. Given the stark differences in the responses, a model that does not permit different responses to the type of shock will result in estimated dynamic paths that are amalga of the two responses.[8]

Our findings have several implications. First, it is clear that the prognoses for these two situations are highly different: It takes much longer for migration channels to eliminate differences between state-level unemployment rates when these differences have been brought about by aggregate shocks. Second, we find a greater role for firm mobility in the recovery from a labor demand shock. This finding is more commensurate with other evidence regarding firm and worker mobility. For example, Kennan and Walker (2005) and Bishop (2008) show that workers face prohibitively high movement costs ($300,000 on average), while Shimer (2001) finds the idea of mostly worker-driven local responses puzzling given that he finds 98% of the variation in the youth share of population in a state is driven by the birth rate a generation earlier. Using events studies Bartik (1991) shows that firms do respond to wage differentials when making plant location decisions. Saiz (2003) shows that the effects of immigrants on labor markets are rapidly arbitraged away, a result that is puzzling in a world in which it takes many years for local market conditions to respond to local shocks. Finally, we find that the absorption of the initial labor demand shock into unemployment and participation varies greatly according to the source of shock. Location-specific shocks decrease the participation rate more than they increase the unemployment rate, whereas common shocks increase the unemployment rate more than they decrease the participation rate. We believe this interesting finding warrants further exploration in the future using a more detailed model of the labor supply decision.

We organize the remainder of the paper as follows: First, we present a simple model as a guide to the empirical specification, and as a way of interpreting the impulse responses. In this section, identification of worker and firm movement costs is also discussed. Following the model section, we discuss the particular empirical specification and application of the factor model decomposition to this problem, along with estimation of the model parameters and number of factors. Finally, we conclude.

[8] In addition, estimation may be inefficient in the CTE model, as the common and idiosyncratic shocks may require VARs with different lag lengths to generate shocks that are approximately iid across time.

2 Model

In this section we present a generalized version of the BK model which will be used to guide the empirical specification. We use labor supply and demand to model employment, wages, and participation. The stochastic process that the errors in this model follow allows cross-sectional dependence between demand and supply shocks in different locations. This model will guide the choice of empirical specification and the later discussion on identification.

This section contains three subsections. The first includes a description of the model environment, and the second a discussion of identification. The third discusses how the features of this model should be used as a lens through which to view the VAR impulse responses presented in the sections that follow.

2.1 Environment

This model serves two simple purposes. First, it allows one to decompose short-run changes in employment and wages into changes resulting from two types of structural shock: Labor demand shocks and labor supply shocks. Second, it allows one to decompose the response of the local labor market to such a shock into a short-run and a long-run response.

Similarly, the model contains two pieces. The first piece is a static (short-run) labor market. In each period, supply and demand schedules determine the wage and employment levels in the local labor market. The second piece describes the dynamic responses of labor supply and demand to local conditions. These two pieces are combined into a model of the dynamics of labor market outcomes in response to shocks to labor supply and labor demand. All variables will be indexed by states (i) and time (t).

For ease of exposition, the model that we present restricts firm and worker migration in response to local labor supply or demand shocks to only periods subsequent to the shock – that is, all migration decisions are made based on past shocks, not the current one. Since annual data are used, this assumption may not be accurate, and so in the empirical model we relax the assumption that workers cannot move in response to a labor supply or demand shock in the period in which the shock occurs. However, following the literature, we maintain the assumption that firms cannot respond via migration to a shock in the current period.

The Local Market. The labor market is characterized by short-run supply

$$e_{it}^S \equiv \alpha_{it}^S + \beta^S w_{it} \tag{2}$$

and demand

$$e_{it}^D \equiv \alpha_{it}^D - \beta^D w_{it} \tag{3}$$

where e_{it}^S represents log units of labor supplied, e_{it}^D represents log units of labor demanded, and w_{it} is the log wage. The quantities α^S and α^D in equations 2 and 3 are termed the "levels" of labor supply and demand. Here, changes in supply levels (α^S) represent in-migration and out-migration flows, and changes in demand levels (α^D) represent job creation and destruction; these quantities will vary over time (discussed below). β^S and β^D are short-run wage elasticities, which do not depend on labor demand levels. Thus, two margins govern the labor market response to changes in location conditions: For workers, there is a migration margin (changes in α^S) and a participation margin (governed by parameter β^S); on the demand side, there is a margin which may be thought of as firm mobility and accumulation of capital governed by changes in α^D, and an intensive margin (representing utilization) governed by β^D.

The equilibrium condition in the market determines wages and employment as functions of labor supply levels α^S and α^D, and parameters β^S and β^D. Log wages are given by

$$w_{it} = \frac{\alpha_{it}^D - \alpha_{it}^S}{\beta^S + \beta^D} \tag{4}$$

and log employment is given by

$$e_{it} = \frac{\beta^S}{\beta^S + \beta^D}\alpha_{it}^D + \frac{\beta^D}{\beta^S + \beta^D}\alpha_{it}^S. \tag{5}$$

Equation 4 says that wages depend on the difference between the levels of demand and supply. The magnitude of the wage depends inversely on the sum of the magnitudes of the two elasticities. Equation 5 says that log employment levels are a weighted sum of the levels of labor demand and labor supply, where the weights are proportional to the elasticity on the other side of the market (this is because since the levels of supply and demand are additive, changes in the levels of supply represent movements along the demand curve, and *vice versa*).

Evolutions of Supply and Demand. Supply and demand levels respond to local conditions. The local conditions that are relevant to workers and firms are summarized by a single variable, the wage relative to other locations. High wages attract workers and discourage job creation (the latter because production costs are high); low wages induce out-migration and job creation (production costs are low).[9] These forces will cause wages to return to long-run averages, whenever they deviate.

[9] This formulation is appropriate if the wage contains information only concerning the relative levels of labor supply and demand, among locations with static productivity. If productivity levels also follow a stochastic process, then the wage will contain information about the local productivity level. If high wages indicate high productivity, then positive net job creation and positive net in-migration may occur simultaneously. This assumption is made because it is also maintained by BK. There is also some evidence from studies of individual plant location decisions that firms respond to wages, for example, in Bartik (1991). Unfortunately, there is little evidence concerning whether at the local level wages reflect total factor productivity levels, differences in the levels of labor supply and demand, or a combination of the two. If differences in TFP are permanent or highly persistent, then state-specific fixed effects will alleviate this concern.

When wages are high, labor demand increases and labor supply decreases, both of which push wages down. The opposite occurs when wages are low, pushing wages up. Thus, the forces of supply and demand movement both push wages in the same direction – toward the mean. This makes wages stationary. Employment levels, however, do not exhibit mean reversion. For example, if employment increases without an accompanying change in the wage (which might happen if certain supply and demand shocks occur at the same time), no force acts on the employment level to bring it back down.

Net worker flows are associated with changes in α^S, and are denoted $\Delta\alpha^S$. Net job creation is associated with changes in α^D, denoted $\Delta\alpha^D$. We start by assuming the following evolution equation for supply:

$$\Delta\alpha_{it}^S \equiv b^S \tilde{w}_{it-1} + u_{it}^S \tag{6}$$

where b^S and d^S are positive parameters, $\tilde{w}_{it-1} = w_{it-1} - w_{\cdot t}$ is the de-meaned wage (that is, $w_{\cdot t}$ is the average wage over all locations at time t), and u_{it}^S is an error term which will later be discussed in more detail. Changes in demand are governed by

$$\Delta\alpha_{it}^D \equiv -b^D \tilde{w}_{it-1} + u_{it}^D \tag{7}$$

where $b^D > 0$, $d^D > 0$, and u_{it}^D are defined similarly.

Equations 6 and 7 state that both demand and supply of labor in a given location respond to the local wage premium, $w_{it-1} - w_{\cdot t}$, as opposed to the wage *per se*. Workers and firms are assumed not to respond to the wage level, but to the wage premium, because they can expect to be no better off by moving when aggregate wages change but relative wages remain the same. If a boom or bust affects all locations equally, then workers have no additional incentive to re-locate. Because only last period's wages affect the growth in labor supply and demand level, embodied in equations 6 and 7 is an assumption that contemporaneous wages do not affect α^S or α^D. This assumption allows the long-run impacts of shocks to be distinguished from the shocks themselves.

Combining equations 4 and 5 with 6 and 7 relate these processes to observables. Wage evolutions are given by

$$\tilde{w}_{it} = \left(1 - \frac{b^S + b^D}{\beta^S + \beta^D}\right)\tilde{w}_{it-1} + \frac{u_{it}^D - u_{it}^S}{\beta^D + \beta^S} - \Delta w_{\cdot t}$$

where $\Delta w_{\cdot t} = w_{\cdot t} - w_{\cdot t-1}$ is growth in the average wage. This may be written

$$\tilde{w}_{it} = b_w \tilde{w}_{it-1} + u_{it}^w. \tag{8}$$

Here, wages will be stationary as long as $\left|1 - \frac{b^S+b^D}{\beta^S+\beta^D}\right| < 1$. This will occur if $b^S + b^D < 2\left(\beta^S + \beta^D\right)$ (each of these quantities is positive, so any other needed inequalities hold).[10] That is, wages are

[10] It is doubtful that $b^S + b^D$ would exceed $\beta^S + \beta^D$, which would be associated with over-shooting of wages in

stationary as long as the sum of the wage elasticities of migration and job creation is not more than double the sum of the wage elasticities of demand and supply.

Since employment may not be stationary, the change in employment will be used in all specifications; equation 5 tells us

$$\Delta e_{it} = \frac{\beta^S}{\beta^S + \beta^D}\Delta\alpha^D_{it} + \frac{\beta^D}{\beta^S + \beta^D}\Delta\alpha^S_{it}.$$

Define $\frac{\beta^D}{\beta^S+\beta^D} = q^S$ and $q^D = 1 - q^S$. Then employment may be expressed

$$\begin{aligned}\Delta\tilde{e}_{it} &= q^D\left(b^D\tilde{w}_{it-1} + u^D_{it}\right) + q^S\left(b^S\tilde{w}_{it-1} + u^S_{it}\right) - \Delta e_{\cdot t} \\ &= b_e\tilde{w}_{it-1} + u^e_{it}.\end{aligned} \tag{9}$$

The effect of wages on employment, $b_e = q^S b^S - q^D b^D$, governs how rapidly employment levels react to wage differentials. This quantity is related to the *relative* mobilities of labor supply and demand.

This model is specified in terms of wages. However, we would like to relax the assumption that workers cannot respond to shocks in the current period; to do so, we need to measure the response of workers along the intensive margins, i.e., through unemployment and participation. Thus, we include these measures as dependent variables. Normally, unemployment and participation rates depend on the wage, that is,

$$\gamma\tilde{p}_{it} = \tilde{w}_{it}.$$

where $\tilde{p}_{it} = \tilde{e}_{it} - \tilde{n}_{it}$ is the de-meaned employment-to-population ratio ($\tilde{n}$ is population). By including the employment to population ratio (or the participation and unemployment rates) as dependent variables, we may exclude wages from our main specification entirely.[11] In doing so, we are able to avoid any problems that may arise that wages are not good measures of current labor demand and supply conditions. First, nominal or real wage stickiness affects how much we believe that the wage actually represents local conditions, as the existence of explicit and implicit long-term wage contracts causes a rift between the measured wage and the actual wage that would exist in a spot market (for an overview of evidence for sticky wages see Taylor, 1999 and references therein, among many others). Second, no reliable price index exists for deflating state-level wages over the time period in question (see, for example, the discussion in Aten and Reinsdorf, 2010). Third, the wage may be a poor proxy for local conditions for the reasons discussed in Kline (2008).

periods subsequent to a shock. These parameters stem from behavioral foundations, in which workers are attracted to locations with high wages; if $b^S + b^D = \beta^S + \beta^D$, then adjustment occurs immediately, which corresponds to the frictionless situation. Any frictions will reduce, not increase, b^S and b^D.

[11] BK also do not employ any specifications which include both wages and unemployment/participation rates. Just as we do, BK maintain the assumption that firms cannot respond to a labor demand shock by migrating in the current period.

In particular, a positive labor demand shock may initially reduce wages, as workers may be willing to accept lower wages in anticipation of higher wages in the future; in contrast unemployment and participation do not experience this effect. Finally wages must be adjusted for the composition of workers. Past work has not been able to appropriately adjust the wage for composition because the source of data for this – the current population survey – did not provide information on worker composition by state for a sufficiently long time series for such an adjustment to be fruitful.[12] For these reasons, our main specification will include employment, unemployment, and labor force participation; subsequently, for completeness, we present a specification which includes wages and employment.

Aggregate shocks. Up to this point our model resembles those employed elsewhere in the literature. For example, equations 6 and 7 appear to be identical to the supply and demand evolution equations introduced by BK. Equations 9 and 8 describe dependence between wages and employment in each location over time. Yet as it stands, the model does not describe dependence between employment and wages across different locations, and thus cannot generate the pervasive cross-sectional dependence that we described in the introduction. The dependence that we observe in the data will be subsumed into the error terms (u^D and u^S). We therefore explicitly introduce a parametric model of cross-sectional dependence into the error terms to account for this behavior. Under the model, a labor supply or demand error in a given location is comprised of both a purely idiosyncratic error which is independent of errors in other locations, and a common error which is manifest in all locations but to a varying degree. We permit the errors to follow a factor structure, in which different locations exhibit different sensitivities to the aggregate shock. That is, for $m \in \{D, S\}$

$$u_{it}^m \equiv c_i^m + \lambda_i^{m\prime} f_t^m + v_{it}^m + u_{\cdot t}^m, \;\; N^{-1} \sum_{i=1}^N \lambda_i^m = 0 \tag{10}$$

where f_t^m is a common factor error vector, λ_i^m is the loading vector on the factor for $(i,\, j)$, v^m is an idiosyncratic error, and $u_{\cdot t}^m$ is a common time component. The model permits aggregate shocks to affect all locations to a varying degree, but the condition $N^{-1} \sum_{i=1}^N \lambda_i^m = 0$ ensures that the average impact across all locations is zero. (The average effect is captured in $u_{\cdot t}^m$.) Hence, just as shocks that are purely idiosyncratic, these shocks may induce movement of workers and firms because aggregate shocks can likewise generate wages differentials between different locations. By splitting the errors in two, it may be determined whether aggregate shocks have a different effect on the trajectory of state-level recovery than do shocks that are purely state-specific.

Using (8) and (10) we can then re-express the reduced form equation for wages in more detail

[12] Happily, the time period that we have to study has become larger in the interim. Nevertheless, we leave such an adjustment of the wage to future research.

as follows:

$$w_{it} = \sum_{j=0}^{\infty} b_w^j \left(c_i^w + u_{it-j}^w\right) = \mu_i^w + \frac{1}{\beta}\sum_{j=0}^{\infty} b_w^j \left(\lambda_i^{D\prime} f_{t-j}^D - \lambda_i^{S\prime} f_{t-j}^S\right) + \frac{1}{\beta}\sum_{j=0}^{\infty} b_w^j \left(v_{it}^D - v_{it}^S\right).$$

Equivalently, we have

$$w_{it} = \mu_i^w + \lambda_i' F_t^w + w_{it}^0, \tag{11}$$

where $\lambda_i := \frac{1}{\beta}(\lambda_i^{D\prime}, \lambda_i^{S\prime})'$, $F_t^w := (\sum_{j=0}^{\infty} b_w^j f_{t-j}^{D\prime}, -\sum_{j=0}^{\infty} b_w^j f_{t-j}^{S\prime})'$ and $w_{it}^0 := \sum_{j=0}^{\infty} b_w^j \left(v_{it}^D - v_{it}^S\right)$. The wage premium w_{it} can be decomposed into three additive components. The first component is the state-level mean, the second component $\lambda_i' F_t^w$ is the manifestation of recent common labor supply and demand shocks in the wage premium, while the third component is the manifestation of the past history of idiosyncratic labor supply and demand shocks in the wage premium. Importantly, the relative magnitude of the elements of λ_i determine how a given aggregate supply or demand shock affects location i. Given that $N^{-1}\sum_{i=1}^{N} \lambda_i = 0$, it holds that a negative aggregate labor demand shock causes the wage premium to increase in some locations and decrease in others. In this way aggregate level shocks that cause a reduction in the wage level in all locations create cross-sectional variation in the variable of interest to firms and workers, namely the wage premium.

Similarly for employment growth under (9), (10), and (11) we have

$$\Delta e_{it} = c_i^e + b_e w_{it-1}^0 + b_e \lambda_i' F_{t-1}^w + q_S \lambda_i^{D\prime} f_t^D + q_D \lambda_i^{S\prime} f_t^S + q_S v_{it}^D + q_D v_{it}^S$$

or for $F_t^e \equiv \left(b_e F_{t-1}^{D\prime} + q_S f_t^{D\prime}, q_D f_t^{S\prime} - b_e F_t^{S\prime}\right)'$, $\Delta e_{it}^0 \equiv b_e w_{it-1}^0 + q_S v_{it}^D + q_D v_{it}^S$ and $\mu_i^e \equiv c_{ei} + b_e \mu_i^w$, we have

$$\Delta e_{it} = \mu_i^e + \lambda_i' F_t^e + \Delta e_{it}^0 \tag{12}$$

Thus, relative employment growth can also be decomposed into three components: The state-level mean, $\lambda_i' F_t^e$ reflecting the manifestation of recent common labor supply and demand shocks, and Δe_{it}^0 reflecting the manifestation of the past history of idiosyncratic labor supply and demand shocks. The common shocks create dispersion in state-level employment growth through heterogeneity in the factor loadings λ_i.

Similar structures to the reduced form for employment growth (12) have been explored in the extant literature by specifying the common factors F_t^e. For example, BK regress state-level employment growth on US employment growth and cannot reject the null of homogeneity in the slope coefficients for most states. The factor model (12) nests the alternative hypothesis as a special case by having a single common factor F_t^e that is equal to US employment growth. However, as a model of pervasive covariation in the panel, the factor model (12) offers significantly more flexibility than methods that seek to specify what the sources of pervasive covariation are. In particular it allows the possibility that there are significant disparate sources of this covariation – it permits, for example, lag/lead structures in the responses to common shocks (see, e.g., Amengual and Watson, 2007).

2.2 Identification

Labor demand shocks and labor supply shocks must be disentangled, which is the standard problem of price endogeneity. This model has been presented in a sufficiently general way that this problem may arise. The supply errors (u^S) and demand errors (u^D) affect both the observed residuals in the wage and employment change equations, u^w and u^e. The question of price endogeneity can be dealt with using knowledge about the behavior of individuals and firms from other sources.

Demand errors are decomposed into

$$u_{it}^D = c_i^D + u_{\cdot t}^D + v_{it}^D$$

where v_{it}^D is mean-zero, but may exhibit time-series and cross-sectional dependence. There is a similar equation for supply,

$$u_{it}^S = c_i^S + u_{\cdot t}^S + v_{it}^S.$$

Recall that the reduced-form specification errors are related to the structural errors through

$$u_{it}^w = \frac{1}{\beta^S + \beta^D}\left(u_{it}^D - u_{it}^S\right) - \Delta w_{\cdot t} \tag{13}$$

and

$$u_{it}^e = q^S u_{it}^S + q^D u_{it}^D - \Delta e_{\cdot t}. \tag{14}$$

The residuals from the reduced-form VAR can be mapped into structural shocks – shocks to v^S and v^D – given knowledge of β^S and β^D,[13] the supply and demand elasticities. We follow BK and maintain an assumption that current period employment can only be affected by demand shocks, which is equivalent to assuming that $\beta^D = 0$. From here on, we will omit β^D from the discussion.[14]

[13] Actually, only knowledge of $\frac{\beta^D}{\beta^D+\beta^S}$ is required. In their estimated model, BK assume shocks to Δe_{it} (changes in employment) are associated only with labor demand shocks. If the labor demand curve were vertical ($\beta^D = 0$), then shocks to labor supply would affect wages but not employment. Evolutions in employment would be entirely driven by evolutions in labor demand, and the only effect that labor supply would have on employment would occur through the effect of supply evolutions on wages (and the effect of wages on employment). Presumably, this is what they are assuming, although they do not explicitly tie their identification assumption into their model.

[14] If no migration of workers occurs in the period of a labor demand shock, then we will observe a one-to-one correlation between changes in per capita employment and the changes in employment as a result of a labor demand shock. We show in the results section that this is not the case empirically. Thus, we allow worker migration to absorb some of the initial shock to employment.

2.3 Interpretation of Impulse Responses

Impulse responses provide information regarding (i) the recovery duration; (ii) how the shock is initially absorbed by unemployment, participation and labor out-migration ("initial absorption"); and (iii) the relative mobility of firms and workers. Each of these is discussed individually below.

Recovery duration. When the impulse response of per capita employment (or the wage, in the model in section 2.1) has returned to zero, long-run labor market equilibrium has been restored by firm and worker migration. Thus we can read directly off the IRF the recovery duration given a -1% labor demand shock. Relating back to the model presented in section 2.1, recovery duration is decreasing in total mobility.

The toy model presented in the previous section precludes different responsiveness to the source of wage dispersion (that is, firms and workers react in the same way regardless of whether and aggregate or an idiosyncratic shock created the wage differential). However, our empirical strategy is easily amenable to such an extension. This is because we decompose variation in labor market variables into common and idiosyncratic components before applying a VAR to each component separately. Because both total mobility and possible serial correlation in labor demand shocks affect the wage impulse response (see equation 20 in appendix A.2, for example), it is difficult to tease out as total mobility in response to common shocks. A prolonged recovery could thus be due to serial correlation or due to low total mobility. Nonetheless, we conjecture that firm and worker responses to a common labor demand shock may be muted because migration cannot resolve the underlying aggregate labor demand conditions; migration can only address the dispersion in wages that such a shock generates. (Recall that although common shocks are identified after removing the common time effect from the variables, the underlying aggregate demand shocks are not mean-zero.)

Initial absorption. The given initial shock to labor demand will be absorbed either through per capita employment (the intensive margin) or migration of workers (the extensive margin). The share of the shock absorbed by the intensive margin can be read off the per-capital-employment IRF in the first period. If, for example, a labor demand shock that reduces employment by 1% is accompanied by a 0.6% decrease in the per capita employment rate, then we can conclude that 0.4% of the change in employment was absorbed via the extensive margin (immediate out-migration).

Later we will split out per capita employment rate into participation and unemployment rates, which provides additional detail regarding how the initial absorption is affected by workers' decisions about whether to stay in the labor market.[15]

[15] Employment is given by $e = n * \frac{lf}{n} * \frac{e}{lf}$ where n is population, lf is the labor force, and e is employment. Taking log differences, this is $\Delta \ln e = \Delta \ln n + \Delta \ln (lf/n) + \Delta \ln (e/lf)$. This identity asserts that growth in e that not directly associated with growth in lf/n and e/lf can be "explained" by growth in population. We may compute

Relative mobility. The log-run level of the employment IRF provides information regarding relative labor mobility. Consider a negative labor demand shock. If the long-run employment IRF is zero, then workers are totally immobile. Intuitively, in the long run, employment in a particular location is constant because workers never move. Another way of putting this is that over a sufficiently long time horizon, labor demand is infinitely elastic. Conversely, if the IRF is non-increasing over the entire domain (after a negative shock), then firms are completely immobile. In this case, long-run labor supply is infinitely elastic.

Pinning down relative mobility precisely in intermediate cases can be difficult, because we cannot disentangle serial dependence in the labor demand shock from worker and firm movement. We can, however, place an upper bound on relative labor mobility under assumptions about the nature of the serial dependence of the labor demand shock. If the labor demand shock exhibits positive serial dependence, then the ratio of the long-run employment IRF to the infimum of the employment IRF after a labor demand shock provides an upper bound. This is shown in the appendix A.2 for an AR(1) error.[16]

As a special case of our model, the BK model pins down relative mobility precisely when the labor demand shocks are white noise. In this case, the employment IRF is non-decreasing subsequent to a negative shock (the "recovery" begins immediately), and the long-run level of the employment IRF indicates the share of labor mobility exactly. For example, if the employment IRF approaches -0.3% in response to a -1% initial labor demand shock, then labor mobility makes up 30% of the return to equilibrium, and firm mobility makes up the remaining 70%.

3 Empirical Specification

Following BK, Decressin and Fatás (1995) and Tani (2003) we use a panel VAR in order to both identify labor demand shocks and to trace out recoveries. The variables in the VAR specification are Δe_{it}, growth in employment; $le_{it} = lf_{it} - e_{it}$, the log unemployment rate;[17] and $lp_{it} = lf_{it} - n_{it}$, the log labor for participation rate.[18] This specification provides the clearest picture of the local responses to differing local conditions.[19] Below the main results, we also present a two-variable specification using Δe_{it} and nominal per-worker wage and salary income, w_{it}.

The model described in the previous section implies that if the errors in the changes in supply

implied changes in population via $\Delta \ln n = \Delta \ln e - \Delta \ln (lf/n) - \Delta \ln (e/lf)$.

[16] The arguments in the appendix hold, however, for a more general error exhibiting positive autocorrelation that meets the criterion that the impulse response of the error to a white noise shock has the same sign as the shock over the entire time domain.

[17] Actually, this is the negative of the log employment rate. lf_{it} is the labor force.

[18] n_{it} is the working-age population.

[19] A specification that includes wages is unappealing because of issues discussed in Kline (2008) and BK, and because quality state-level price indices are not available, making computation of the local real wage impossible. Other specifications considered by BK are not central to the paper's message. In addition, we are limited by the availability of data at the state level as well as time series of sufficient length.

and demand are white noise over time, the residuals from the reduced form VAR(1) map into the structural supply and demand shocks. However, predicating identification on the errors being white noise is unnecessarily stringent, and above we have above included a discussion of a more general case. In particular, we can permit a degree of unobserved persistence in the errors, and still achieve identification, by introducing additional lags into the VAR. Specifically, a lag order sufficient for the reduced form residuals to be uncorrelated over time is required before mapping the reduced form residuals into the structural shocks. For example, for $X_{it} := (\Delta e_{it}, le_{it}, lp_{it})'$ and structural shocks $\varepsilon_{it} := \left(\varepsilon_{it}^{d}, \varepsilon_{it}^{s}\right)'$, we would have

$$A(L) X_{it} = R\varepsilon_{it} \tag{15}$$

for a sufficiently long lag structure in the polynomial $A(L)$ to ensure that $R\varepsilon_{it}$ is uncorrelated over time. As is standard for recursive VARs, our identification conditions will impose a specific structure on R. We can then observe how the key variables of interest respond to shocks in labor supply and demand through standard methods (impulse response functions). These impulse response functions can provide information about the parameters, as discussed in section 2.3 above.

The key innovation in our approach is to introduce an explicit parametric form of dependence – the factor model – into the structural errors $\varepsilon_{it} := \left(\varepsilon_{it}^{d}, \varepsilon_{it}^{s}\right)'$ through (10). As argued above we wish to permit the degree of serial dependence in the common and idiosyncratic components of the structural errors to differ. Therefore in our empirical specification we decompose the observable panel X_{it} into common and idiosyncratic components before estimating a VAR for each component. That is, we first decompose $X_{it} = X_{it}^{0} + X_{it}^{k}$. For $X_{it}^{0} = \left(\Delta e_{it}^{0}, le_{it}^{0}, lp_{it}^{0}\right)'$ we then run the linear filter

$$A_0(L) X_{it}^{0} = R_0\varepsilon_{it}^{0} \tag{16}$$

where, as above, the number of lags in the polynomial $A_0(L)$ should be sufficient to ensure that $R_0 u_{it}^{0}$ is uncorrelated over time. We then compute the relevant measures of the response of key variables of interest to idiosyncratic labor supply and demand shocks. The second component $X_{it}^{k} = \left(\Delta e_{it}^{k}, le_{it}^{k}, lp_{it}^{k}\right)'$ represents the manifestation of the common labor supply and demand shocks in the data. We then run a separate filter for $X_{it}^{k} = \left(\Delta e_{it}^{k}, le_{it}^{k}, lp_{it}^{k}\right)'$ of the form

$$A_k(L) X_{it}^{k} = R_k\varepsilon_{it}^{k} \tag{17}$$

where the number of lags should be chosen to ensure that $R_k u_{it}^{k}$ is uncorrelated over time. Importantly, we permit $A_0(L)$ and $A_k(L)$ to be different between the two models, permitting the persistence of the idiosyncratic and common shocks to differ. We then compute the responses of key variables of interest to common labor supply and demand shocks.

Of course, X_{it}^{0} and X_{it}^{k} are not separately observable. They are however identifiable using well-developed econometric techniques, such as principal components, under fairly general statistical conditions (see, e.g., Bai, 2003). Intuitively, the common components X_{it}^{k} can be identified because they generate strong-form dependence in panel. One important feature of the toy model with factor errors is that employment growth and wages have the same factor loadings (see equations 11 and 12 above), so that efficiency gains can be obtained by pooling the variables when estimating the factor loadings. We refer the reader to the appendix for a more detailed overview of our empirical method for estimating X_{it}^{0} and X_{it}^{k}.

The first step in our estimation procedure is to estimate X_{it}^{0} and X_{it}^{k}. The variables used in estimation of models (16) and (17) are therefore subject to measurement error. However, in contrast to classical measurement error and its associated problems, the measurement error decreases as the sample size grows because X_{it}^{0} and X_{it}^{k} are consistently estimated. In particular we require that both N and T grow large for this measurement error to dissipate. See the discussion in Bai (2003).

3.1 Model Selection

Our reduced form models (16) and (17) require both a lag-number p and factor-number r. However, given that the factors are estimated in the first step of the procedure, we can follow a hierarchical approach in which we estimate the factors in the first step, and then consider the lag structure in the VAR.[20]

3.1.1 Factor number selection

In order to estimate the number of factors r we use the Bai-Ng $IC_{p2}(k)$ criterion. The estimated factor number $\hat{r}$ is given by k that minimizes

$$IC_{p2}(k) = \ln \hat{\sigma}^2(k) + k\frac{n^*T^*}{n^* + T^*} \ln\left(\min\left(n^*, T^*\right)\right),$$

where $\hat{\sigma}^2(k)$ is the estimated variance of the idiosyncratic component when k factors are imposed under principal component estimation, and $k = 0, \ldots, k_{\max}$ (we set $k_{\max}$ to 10 in this application). The $IC_{p2}(k)$ criterion performs well in the presence of weak dependence and heteroskedasticity in the idiosyncratic terms because it has the strictest penalty function amongst the Bai-Ng $IC_p(k)$ family. Here N^* and T^* denotes the number of cross section and time series observations in the panel. As demonstrated in section 2 above, the variables in X_{it} share the same factor loading vectors, so that the factor number can be more efficiently estimated by pooling the three panels in

[20] We chose not to go down the avenue of jointly selecting p and r because such criteria have not been developed, and the task may be rather difficult. For example, Greenaway-McGrevy, Han and Sul (2010b) show how estimated spurious factors can mop up any temporal dependence in the idiosyncratic component in the finite sample. Since our specific interest is the temporal dependence in the idiosyncratic component, we avoid this thorny issue by pinning down each parameter sequentially.

$X_{it} = (\Delta e_{it}, le_{it}, lp_{it})$. As the factor loadings are the same, but the common factors are different, we have $n^* = n$ and $T^* = 3T$ in this particular application. We refer the reader to the appendix for more details on how the common factors are estimated when the variables share the same loadings.

To guard against possible overestimation of the factor-number due to dependence and heteroskedasticity in the idiosyncratic component (see, e.g., GHS 2010b, 2010c), we use both the AR1 filter "minimum rule" of GHS (2010b) and the Hallin-Liska cross validation exercise to further refine the accuracy of the $IC_{p2}(k)$ criterion. The GHS minimum rule estimates 3 factors, while the HL method estimates 4 factors. We elect to use 3 factors, but check the robustness of our results by re-estimating the model with 4 factors. We find little substantive difference with 4 factors.

3.1.2 Lag number selection

We chose not to estimate p empirically, but rather to set $p = 2$ as this is appears to be the norm in the related literature (see BK, Descressin and Fatás, 1995, and Tani, 2003). Nonetheless, for robustness, we also estimated the model with three lags. We find no substantive difference in our results, suggesting that two lags is sufficient.

3.2 Impulse Response Confidence Intervals

To construct confidence intervals for the structural impulse response functions we bootstrap the estimated reduced-form VAR. In constructing a panel of residuals for each iteration, we draw repeated cross sections from the reduced-form residuals. 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 both according to geography as well as according to industry mix. (A downturn in agricultural prices will affect farming states, for example.) This bootstrap method will be robust to such correlations in the residuals.

3.3 Identification

Our identification assumption discussed in section 2.2 corresponds to a "recursive" VAR identification strategy, in which the first variable in the appropriately order vector of variables is employment growth. Structural employment shocks are allowed to have a contemporaneous effect on wages but not vice versa, inducing all of the correlation between the reduced-form residuals to be attributed to the structural labor demand shock. This form may be estimated either by appropriate inclusion of contemporaneous variables on the RHS during estimation of the VAR equations, or via a Cholesky decomposition of the residual variance-covariance matrix of the reduced-form VAR (see, e.g., Stock and Watson, 2001). We use the Cholesky approach here.

4 Results

Data and results from estimating the system (16) and (17) are discussed here. In estimation, the first step is to obtain estimates of the number of factors using the model selection criterion discussed above. From this, we decompose the panel variables into common and idiosyncratic components. We then estimate a separate VAR for the idiosyncratic component and the common component. Our interest centers on the impulse response functions of employment, unemployment and participation to a labor demand shock. In section 4.3 we present results for wages and employment. We then decompose the variation from the first specification variables into common and idiosyncratic variation in labor demand and supply shocks.

4.1 Data

The data used in this paper are obtained from the Bureau of Labor Statistics (BLS) monthly Local Area Unemployment (LAU) series, downloaded from the BLS website.[21] This series contains monthly state-wide employment, unemployment, and labor force figures. Simple arithmetic averages provide annual values. These data are combined with annual civilian noninstitutional population data from the BLS.[22] Log changes in employment and log employment and participation rates are then computed. These data are available beginning in 1976 and ending in 2009, providing 34 time periods. We remove both time-period and cross-sectional fixed effects prior to estimation.

After presenting the main results, we present a model of employment and wages. The U.S. Bureau of Economic Analysis (BEA) releases total annual state-level wages and salaries and wage and salary employment data for US states. These data are available from 1976 to 2009. From these two series, annual average wages and salaries (per employee) are constructed as a ratio. In the wage specification below (in section 4.3), the log of this quantity is used.[23] These data represent

[21] http://www.bls.gov/lau/. Note that these are not the same data that BK use. The LAU data are filtered, 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). This publication is no longer produced. We have tested our results using the QCEW data in place of the LAU employment data; this exercise produces similar results to the ones presented below. However, there are a number of reasons to avoid using the *Geographic Profile* data. First of all, these data are based on the CPS, and 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 concerns about reliability and measurement error. Rowthorn and Glyn (2006) discuss the implications of measurement error for BK's results. In any case, since these data were discontinued in 2002, only an additional 12 years of data would be available. The reason that we use the LAU and not QCEW employment data for most of the results below is that we feel the most consistent approach is to either use only LAU data (unemployment and employment) or none. Since we do not have access to other reliable unemployment data at the state level, we choose to use the LAU data for both employment and unemployment.

[22] http://www.bls.gov/lau/ststdsadata.txt

[23] As mentioned above, there is a lack of any deflator for wages at a sub-national level in the U.S. Our empirical specification will "wash out" any attempt to deflate using a common deflator, and so none is employed.

Table 1: Variance of Factor Model Components

	employment growth	unemployment	participation
common component	0.523	0.656	1.753
idiosyncratic component	0.898	0.571	1.275
total variance	1.421	1.227	3.028

annual wages by state of work, rather than by state of residence. In the wage specifications, the QCEW employment data are used, as these data represent employment also by state of work.

4.2 Impulse Responses

Recall that the model is estimated using 2 lags and 3 factors. The impulse responses are the responses of the three model variables to a -1% shock to the change in log employment, in which all contemporaneous covariation between the change in log employment and the log employment and participation ratios is due to the shock to the change in employment.

4.2.1 Conventional Model

The impulse responses from the 2-lag VAR model are presented first as a baseline. These appear in figure 2.[24] It is striking that the IRFs look very similar to those reported by BK for the 1976-1990 period based on the same data.

The conventional model suggests a recovery duration of approximately ten years. Furthermore, approximately 70% of the shock is initially absorbed by unemployment and participation, leaving about 30% to labor migration in the first year. A slightly larger proportion of the shock is absorbed by participation than by unemployment. In the long run, the employment IRF approaches -0.95%, meaning that the labor demand shock has an almost permanent effect on employment.

4.2.2 Factor Decomposition Model

As discussed in the previous section, we use three common factors when decomposing the panels into common and idiosyncratic components. Table 1 shows the decomposition of the variation of each of the three employment variables into variation by common and idiosyncratic sources when three factors are estimated.

[24] These impulse responses are similar in appearance to the impulse responses reported in BK (figure 7), with a few minor differences (likely due to the longer time series dimension).

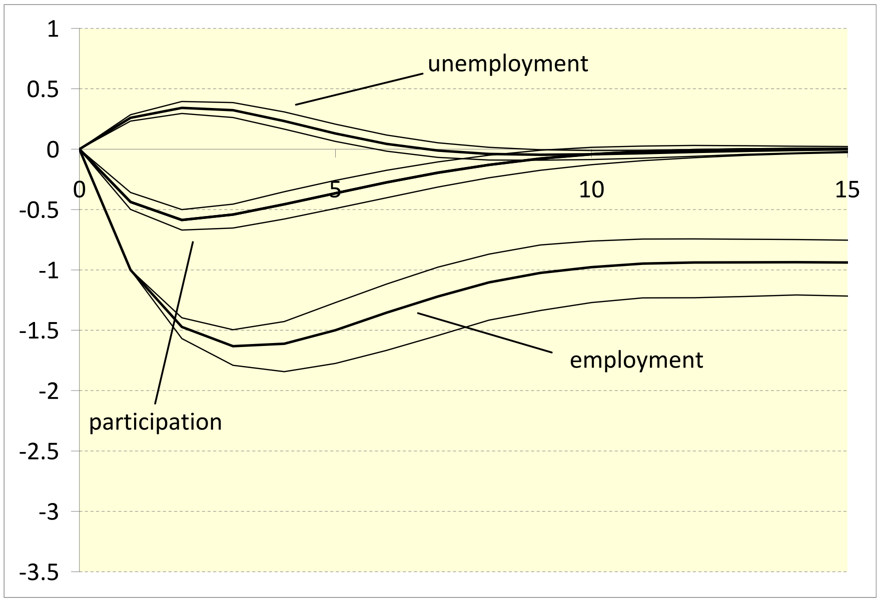

Figure 2: Impulse responses from a -1% shock to $\Delta \ln e$, CTE model with 2 lags. Confidence bands represent a 95% confidence interval.

While the variance of employment growth exceeds the variance of unemployment, it is interesting that the variance in the common component of employment growth is less that of unemployment. More than half the variation in unemployment and participation is attributable to the common component, whereas less than half of the variation in employment growth is attributable to the common component.

Table 1 masks marked cross sectional heterogeneity in the variation attributable to common components. In table 2 we tabulate the proportion of total variance explained by the estimated common component for each state.

This table shows there is marked variation in the sensitivity state-level employment to common factors. For example, the three factors explain about 80% of the variation of employment growth in Texas and Oklahoma, but only 8% of the variation in Arizona.

Impulse Responses to Idiosyncratic Shocks. Impulse responses to idiosyncratic shocks are shown in figure 3. They are markedly different from those obtained from the conventional model. Most strikingly, the duration of the recovery is much shorter, at approximately 5-6 years. Unemployment and participation rates initially absorb approximately 70% of the shock in the first period, leaving 30% to worker migration. This is very similar to the result from the conventional model. However, in contrast to the conventional model, the -1% shock causes unemployment to

Table 2: Variance of common component as proporition of total variance by state

(3 factors; de = employment growth; un = unemployment; pt = participation)

state	de	un	pt	state	de	un	pt	state	de	un	pt
AL	0.51	0.67	0.27	KY	0.38	0.76	0.56	ND	0.55	0.07	0.43
AK	0.65	0.09	0.41	LA	0.44	0.52	0.36	OH	0.70	0.60	0.41
AZ	0.08	0.17	0.46	ME	0.47	0.73	0.43	OK	0.81	0.45	0.81
AR	0.24	0.51	0.28	MD	0.46	0.69	0.16	OR	0.45	0.46	0.13
CA	0.71	0.62	0.78	MA	0.37	0.75	0.71	PA	0.18	0.15	0.34
CO	0.50	0.07	0.39	MI	0.69	0.53	0.16	RI	0.43	0.59	0.53
CT	0.69	0.77	0.85	MN	0.26	0.08	0.59	SC	0.14	0.09	0.32
DE	0.70	0.68	0.31	MS	0.12	0.72	0.08	SD	0.44	0.25	0.50
DC	0.25	0.60	0.44	MO	0.46	0.11	0.77	TN	0.39	0.54	0.44
FL	0.53	0.75	0.34	MT	0.48	0.05	0.43	TX	0.81	0.43	0.33
GA	0.58	0.22	0.11	NE	0.48	0.43	0.72	UT	0.41	0.46	0.71
HI	0.29	0.61	0.46	NV	0.32	0.00	0.63	VT	0.40	0.78	0.29
ID	0.51	0.13	0.58	NH	0.48	0.60	0.45	VA	0.32	0.71	0.56
IL	0.47	0.65	0.26	NJ	0.60	0.87	0.22	WA	0.28	0.27	0.26
IN	0.68	0.56	0.40	NM	0.27	0.05	0.41	WV	0.62	0.47	0.61
IA	0.36	0.67	0.72	NY	0.54	0.81	0.06	WI	0.70	0.68	0.87
KS	0.11	0.57	0.21	NC	0.60	0.20	0.54	WY	0.76	0.37	0.50

increase by about 0.2% and participation to decrease by about 0.5%, meaning that more of the initial shock is absorbed through workers choosing to leave the workforce. Turning to relative mobility, the long-run effect of a -1% labor demand shock is to reduce employment by approximately 0.67%. The bound computed by dividing long-run employment by the nadir of the employment response is 0.56, suggesting that worker movement can only explain just over half of the total recovery.[25]

Impulse Responses to Common Shocks. The recovery from common labor demand shocks differs substantially from the responses to idiosyncratic shocks. Impulse responses are shown in figure 4. In this case, recovery does not appear to occur until 12 or 13 years after the shock. As noted above in section 2.3, we take this as evidence that worker and firm migration is less effective at resolving the dispersion brought about by aggregate shocks. The initial absorption on the intensive margins is slightly lower as well, making up only about $60-65\%$ of the initial shock, implying higher initial worker out-migration. A large proportion of the initial response (more than half)

[25] It is a bit puzzling that we see a pronounced worker response to the initial shock within the first two years, followed by what appears to be little worker movement and substantial job creation over the next three or four years. A framework such as Shimer's (2007) model of mismatch would suggest that even after job creation has taken place, it might take time to recover from a shock as new vacancies are matched with existing workers. Worker out-migration, on the other hand, may not be slowed by such considerations. Our results seem to fit nicely into this framework.

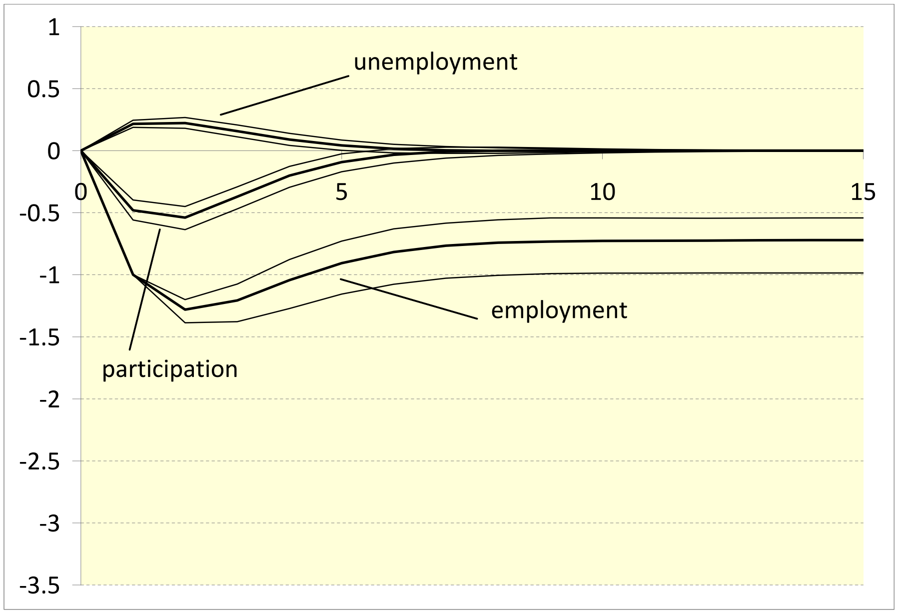

Figure 3: Impulse responses from a -1% shock to $\Delta \ln e$, idiosyncratic component. Confidence bands represent a 95% confidence interval.

is absorbed by unemployment rather than participation. An initial -1% shock results in a -2.8% decrease in the employment level 5 years after the shock – a much higher peak than is evident in the idiosyncratic case. The long-run effect of the shock on employment is -1.5%, which is above the level of the initial shock. Interestingly, this means that the ratio of long-run employment to the trough is 0.55, quite similar to the idiosyncratic employment impulse response. Given the extended duration of recovery in this picture, this would be consistent with the aggregate labor demand shock having a greater degree of serial dependence than the location-specific shock. Although it appears that there is higher initial worker out-migration in response to the aggregate labor demand shock, in the long run worker migration still can only explain slightly more than half of the recovery from an aggregate shock.

Lastly, recall that a common labor demand shock of -1% is actually a positive labor demand shock for states with negative factor loadings. Since these factor loadings must sum to zero, approximately half the states will have negative shocks. Thus while it is useful to refer to the above figure as an impulse response to a negative common labor demand shock, this may be somewhat misleading. Indeed if we wished to consider the effect of a -1% shock to a given state, we must interact the shock with the factor loading of the particular state.

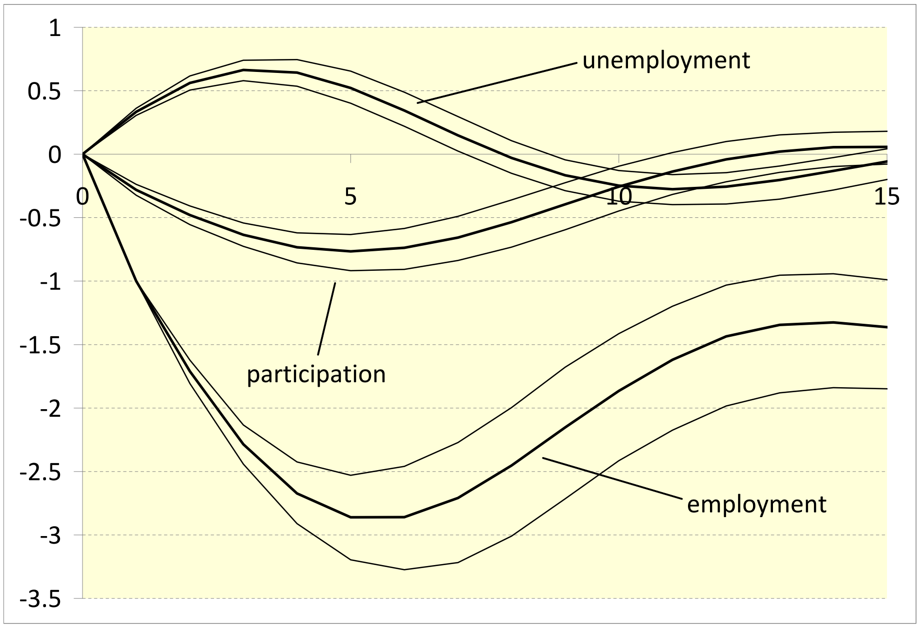

Figure 4: Impulse responses from a -1% shock to $\Delta \ln e$, common component. Confidence bands represent a 95% confidence interval.

Reconciling our results with the conventional VAR from section 4.2.1. The impulse responses of the conventional model from section 4.2.1 typically lie in between the response to an idiosyncratic shock and the response to a common shock. This reflects the fact that the labor demand shocks identified in the conventional model contain both the common and idiosyncratic components. In fact, the weighted average of the impulse responses to the common and idiosyncratic shocks, with weights given by the variance of the common and idiosyncratic labor demand shocks (given in table 3 below), looks very similar to the impulse response from the conventional model. In the figure 5 we depict the average of the common and idiosyncratic response functions to the common and idiosyncratic labor demand shocks, weighting each response by the variance of the two types of shock. We include the conventional model IRFs for comparison.

In this sense we may interpret the conventional model's impulse responses as a weighted average of the impulse response to common shocks and the response to idiosyncratic shocks.[26]

These results show that by using additional information about the aggregate economy, more can be said about a particular state's fate in the case of a local downturn. Whether a state is sensitive

[26] The weighted average will never be perfect since the CTE VAR is necessarily misspecified if the common and idiosyncratic components of the panel follow distict VAR processes. For example, a variable that is is the sum of two independent and distinct AR(1) processes follows an ARMA(2,1). An infinite number of lags is then required in the AR filter in order to ensure that the filtered series is uncorrelated over time.

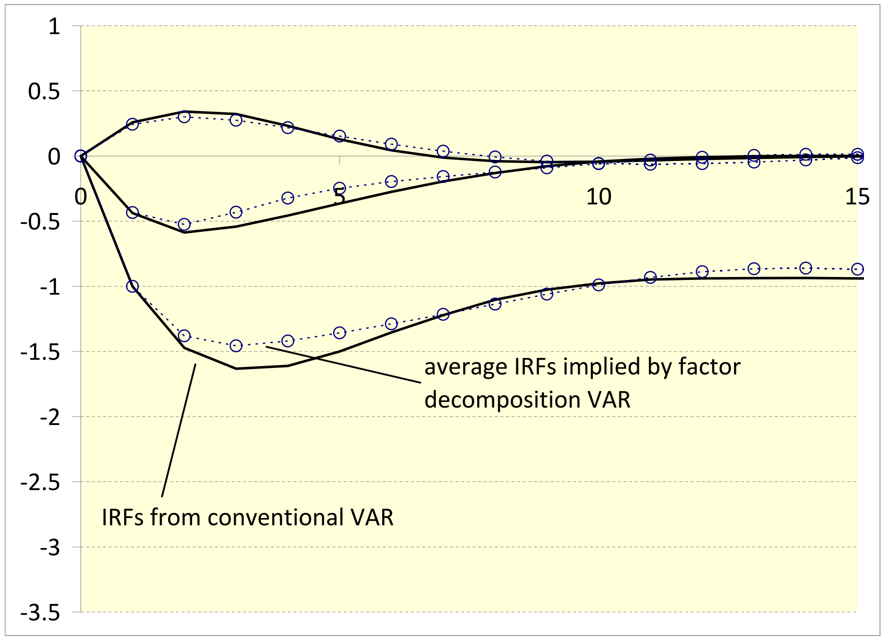

Figure 5: Impulse responses from a -1% shock to $\Delta \ln e$, combined.

to common shocks is useful in providing a prognosis for its recovery. If a state is more sensitive than average to common shocks – and if a common shock appears to be the culprit for a state's current situation – the recovery process is likely to be more protracted than if the shock appears to result from location-specific events.

4.3 Wages and Employment

We have considered the effects of a labor demand shock on employment, unemployment, and participation. Doing so, we have found that while a large portion of the initial shock is absorbed by workers, worker migration can explain only a bit more than half of the long-run recovery. An important remaining consideration is whether this worker out-migration and job creation is responding to the wage differential that is created by the shock. To this end, we consider the effect of such a shock on average wages.

Figure 6 shows the effect of an labor demand shock on employment and wages using the baseline model. In comparing with previous results, we note several similarities. Figure 13 in BK, for example, shows the effect of such a shock on per capita income, a proxy for the wage; in this case, there is a large, immediate response of wages to a labor demand shock. The paths of employment seen in BK look similar, although the magnitude is greater in the figure seen here (a peak of

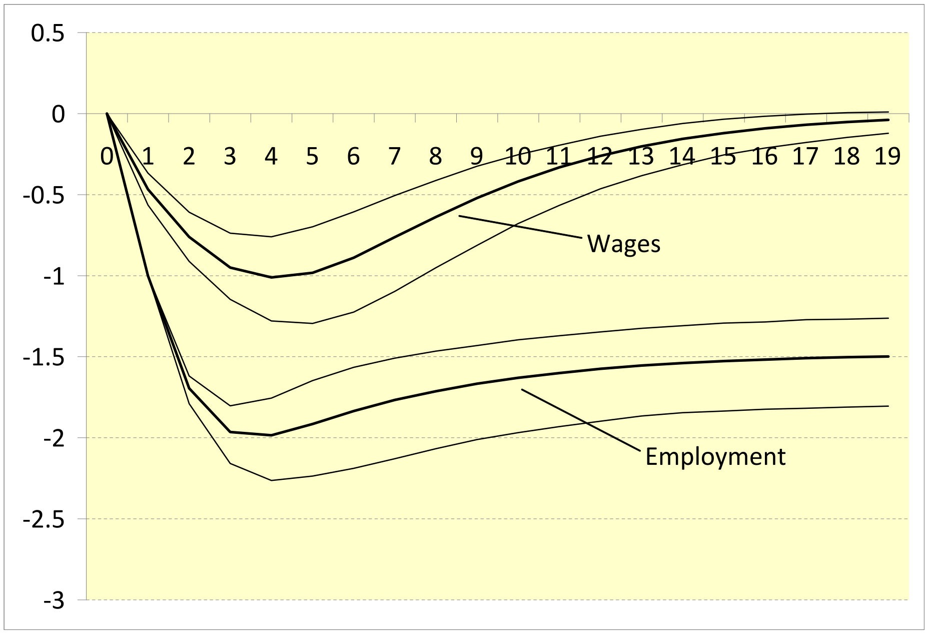

Figure 6: Impulse responses from a -1% shock to $\Delta \ln e$, CTE model with 2 lags – specification with wages. Confidence bands represent a 95% confidence interval.

approximately -2, compared in BK with a peak of approximately -1.75).In general, this figure does not provide a picture of the recovery process substantially different from figure 2 above, except that the recovery process appears even more protracted. Employment and wages reach a nadir approximately 4 periods after the shock (instead of 3), with employment recovering after about fifteen years.

Figure 7 shows the effect of an idiosyncratic labor demand shock on employment and wages. The employment response is again quite similar to the corresponding figure 3 above, although as in the last picture, there is a one period delay in the peak (from 2 years to 3 years). Employment reaches a nadir of about -1.7 and recovers to just below -1.5 times the shock, with most of the recovery occuring withing 6 or 7 years. In this case, the wage response is somewhat less pronounced. The wage peaks at approximately 0.7.

Figure 8 shows the effect of a common labor demand shock on employment and wages. This figure suggests an enormous response for wages to a common labor demand shock. Wages do not reach the long-run level until 16 years after the shock. Employment, reaching a peak of -2.5 in the fourth year, also takes nearly 15 years to reach the long-run level. The employment response appears quite similar to figure 4 above, while the contrast between the wage responses in figures 7 and 8 is more pronouned than the contrast between the unemployment and participation responses

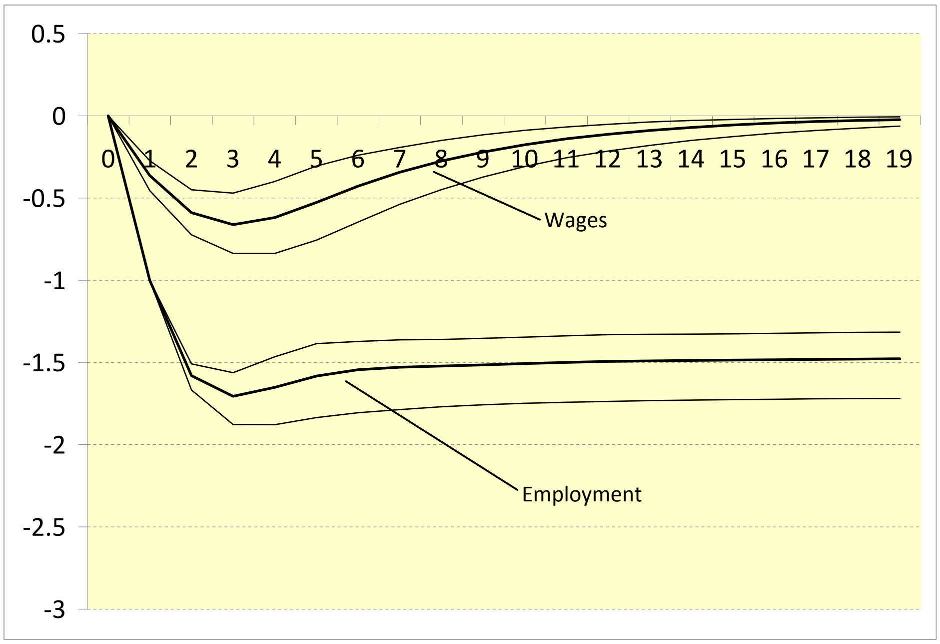

Figure 7: Impulse responses from a -1% shock to $\Delta \ln e$, CTE model with 2 lags – specification with wages. Confidence bands represent a 95% confidence interval.

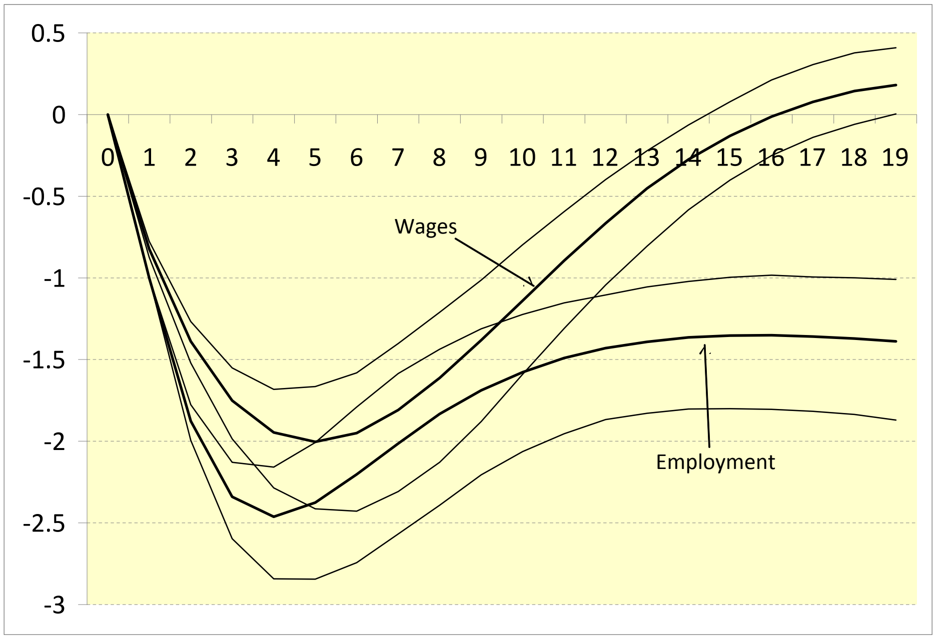

Figure 8: Impulse responses from a -1% shock to $\Delta \ln e$, CTE model with 2 lags – specification with wages. Confidence bands represent a 95% confidence interval.

in figures 3 and 4.

5 Variance Decomposition

In this section we present a set of variance decompositions to show how variation in the labor market variables (employment growth, unemployment and participation rates) can be attributed to the various shocks. We begin by exhibiting the estimated variance of the shocks in Table 3. Note that we have a 2-dimensional taxonomy of shocks; labor demand and supply shocks, and common and idiosyncratic shocks.

Evidently the idiosyncratic labor demand shock has more than three times the variance of the common labor demand shock. This is also true of the labor supply shocks. Because demand and supply shocks drive the initial changes in labor market variables, the idiosyncratic shocks thereby account for more of the short-run (that is, high frequency) variation in local labor markets than the common shocks. Labor demand shocks - both idiosyncratic and common - have about twice the variance of labor supply shocks.

We next consider what drives the long-term variation in labor market variables. Using the fitted VAR parameters we can attribute variation in the observable variables to labor supply and demand

Table 3: Variance of shocks

	labor demand	labor supply
common	0.192	0.118
idiosyncratic	0.639	0.370
total (common + idio.)	0.831	0.487

Table 4: Variance decomposition

	employment growth			unemployment			participation		
	labor demand	labor supply	total	labor demand	labor supply	total	labor demand	labor supply	total
common	0.480	0.043	0.523	0.429	0.227	0.656	1.603	0.150	1.753
idiosyncratic	0.734	0.164	0.898	0.094	0.477	0.571	0.532	0.743	1.275
total	1.214	0.207	1.421	0.523	0.704	1.227	2.135	0.893	3.028

shocks by standard methods. However, given that we have two types of each shock – common and idiosyncratic – we can also attribute the variation according to common and idiosyncratic shocks. Table 4 presents this decomposition.

Common shocks – both supply and demand – account for more of the variation in participation and unemployment than idiosyncratic shocks. Together, common supply and demand shocks account for more than half of the variation in unemployment and participation, and about 37% of the variation in employment growth. Thus although Table 3 showed that the short-run variation in these variables is dominated by the idiosyncratic shocks, the common shocks drive more of the long-run variation in these variables. Labor demand shocks – both idiosyncratic and common – account for 85%, 42% and 70% of the variation in employment growth, unemployment and participation, respectively.

Table 5 tabulates the variation in the three employment variables attributable to common and idiosyncratic labor demand shocks as a proportion of the overall variation in the three variables attributable to both common and idiosyncratic labor demand shocks. Common labor demand shocks create three times as much variation in participation, and four and a half times as much variation in unemployment, than idiosyncratic labor demand shocks. Thus, although idiosyncratic labor demand shocks have higher variance than common labor demand shocks, they cause substantially less long-run variation in unemployment and participation. Common labor demand shocks account for only 40% of the variation in long-run employment growth. This however still represents an

Table 5: Proportion of labor demand variation by common and idiosyncratic shocks

	shock	employment growth	unemployment	participation
common	0.231	0.395	0.820	0.751
idiosyncratic	0.769	0.605	0.180	0.249

amplification of the common shock, since the common shock has only 1/3 that variance of the idiosyncratic shock.

In summary, although the variance of idiosyncratic labor demand shocks is far greater than that of common shocks, common shocks account for a greater proportion of the long-run variation in the variables. This is commensurate with the path of the recovery implied by the IRFs presented above in Figures 3 and 4. Specifically, our IRFs suggest that a common labor demand shock takes much longer to dissipate than an idiosyncratic shock. Thus a -1% common labor demand shock will have an ongoing effect on employment, unemployment and participation for the following 12-13 years, whereas an equivalent idiosyncratic labor demand shock will impart no effect beyond the 6 year horizon.

6 Discussion

How do workers and firms respond when a state experiences relatively good or bad labor market conditions? While differences between local labor markets can be brought about by *location-specific* shocks (labor demand and supply shocks that are by-in-large realized in a only in a specific location), they may also be brought about *aggregate* shocks, given that different locations exhibit different sensitivities to aggregate-level events. In this paper we model the recovery of a region in an environment that permits different responses to aggregate and idiosyncratic shocks. In order to account for location specific heterogeneity in the sensitivity to aggregate shocks, we begin by introducing a factor structure into labor supply and demand shocks. This framework permits us to decompose the variation in local labor markets into a common component, reflecting evolutions in response to aggregate shocks, and an idiosyncratic component, reflecting evolutions in response to location-specific shocks. We then apply the conventional VAR toolkit to these two separate components in order to assess how workers and firms respond when a state experiences relatively good or bad labor market conditions.

The differences between the responses to the two different types of shock are stark. For an idiosyncratic shock to labor demand, recovery occurs within five or six years, with employment leveling off to about two thirds of the initial shock. The impulse response suggests firm migration is an important part of the regional recovery from idiosyncratic shocks. For a common shock to labor demand, the recovery is likely to be highly protracted, with employment reaching its long-run level after no less than twelve years. It is clear that the prognoses for these two situations are highly different: It takes much longer for migration channels to eliminate differences between state-level unemployment rates when these differences have been brought about by aggregate shocks. We also find that location-specific labor demand shocks exhibit far more variance than the aggregate labor demand shocks, meaning that short-run variation in local labor market conditions is largely driven by location-specific events. However, because the recovery process in response to aggregate shocks is far more protracted than the recovery process in response to local shocks, much of the long-term variation in state-level labor markets is driven by aggregate-level events.

Our results suggest a larger role for firms in the recovery process than previously thought. Firms quickly respond to location-specific shocks by creating jobs in relatively depressed areas and reducing jobs in relatively booming states. While this finding contrasts with contemporary interpretations of earlier work in the field, it is commensurate with micro-level studies of the relative costs of firm and worker movement, such as Kennan and Walker (2008) and Bishop (2008). In addition, we provide evidence that the speed of recovery found by BK is slower than the speed of recovery in response to shocks that are purely idiosyncratic. We hypothesize that the reason for this is the inability of movement of workers and firms to resolve underlying aggregate labor demand conditions. This would be consistent with the large and protracted wage response observed in figure 8.

These results also have stark implications for measuring welfare effects of policies affecting labor markets, underscoring the importance of firm decisions in labor market dynamics. Our results suggest that future extensions of the work of Alvarez and Veracierto (1999, 2006) could allow an endogenous firm response to labor market policies. We also find that common shocks account for a significant proportion of the variation between state labor markets, and we provide estimates of how these shocks are initially absorbed and how their paths of recovery differ. Extending models of location decisions such as Alvarez and Shimer (2008) and Shimer (2007) to permit common shocks that generate regional labor market disparities could provide further insight into these findings.

A Appendix

A.1 Separating the panels into estimated common and idiosyncratic components.

Let X_1, X_2, and X_3 denote the $T \times n$ panels of employment growth, unemployment and participation, respectively, after removing both cross section and time period fixed effects. Before estimation we standardize each cross section in X_1, X_2, and X_3, by its time-series standard deviation. As shown in GHS (2010c) this can increase efficiency of the principal component estimator when idiosyncratic components exhibit marked cross sectional heteroskedasticity. Let $\tilde{X}_1$, $\tilde{X}_2$, and

$\tilde{X}_3$ denote the standardized panels. Let $\tilde{X} := [\tilde{X}_1' : \tilde{X}_2' : \tilde{X}_3']'$ denote a $3T \times n$ concatenated panel. The $n \times r$ estimated loading vector $\hat{\Lambda}$ is given by the first r eigenvectors of the matrix $\tilde{X}'\tilde{X}/3nT$. Then define $\hat{P}_\Lambda := \hat{\Lambda}\left(\hat{\Lambda}'\hat{\Lambda}\right)^{-1}\hat{\Lambda}'$ and $\hat{M}_\Lambda := I_n - \hat{P}_\Lambda$. Then our estimate of the common component is given by $\hat{X}_{j,k} := X_j \hat{P}_\Lambda$ for $j = 1, 2, 3$; while the estimated idiosyncratic component is given by $\hat{X}_{j,0} := X_j \hat{M}_\Lambda$ for $j = 1, 2, 3$. We then run two separate VARs for $\hat{X}_{j,0}$ and $\hat{X}_{j,k}$. Each VAR uses the same

assumptions to identify the labor demand shock from the reduced from errors.

A.2 Derivation of model impulse responses

Here, we allow a labor demand shock from the model in section 2 to follow an AR(1) with parameter $\rho \in [0, 1)$. All impulse responses discussed below are to a -1% shock to labor demand, and it will be important to keep in mind that the shock is negative. We use the symbol $\Psi_x(j)$ to denote the impulse response of variable x in the j^{th} period following the shock.

From equations 13 and 14 and the assumption that $\beta^D = 0$, the errors resulting from a demand shock are related by the equations $u^e = u^D$ and $u^w = \frac{1}{\beta^S} u^D$. Thus, (1) If the demand error follows an AR(1) process with parameter ρ, then so do the employment and wage shocks; and (2) the wage shock is a multiple of the employment shock, $u^w = \frac{1}{\beta^S} u^e$. The errors that result from such a shock decline geometrically via

$$\Psi_{u^e}(j) = -\rho^j \tag{18}$$

and

$$\Psi_{u^w}(j) = -\frac{1}{\beta^S}\rho^j. \tag{19}$$

We first show that the wage impulse response function to a -1% shock exhibits the following form:

$$\Psi_w(j) = -\frac{1}{\beta^S}\frac{\rho^{j+1} - b_w^{j+1}}{\rho - b_w}. \tag{20}$$

From equations 8 and 9, employment and wages react only to last period's wage. Thus, we discuss the behavior of the wage first. The derivation of employment will follow easily. Since wages are autoregressive with parameter $b_w \in [0, 1)$, we can write it as a geometric sum of past errors,

$$\Psi_w(j) = \sum_{k=0}^{j} b_w^k \Psi_{u^w}(j - k).$$

From (19), this is

$$\Psi_w(j) = -\frac{1}{\beta^S}\sum_{k=0}^{j} b_w^k \rho^{j-k}.$$

Thus,

$$\Psi_w(j) = -\frac{1}{\beta^S}\frac{\rho^{j+1} - b_w^{j+1}}{\rho - b_w}$$

In this case, wages are stationary only if $|b_w| < 1$ and $|\rho| < 1$. If $b_w = 0$, then the wage IRF follows a geometric decline, $\Psi_w(j) = \frac{1}{\beta^S}\rho^j$, which is the impulse response of an AR(1) process. If $b_w = 1$ then wages are nonstationary. Other values of b_w cause the wage process to fall in between these two.

The impulse response for employment growth may be expressed

$$\Psi_{\Delta e}(j) = -\rho^j + \frac{b^D}{\beta^S}\frac{b_w^j - \rho^j}{b_w - \rho}. \tag{21}$$

To show this, we re-write 9,

$$\Psi_{\Delta e}(j) = b_e \Psi_w(j-1) + \Psi_{u^e}(j).$$

Using equations 18 and 20,

$$\Psi_{\Delta e}(j) = -\rho^j - \frac{b_e}{\beta^S}\sum_{k=0}^{j-1} b_w^k \rho^{j-1-k}. \tag{22}$$

Then using the formula $\sum_{x=0}^{X} a^x = \frac{1-a^{X+1}}{1-a}$ and rearranging terms,

$$\begin{aligned}
\Psi_{\Delta e}(j) &= -\rho^j - \frac{b_e}{\beta^S}\sum_{k=0}^{j-1} b_w^k \rho^{j-1-k} \\
&= -\rho^j - \rho^j \frac{b_e}{\rho\beta^S}\sum_{k=0}^{j-1}\left(\frac{b_w}{\rho}\right)^k \\
&= -\rho^j - \rho^j \frac{b_e}{\rho\beta^S}\frac{1-\left(\frac{b_w}{\rho}\right)^j}{1-\frac{b_w}{\rho}} \\
&= -\rho^j - \frac{b_e}{\beta^S}\frac{\rho^j - b_w^j}{\rho - b_w}
\end{aligned}$$

which was to be shown. Since $b_e = -b^D \leq 0$, $\beta^S \geq 0$, $b_w \geq 0$, and $\rho \geq 0$, then the employment impulse response is bounded below by the shock, $\Psi_{\Delta e}(j) \geq -\rho^j$.

If firm mobility is shut down ($b^D = 0$), then employment growth equals the labor demand shock (which follows an AR(1) process); after the shock, employment will continue to decrease monotonically, asymptoting to $-\frac{1}{1-\rho}$ times the initial shock. Otherwise, since for normal parameter values the second term is always nonnegative, employment growth will exceed the labor demand shock. To a large extent, the second term in (21) is dominated by b^D, so that as firm mobility increases, employment recovers more after a negative shock. With non-zero firm movement, employment will no longer decrease monotonically, but will reverse direction and eventually overcome the momentum of the shock, causing an increase in employment beyond its trough level.

The long-run effect of a shock on the employment level can be represented as the series of employment log changes. We use the symbol $\Psi_e(\infty) = \lim_{j\to\infty} \sum_{j'=0}^{j} \Psi_{\Delta e}(j')$ to represent log long-run employment. This quantity is given by

$$\Psi_e(\infty) = -\frac{1}{1-\rho}\pi^S$$

where $\pi^S = \frac{b^S}{b^S+b^D}$ is the proportion of total mobility that is due to workers.

To show this, note that wages are AR(1), given by 8. Then we may write wages as a linear combination of errors, which are given by the above equation 19, we get equation 20 (reproduced here):

$$\Psi_w(j) = \frac{1}{\beta^S}\sum_{k=0}^{j} b_w^k \rho^{j-k}.$$

Taking sums and limits and using definitions $b_w = 1 - \frac{b^S+b^D}{\beta^S}$ and $b_e = -b^D$, algebra can be used to derive long-run employment,

$$\begin{aligned}
\lim_{J\to\infty}\sum_{j=0}^{J}\Psi_{\Delta e}(j) &= \lim_{J\to\infty}\sum_{j=0}^{J}\left[-\rho^j - \frac{b_e}{\beta^S}\sum_{j=0}^{J}\frac{\rho^j - b_w^j}{\rho - b_w}\right] \\
&= -\frac{1}{1-\rho} - \frac{b_e}{\beta^S}\lim_{J\to\infty}\sum_{j=0}^{J}\frac{\rho^j - b_w^j}{\rho - b_w} \\
&= -\frac{1}{1-\rho} - \frac{b_e}{\beta^S(\rho - b_w)}\left(\frac{1}{1-\rho} - \frac{1}{1-b_w}\right) \\
&= -\frac{1}{1-\rho} - \frac{b_e}{\beta^S}\left(\frac{1}{(1-\rho)(1-b_w)}\right) \\
&= -\frac{1}{1-\rho} - \frac{b_e}{\beta^S}\left(\frac{\beta^S}{(1-\rho)(b^S+b^D)}\right) \\
&= -\frac{1}{1-\rho} - \frac{b_e}{(1-\rho)(b^S+b^D)} \\
&= -\frac{1}{1-\rho}\left(-1 + \frac{b^D}{b^S+b^D}\right) \\
&= -\frac{1}{1-\rho}\frac{b^S}{b^S+b^D}
\end{aligned}$$

which was to be shown.

This equation shows that $\Psi_e(\infty) \to -\pi^S$ as $\rho \to 0$, and $\Psi_e(\infty) \leq -\pi^S$. Thus, the negative of $\Psi_e(\infty)$ serves as an upper bound for the proportion of mobility due to workers. A better bound can be obtained for $\rho \neq 0$. For ease of notation, we index Ψ by ρ and π^S, writing $\Psi_e\left(j|\rho,\pi^S\right)$. It is easily established from the above relationships that $\Psi_e\left(j|\rho,\pi^S\right) > \Psi_e(j|\rho,1)\ \forall j \in \{1,2,...\}$. Then $\inf_j \Psi_e\left(j|\rho,\pi^S\right) \geq \inf_j \Psi_e(j|\rho,1) \geq -\frac{1}{1-\rho}$. Thus, $\pi^S \leq \Psi_e\left(\infty|\rho,\pi^S\right)/\inf_j \Psi\left(j|\rho,\pi^S\right)$. This is the ratio of the long-run effect of a labor demand shock on employment divided by the magnitude of the dip that is induced by the shock. Such a ratio provides a tighter upper bound for the proportion of mobility due to workers, π^S, than just $\Psi_e\left(\infty|\rho,\pi^S\right)$ when ρ is different from 0 and π^S is different from 1.

A.3 Tables

Proportion of labor supply variation by common and idiosyncratic shocks

	shock	employment growth	unemployment	participation
common	0.241	0.208	0.322	0.168
idiosyncratic	0.759	0.792	0.678	0.832

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