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LABOR REALLOCATION: PANEL EVIDENCE FROM U.S. STATES

Labor Reallocation: Panel Evidence from U.S. States [⋆]

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Abstract

This paper re-examines Lilien's sectoral shifts hypothesis for U.S. unemployment. We employ a monthly panel that spans from 1990:01 to 2011:12 for 48 U.S. states. Panel unit root tests that allow for cross-sectional dependence reveal the stationarity of unemployment. Within a framework that takes into account dynamics, parameter heterogeneity and cross-sectional dependence in the panel, we show that sectoral reallocation is significant not only at the aggregate level but also at the state level. The magnitude and the statistical significance of the latter as measured by Lilien's index increases when both heterogeneity and cross-sectional dependence are taken into account.

Keywords: *Unemployment · Sectoral Shifts · Employment Fluctuations · Dynamic Panel Data · Parameter Heterogeneity · Cross-Sectional Dependence.*

JEL Classification: *C33 · E24 · E32 · J21 · R23*

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1 Introduction

The analysis of the macroeconomic effects of labor reallocation has been developed along several dimensions. Earlier analysis have focused on one-dimensional characteristics: sector, plant, dimension, labor turnover, region, real wage, exchange rate and money supply among others, while subsequent work has deepened their analytical frameworks by embodying concurrent disaggregations along multiple dimensions.[1] This study follows the latter and, by bringing together the sectoral and regional dimensions, follows the path set by the pioneering efforts of Medoff (1984) and Neumann and Topel (1991). In this work, we explore the impact of a purged measure of labor reallocation on unemployment using an extensive panel data for the United States.

The novel aspects of this article are linked to recent developments in panel data econometrics concerning dynamics, heterogeneity and cross-sectional dependence which, to the best of our knowledge, have never been applied before in this area of research and certainly not in the context of our model. First, we extend the fixed effects approach, by using the Driscoll and Kraay's (1998) estimator. Second, in order to obtain consistent estimates in a dynamic panel with substantial heterogeneity across regions, we use both the Pesaran and Smith's (1995) Mean Group Estimators (MG) and Pesaran *et al.*'s (1999) Pooled Mean Group estimator (PMG). Third, since estimators assuming cross-sectional independence across regions could be inefficient, we extend the previous heterogeneous slopes estimation procedure by implement the Common Correlated Effects (CCE) estimator, its pooled-CCE (CCEP) and mean group-CCE (CCEMG) extensions proposed by Pesaran (2006), as well as the recently developed Augmented Mean Group (AMG) estimator by Bond and Eberhardt (2009) and Eberhardt and Teal (2010) that accounts for cross-sectional dependence by means of a 'common dynamic process'. Finally, we have generated one of the richest dataset for such a macroeconometric experiment given that previous studies have suffered from limited degrees of freedom.

The remainder of the paper is organized as follows. Section 2 provides a short review of the essential literature background. Section 3 discusses the econometric model and estimation methodology. Section 4 presents the data and provides a preliminary data analysis. Section 5 reports the empirical results. Finally, in Section 6, concluding remarks are provided.

2 Literature Background

Medoff (1984) is the pioneering work on the effects of the sectoral shifts hypothesis (SSH) on unemployment at a regional level following the seminal paper of Lilien (1982). The former study sheds light upon the differences in labor market imbalance in the North-East-Atlantic U.S. states and South-West-Pacific U.S. states. Using a battery of alternative definitions of the Beveridge curve and of reduced form equations, Medoff could relate the outward shift of the U.S. Beveridge curve(s) between the pre- and post-1973 periods and the variable labor conditions across areas in the same period. The emerging evidence in favor of labor market imbalance across time and regions corroborates the possibility that much of that period unemployment was structural. The analytical framework of the paper reflects the state of the art at the time of its writing and has been inevitably superseded by subsequent developments.

Neumann and Topel (1991) brings the analysis in the modern era. Their paper studies the determinants of geographic unemployment differentials in the United States for the period 1948-1981. Neumann and Topel examine an 'islands model' featuring independent labor markets characterized by specific industries and labor force. They wish to test whether demand uncertainty and diversification are important determinants of equilibrium unemployment differentials among labor markets. Using pooled time-series-cross-section regional data they propose unemployment as a function of a period effect component common to all markets and three regressors: an estimate of the covariance structure of local labor demands, an index of local sensitivity to industry specific oscillations and a market-specific index of structural change in the sectoral distribution of employment. Neumann and Topel strategy is to construct a measure of sectoral shocks which can be separated in permanent (related to labor reallocation) and transitory (associated with local cycles and other random events) changes in the sectoral composition of demand. They run alternative specifications of their basic model pooled across states and over time for the selected period using fixed effects estimators as dictated by the prevailing state of the art. The emerging outcomes bear out that demand uncertainty and diversification are important determinants of equilibrium unemployment regional differentials and that regional differences in unemployment are quite large, and remarkably persistent over time. A third result is that permanent sectoral demand shifts are significant determinants of unemployment but their impact is modest relative to typical cyclic fluctuations in unemployment. Thus the regional analysis of Neumann and Topel (1991), contrary to Medoff (1984), cannot corroborate the relevance of sectoral shifts.

Two factors may affect negatively their analysis. First, their dispersion index may belittle the role of allocative shocks (Shaw, 1989). Second, as they use fixed effect estimators their outcomes could be subject to significant potential bias. Subsequent sectoral shifts analyses using panel data techniques have mostly focused on the sectoral and not the regional dimension and have employed fixed effects estimators (Shaw, 1989; Keane, 1991; Keane and Prasad, 1996; De Serres *et al.*, 2002).[2]

In the light of the more recent developments in panel data econometrics (dynamics, heterogeneity, cross-sectional dependence) it appears that these previous results need to be extended and revised. As we have stressed above, all of the existing contributions have not or could not properly handle panels which are long and wide and as a consequence could not take into account the potential interdependence of the individual units. It is the purpose of this paper to remedy this state of the art by looking at both a more complete dataset on the one hand and expliciting accounting for cross-sectional dependence on the other.

3 Econometric Model and Methodology

Using pooled time-series-cross-section data on state unemployment and employment for the United States, we estimate Lilien's dynamic reduced equation of the form:

$$U_{i,t} = \mu_i + \phi_i U_{i,t-1} + \beta_i \sigma_{i,t} + \sum_{j=1}^{p} \lambda_{ij} z_t + \varepsilon_{i,t}, \tag{1}$$

where $U_{i,t}$ is the unemployment rate for state i at time t; $\sigma_{i,t}$ is a measure of employment cross-sectoral dispersion; the vector z_t represents a vector of control variables that capture aggregate demand shocks, common to all states, which in our specification includes the measures of expected, $\Delta Log(M_t)$, and unexpected, H_t, money growth.[3] Finally, μ_i stands for a set of state-specific fixed effects capturing the influence of unobserved state-specific heterogeneity and $\varepsilon_{i,t}$ is the error term.

Following Lilien (1982), the dispersion proxy for state i at time t is calculated as the weighted standard deviation of the cross-sectoral employment growth rates using a K-sectors decomposition for each state i as follows:

$$\sigma_{i,t} = \left[\sum_{j=1}^{N} w_{j,t} (\Delta \ln n_{j,t} - \Delta \ln N_t)^2 \right]^{1/2}, \tag{2}$$

where $n_{j,t}$ is employment in sector j at time t, $N_t = \sum_{j=1}^{N} n_{j,t}$ is aggregate employment at time t for state i, K is the number of sectors (with $j = 1, 2, \ldots, K$ sectors) in the state i and $w_{j,t} = \frac{n_{j,t}}{N_t}$ are weights defined as the relative size of each sector j.

Because of the problem of 'observation equivalence' embedded in the Lilien's $\sigma_{i,t}$ measure (Lilien, 1982; Abraham and Katz, 1986; for a full discussion of the issue see Gallipoli and Pelloni, 2008), we filter out aggregate effects from the dispersion proxy ($\sigma_{i,t}$) by decomposing it into an idiosyncratic component and a component measuring the response to aggregate shock. To obtain the 'purged' measure, we have regressed $\sigma_{i,t}$ on the vector of aggregate variables $\tilde{z}_t$:[4]

$$\sigma_{i,t} = \alpha_i + \sum_{j=1}^{q} \varphi_j \tilde{z}_{t-j} + u_{i,t}. \tag{3}$$

The estimated residual $\widehat{u}_{i,t}$ from Equation 3 stands as the 'purged' component of $\sigma_{i,t}$. This 'purged' dispersion index, measuring only the reallocation shocks, is then used in the reduced form unemployment Equation 1.

We have included expected and unexpected money growth to capture the potential money surprises of segmented markets models (Lucas, 1990; Fuerst, 1992).[5] In our analysis, the measure of unanticipated money growth has been generated by estimating a GARCH (1,1) model for $\Delta Log(M_t)$ and interpreting the estimated conditional variance as a parametric proxy of unanticipated money growth.[6]

In order to analyze the effect of sectoral shifts using panel regressions for the U.S. states we need to consider the issues of dynamics, heterogeneity and cross-sectional dependence that emerges from the specification form of Equation 1.

The standard empirical macroeconometric literature suggests using traditional pooled estimators adopted from the microeconometric literature, such as the least square dummy variable estimator allowing for individual fixed effects. The fixed effects (FE) model allows the intercepts to be differ across regions, while all other coefficients forced to be identical, and can be estimated by OLS method using a simple transformation (within estimator). We extend the fixed effects estimator, by using the Driscoll and Kraay's (1998) extension of nonparametric variance-covariance matrix estimation, which produces heteroskedasticity and autocorrelation consistent standard errors that are robust to the presence of general forms of spatial and cross-sectional dependence. The presence of a lagged dependent variable among the regressors ($U_{i,t-1}$) results to a biased OLS fixed effects estimator (Nickell, 1981). Therefore, several suggestions have proposed in the literature. Kiviet (1995) proposes a bias corrected fixed effects estimator, while Arellano and Bond (1991) propose a Generalized Method of Moments (GMM) estimation procedure to deal with the issue of lagged dependent variable. Specifically, the difference GMM estimator (AB-GMM) of Arellano and Bond (1991) firstly transforms the model by first differencing to eliminate the individual effects and then uses the GMM framework of Hansen (1982). Following the work of Arellano and Bover (1995), Blundell and Bond (1998) propose an extended system estimator that applies additional moment conditions, the system GMM estimator (BB-GMM).

The previous standard pooled estimators assumes slopes homogeneity across regions, and according to the work of Pesaran and Smith (1995), these estimators yield inconsistent estimates in the case of a dynamic panel data model when the slope coefficients differ across regions. Given the existing differences in labor market across the U.S. states, the homogeneity assumption is quite restrictive, and therefore the usage of pooled estimation methods may lead to substantially heterogeneity bias in the estimated parameters of Lilien's panel version of Equation 1.

One way to obtain consistent estimates in dynamic panels with considerable heterogeneity across regions is to use estimators that allows for considerable slope heterogeneity across regions. In fact, Pesaran and Smith (1995) propose the Mean Group Estimators (MG) that consists of estimating separate OLS regressions for each region and then calculating averages of the specific coefficients over groups. Furthermore, Pesaran *et al.* (1999) suggest an intermediate estimator that imposes long-run slope homogeneity between regions but allows for short-run parameters heterogeneity. The pooled mean group (PMG) estimator involves both pooling and averaging of the individual regression coefficients in order to obtain more efficient estimates that the MG estimators under the assumption of slopes homogeneity.

Another important issue, that evolve in the regional panel sectoral shifts analysis of unemployment, is the issue of cross-sectional dependence among states. Interdependence across cross sections is a considerable characteristic in the analysis of macro and regional panel data models, and estimators based on the assumption of cross-sectional independence may prove inefficient (Sarafidis and Wansbeek, 2012). Therefore, we extend the heterogeneous slopes estimation procedure by implementing the Pesaran (2006) Common Correlated Effects (CCE) estimators that account for the presence of unobserved common factors by using cross-section averages of the dependent and independent variables as additional regressors. Moreover, it has been shown that the CCE estimator still provides consistent estimates of the slope coefficients and their SEs under the more general case of multifactor error structure and spatial error correlation (Pesaran and Tosetti, 2011). Specifically, we consider the mean group CCE (CCEMG) extension of the estimator proposed in Pesaran and Smith (1995) as well as the pooled CCE (CCEP) version that assumes slopes homogeneity while it allows for different common effects coefficients across i.[7] Finally, we implement the recently Augmented Mean Group (AMG) estimator proposed by Bond and Eberhardt (2009) and Eberhardt and Teal (2010) that accounts for cross-sectional dependence by means of a 'common dynamic process' in the regional regressions.[8]

We, therefore, continue our analysis by estimating the Lilien's dynamic reduced form unemployment relationship for the U.S. states panel, taking into account the issues of dynamics, heterogeneity, nonstationarity and cross-sectional dependence, by using alternative estimation approaches for homogeneous and heterogeneous panel data.

3.1 Poolability Tests

An important issue for the estimation of panel data models is the assumption of common slope coefficients across regions and/or over time, i.e. that $\beta_i = \beta$ with $i = 1, 2, \ldots, N$ and/or $\beta_t = \beta$ with $t = 1, 2, \ldots, T$. Following Baltagi (2008), this can be tested by a Chow test, see Chow (1960), that is extended to the case of N and/or T linear regressions. The test for the poolability of the data across regions (time) simply compares the restricted residual sum of squares (RSS^r) of the fixed effects model with the unrestricted residual sum of squares (RSS^u) obtained by the region-specific (time-specific) OLS regressions. Under the null hypothesis of poolability across regions the F-statistic can be defined as:

$$F = \frac{RSS_i^r - RSS_i^u/(N-1)K}{RSS_i^u/N(T-K)} \sim F((N-1)K, N(T-K)), \tag{4}$$

and under the null hypothesis of poolability over time we have:

$$F = \frac{RSS_t^r - RSS_t^u/(T-1)K}{RSS_t^u/T(N-K)} \sim F((T-1)K, T(N-K)). \tag{5}$$

3.2 Cross-Sectional Dependence Test

In order to determine the existence of cross-sectional dependence among states, we employ the simple test suggested by Pesaran (2004). The Cross-Section Dependence test statistic is based on the average of pair-wise correlation coefficients ($\hat{\rho}_{ij}$) of the OLS residuals, obtained from the individual ADF regressions. The CDS test is given by:

$$CDS = \sqrt{\frac{2T}{N(N-1)}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)}. \tag{6}$$

The CDS statistic under the null of cross-independence is distributed as a two-tailed standard normal distribution, i.e. $CD \sim N(0,1)$ for $T_{ij} > 3$ and sufficient large N. Baltagi *et al.* (2007) provide evidence that the CDS test can be also employed as a useful diagnostic test for various models of spatial dependence.

3.3 Panel Unit Root Tests

Prior to the estimation of the panel data analysis, we need to check for the order of integration of the series under consideration. In this way, we use the IPS panel unit root test of Im *et al.* (2003) as well as the CIPS panel test of Pesaran (2007) that takes into account cross sectional dependence among panel members.

3.3.1 Panel Unit Root Tests without Cross Sectional Dependence

The independent panel test is an extension of the univariate ADF regression as follows:

$$\Delta y_{i,t} = \alpha_i + \phi_i y_{i,t-1} + \sum_{j=1}^{p_i}\theta_{i,j}\Delta y_{i,t-j} + \varepsilon_{i,t}, \tag{7}$$

where $y_{i,t}$ stands for each series under consideration for state i at time t. The null hypothesis is that all series contains a unit root, $\phi_i = 0$ for all i (with $i = 1, 2, \ldots, N$), while the alternative hypothesis assumes that some of the N panel units are stationary with individual specific autoregressive coefficients.

Im *et al.* (2003) propose a test based on the average of the ADF statistics computed for each individual in the panel. Specifically, the IPS statistic is defined as:

$$\bar{t}_{N,T} = \frac{1}{N}\sum_{i=1}^{N} t_{iT}(p_i, \theta_i). \tag{8}$$

Under the assumption of cross-sectional independence, this statistic is shown to converge to a normal distribution.

3.3.2 Panel Unit Root Tests with Cross Sectional Dependence

The IPS test that is based on the restrictive assumption that the series are independent across states i, suffers from serious size distortion and restricted power in the presence of cross-sectional dependence (O'Connell, 1998) and cross-sectional cointegrating relationships (Banerjee *et al.*, 2004). In order to overcome this, Pesaran (2007) proposes a simple approach to deal with the problem of cross-sectional dependence. A one-factor model is considered with heterogeneous factor loadings for residuals and suggests to augment the standard ADF regression with the cross-section averages of lagged levels and first-differences of the individual series. The regression used for the i^{th} cross-section unit is defined as:

$$\Delta y_{i,t} = \alpha_i + \phi_i y_{i,t-1} + c_i \bar{y}_{t-1} + \sum_{j=0}^{p_i} \theta_{i,j} \Delta \bar{y}_{t-j} + \sum_{j=1}^{p_i} \theta_{i,j} \Delta y_{i,t-j} + \varepsilon_{i,t}, \tag{9}$$

where $\bar{y}_{t-1} = N^{-1}\sum_{i=1}^{N} y_{i,t-1}$ and $\Delta \bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{i,t} = \bar{y}_t - \bar{y}_{t-1}$. The CIPS test is based on the average of individual cross-sectionally augmented ADF statistics (CADF) as follows:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} t_i(N, T). \tag{10}$$

Simulated critical values of CIPS are listed in Pesaran (2007). Baltagi *et al.* (2007) show that the CIPS test is found to be robust to the presence of other sources of cross-sectional dependence such as the spatial form.

4 Data and Preliminary Analysis

4.1 Data

The empirical analysis has been carried out using monthly data over the period 1990:M1–2011:M12 for the 48 contiguous U.S. states.[9] Table 1 presents the abbreviations of the U.S. states used in our analysis. The employment and unemployment states series were obtained from the U.S. Bureau of Labor Statistics (BLS).

The measure of sectoral shifts is computed per state using the employment shares of the available industrial decomposition of monthly non-agricultural employment consisting of the following sectors: I) Goods providing: (1) Mining - Logging - Construction, (2) Manufacturing (with a further disaggregation on (2.1) Durable and (2.2) Non-Durable goods), (3) Trade - Transportations (with a further disaggregation on (3.1) Wholesale trade, (3.2) Retail trade and (3.3) Transportations), II) Services providing: (4) Information, (5) Financial activities, (6) Professional activities, (7) Education - Health, (8) Leisure - Hospitality, (9) Other services and (10) Government sector for the U.S. states. Using this 10-industry decomposition, we compute our benchmark measure $\sigma^9_{i,t}$ using information on the 9 super-sectors of the economy (excluding the government sector) as well as the $\sigma^{13}_{i,t}$, a 13 sectoral decomposition measure of labor reallocation using all the available disaggregation in our dataset. Finally, for robustness purposes and by following the work of Pelloni and Polasek (2003), the measure of sectoral shifts is computed using the employment shares of the construction, finance, manufacturing, and trade sectors for the 48 U.S. states ($\sigma^4_{i,t}$). Panel (A) of Table 2 presents pooled descriptive statistics for the sectoral employment data.

For the purposes of our econometric analysis, we use the logarithm form of the unemployment rate, $U_{i,t} = ln(u_{i,t})$, as well as the logistic transformation, $U_{i,t} = ln(u_{i,t}/(1-u_{i,t}))$ where $u_{i,t}$ is the unemployment rate, following the suggestion by Wallis (1987) to employ the logistic transformation of the unemployment rate, a variable bounded between 0 and 1. The monetary variable, M1, is taken from the FRED database and transformed into logarithmic first-differences ($\Delta Log(M_t)$). An estimated conditional variance (H_t) of a GARCH (1,1) model for $\Delta Log(M_t)$ is used as a measure of unanticipated money growth. Panel (B) of Table 2 presents pooled descriptive statistics for the unemployment series, the sectoral shifts measures and the aggregate monetary variables used in our regression analysis.[10]

4.2 Preliminary Data Analysis

The preliminary part of our analysis includes at looking at the Lilien's proxy for dispersion per state. Table 3 presents Lilien's index in 1990, 2000 and 2011. Looking first at the average, it looks lie that among the four largest U.S. states (population wise) (CA, TX, NY and FL), FL has the highest average through the two decade period (0.0039) followed by CA, NY and TX. A more clear picture is emerging from Table 4 that presents the regional employment structure per U.S. state where we can compare 1990 with 2011. One of the most important characteristics of these two decades was the decline of traditional sectors such as manufacturing. It is evident from Table 4 that this is the case. We focus again on the four largest states. In 1990, manufacturing did represent 15.70% of employment in CA, 13.30% in TX, 12% in NY and 9.46% in FL. Twenty one years later the numbers are: 8.9% (CA), 7.9% (TX), 5.3% (NY), 4.28% (FL). This significant decline was accompanied by an increase in new, more dynamic sectors on the services side of the economy.

5 Empirical Results

We begin our analysis by conducting panel unit root tests to determine the level of integration of our series. Specifically, we employ one first generation (the **IPS** test of Im *et al.* (2003)) and one second generation (the **CIPS** test of Pesaran (2007) that accounts for cross-sectional dependence) panel unit root tests for our panel variables ($U_{i,t}$ and $\sigma_{i,t}$). The results, reported in Table 5, shows that both tests clearly indicates that the unemployment series and the sectoral shifts index are stationary variables.[11]

The issue of cross-sectional dependence is examined by applying the CDS test (Table 6). The null hypothesis of no cross-sectional correlation among the U.S. states panel is strongly rejected at the 5%

level of significance, indicating that the hypothesis of cross sectional independence in our dataset is clearly violated and thus we need to account for cross sectional dependence across the U.S. states.

Furthermore, the assumption of common slope parameters in our states panel estimation can be tested by a Chow test. From Table 7, the poolability tests strongly reject the hypothesis of common slopes. It indicates that heterogeneity among states is considerable.

We therefore continue our analysis by estimating a panel version of Lilien's dynamic reduced form unemployment relationship for the U.S. states, taking into account the issues of dynamics, heterogeneity and cross-sectional dependence, by using alternative estimation approaches for homogeneous and heterogeneous panel data. Table 8 provides an overview of the estimators used in our analysis classified by the assumptions over cross sectional dependence and parameter heterogeneity.

The results highlight the statistical significance of the lagged value of unemployment. This sluggishness is well documented in the literature. Moreover, it is also clear that all the different dispersion indices are affecting unemployment in a positive and statistically significant way.

Before we proceed with the panel estimates, we report the results for the Lilien's dynamic reduced form unemployment relationship at the aggregate level in U.S. over the period 1990:M1–2011:M12 (Table 9). Clearly, in all different specifications of the estimated equation, using alternative transformation of the unemployment series (logistic and logarithmic transformation), alternative disaggregation levels (σ_t^9 and σ_t^{13}), standard as well as the 'purged' dispersion index and different methods of methodology (OLS and GMM), we observe a positive and significant relationship between unemployment rate and the measures of dispersion. These results reaffirm Lilien's hypothesis for positive effect of labor reallocation on unemployment in recent years using aggregate data for U.S.

Having established a significant positive evidence on aggregate level, we proceed to examine the regional dimension of the sectoral reallocation for the 48 U.S. states using panel estimates of the dynamic reduced form Equation 1. Table 10 presents the initial panel estimates of the effects of Lilien's sigma index on the unemployment rate in the U.S. states. In all specifications we observe significant positive effects of the measures of anticipated and unanticipated aggregate demand shocks, with a larger impact based on that of the unanticipated shock (H_t). All alternative estimations methods yield a positive and significant effect of the dispersion index on unemployment.[12]

In order to produce results that clearly distinguish the aggregate effects from the dispersion proxy, we proceed to estimate the dynamic reduced form Equation 1 using the 'purged' dispersion index in our analysis (Abraham and Katz, 1986). As expected, the lagged level of unemployment is highly significant across all estimators. Similarly to the previous results, we observe in Table 11, that the effect of the 'purged' dispersion index on unemployment rate over the 48 U.S. states is positive and significant and with similar magnitude to the one of the regular Lilien index. The sigma ($\sigma_{i,t}$) coefficient ranges from 0.435 (0.404) in the logistic transformation (logarithmic transformation) using the heterogeneous common correlated effects mean group (CCEMG) estimator of Pesaran (2006) that accounts for cross sectional dependence to 1.055 (0.982) in the pooled mean group (PMG) estimator of Pesaran *et al.* (1999) that imposes slope homogeneity and assumes cross sectional independence.

For robustness purposes, in Table 11, we also report the results for a variety of alternative estimators, from the homogeneous and cross sectional independent pooled OLS estimator (column 1[11]), the

Fixed Effect counterpart of the pooled OLS as well as the cross-sectional dependence corrected Fixed Effect estimator of Driscoll and Kraay (1998) (column 2[12] and 3[13]), the dynamic GMM estimators of Arellano and Bond (1991) and Blundell and Bond (1998) (columns 4[14] and 5[15]), to the heterogeneous estimators of Pesaran and Smith (1995) (column 7[17]) and the recently Augmented Mean Group (AMG) estimator (column 10[20]).[13] We can see that in all the alternative empirical estimators, independent from the assumptions we take into account, clear evidence emerges in favour of a positive and significant effect of the dispersion index on unemployment.

Having established a robust positive relationship of the dispersion index on unemployment rate and taking into account the verification of cross sectional dependence and parameter heterogeneity in the U.S. states panel, we turn our analysis to the impact of different levels of disaggregation of the dispersion index on the unemployment rate using the common correlated effects mean group (CCEMG) estimator of Pesaran (2006). To facilitate the comparison, we implement a homogeneous counterpart, the Driscoll and Kraay's (1998) Fixed Effects estimator. From Table 12, we can clearly notice a robust positive relationship between unemployment and the alternative measures of dispersion.

But how could the first generation estimates would compare with the ones proposed more recently that take into account the dynamics, heterogeneity and cross-sectional dependence. Looking more carefully on Table 10 we are able to compare the effect of the dispersion index on unemployment both under POLS and FE (first generation estimates) and the AMG estimator. It is clear that the former underestimates both in economic terms (0.63 and 0.846 compared to 0.902) but more importantly statistically (*t-stat* 2.4 and 2.71 in the first two compared to 5.75 for the latter). That is, that in terms of statistical significance, the AMG estimator that takes into account both heterogeneity and cross-sectional dependence produces a coefficient with a *t-stat* at least twice as large. The latter holds in the case where the logarithmic transformation is also considered as the dependent variable.[14]

Furthermore, we focus on the effectiveness of the dispersion index on unemployment, and we find that the impact of dispersion index depends on the level of disaggregation and specifically the less disaggregated sigma ($\sigma_{i,t}$) the more significant it appears to be (higher t-stat in the case with 4 sectors, see Table 12). This is of interest since the fourth and the ninth sector decomposition indices do not appear to be that different in Table 2.

To a sum up, the results highlight the positive and significant impact of the dispersion index on unemployment and clearly reconfirms the evidence of Lilien (1982), using recent panel data estimation techniques that accounts for dynamics, heterogeneity and cross-sectional dependence. The estimators that take account these characteristics, provide larger and more significant coefficients.

6 Conclusions

In this article, we have studied the unemployment effects of labor reallocation within U.S. states. To do this, we have extended previous analysis in this field in two dimensions. First we employ a rich monthly dataset that spans for more than two decades for 48 U.S. states. Thus we can overcome the limited data sets constraint of several past aggregate time series approaches. Second, for the first time for this specific research topic, we introduce recent panel data estimation techniques that can account for the dynamics, heterogeneity and cross-sectional dependence. These issues which are endemic to the problem and have not been addressed previously.

Labor reallocation has been captured by a ‘purged’ Lilien’s dispersion index (Lilien, 1982) which was calculated for different disaggregation levels to examine how sensitive the outcome is. Empirical evidence bears out the presence of cross-sectional dependence as well as heterogeneity among states which should then be taken into account explicitly. The empirical findings provide strong support to a positive and significant relationship between unemployment and the alternative measures of dispersion. This outcome is robust to alternative specifications and assumptions. The results show that recently proposed estimators show that the effect of labor reallocations on unemployment was underestimated.

Notes

1. For an extensive survey see Gallipoli and Pelloni (2008).
2. In the wake of Long and Plosser (1987) and Blanchard and Katz (1992) much attention in this field has been paid to multivariate settings such as the VAR of Campbell and Kuttner (1996) or VAR-GARCH-M of Pelloni and Polasek (1999; 2003) or the semiparametric spatial auto-regressive set up of Basile *et al.* (2012).
3. We do not include period fixed effects, γ_t, since vector z_t controls for period effect that are common to all regions.
4. There is wide variation across papers in the choice of variables included in $\tilde{z}_t$. Here, the vector of aggregate variables $\tilde{z}_t$ is exactly the same as the vector z_t. For a full discussion of the issue see Gallipoli and Pelloni (2008).
5. In older days this decomposition would have been introduced to capture the money surprises of Lucas misperception model (Lucas, 1972; 1973).
6. Caporale *et al.* (1996) follow a similar approach.
7. Chudik and Pesaran (2013) provide evidence on the estimation of heterogeneous panel data models with lagged dependent variable and show that the CCEMG estimator continues to be valid asymptotically when dealing with dynamics.
8. Bond and Eberhardt (2009) provide evidence that both the CCEMG estimators and the AMG approach perform very well and with similar results in recent Monte Carlo studies.
9. We exclude from our analysis the no-adjoining states of Alaska and Hawaii.
10. All sectoral series were seasonally adjusted using Eviews Census X12 program.
11. We also employ univariate ADF unit root tests for the aggregate demand shocks control variables (common to all states), $\Delta Log(M_t)$ and H_t which are found to be stationary.
12. With the exception of that of the CCEP estimations which yield positive but not significant in the conventional level results.
13. The numbers in the square brackets are the version of the estimations that uses the logarithmic transformation of the unemployment series.
14. The AMG estimator is preferred to the CCEMG one given that the CCE approach requires the incorporation of cross-section averages for all variables in the model as additional regressors and thus suffers from limited degrees of freedom than the AMG procedure.

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Tables and Figures

Part A: Descriptive Statistics

Table 1: U.S. States and Abbreviations

State	Abbrev.	State	Abbrev.
Alabama	AL	Nebraska	NE
Arizona	AZ	Nevada	NV
Arkansas	AR	New Hampshire	NH
California	CA	New Jersey	NJ
Colorado	CO	New Mexico	NM
Connecticut	CT	New York	NY
Delaware	DE	North Carolina	NC
Florida	FL	North Dakota	ND
Georgia	GA	Ohio	OH
Idaho	ID	Oklahoma	OK
Illinois	IL	Oregon	OR
Indiana	IN	Pennsylvania	PA
Iowa	IA	Rhode Island	RI
Kansas	KS	South Carolina	SC
Kentucky	KY	South Dakota	SD
Louisiana	LA	Tennessee	TN
Maine	ME	Texas	TX
Maryland	MD	Utah	UT
Massachusetts	MA	Vermont	VT
Michigan	MI	Virginia	VA
Minnesota	MN	Washington	WA
Mississippi	MS	West Virginia	WV
Missouri	MO	Wisconsin	WI
Montana	MT	Wyoming	WY
$N = 48$			
$T = 264$ *(1990m01 – 2011m12)*			
Obs $= 12672$			

Table 2: Summary Statistics

	Mean	Std. Dev.	Maximum	Minimum	Skewness	Kurtosis	Jarque-Bera	Prob
PANEL (A): Sectoral Variables								
*Sectoral Employment Shares**								
Total	7.410	0.977	9.632	5.274	-0.092	2.348	242.085	0.000
Mining - Logging - Construction	4.521	0.930	6.884	2.484	-0.071	2.664	70.346	0.000
Manufacturing	5.240	1.153	7.593	2.153	-0.499	2.655	589.474	0.000
Trade - Transportations	5.794	0.971	7.986	3.706	-0.089	2.335	250.428	0.000
Information	3.534	1.098	6.395	1.237	0.066	2.422	185.847	0.000
Financial activities	4.531	1.046	6.841	2.056	-0.069	2.503	140.343	0.000
Professional activities	5.121	1.156	7.728	2.138	-0.227	2.524	228.895	0.000
Education - Health	5.299	1.006	7.526	2.528	-0.044	2.504	133.786	0.000
Leisure - Hospitality	5.048	0.946	7.367	3.136	-0.004	2.365	212.668	0.000
Other services	4.149	0.999	6.248	1.874	-0.098	2.218	342.756	0.000
Government	5.646	0.922	7.836	3.741	-0.069	2.465	161.372	0.000
PANEL (B): Macro Variables								
$U_{i,t}^{Logistic}$	-2.890	0.346	-1.799	-3.842	0.218	2.952	101.900	0.000
$U_{i,t}^{Logarithmic}$	-2.948	0.327	-1.952	-3.863	0.162	2.903	60.216	0.000
$\sigma_{i,t}^{13}$	0.006	0.004	0.085	0.001	5.492	69.419	2.38E+06	0.000
$\sigma_{i,t}^{9}$	0.005	0.003	0.044	0.000	3.328	26.559	3.15E+05	0.000
$\sigma_{i,t}^{4}$	0.003	0.002	0.043	0.000	4.326	43.993	9.23E+05	0.000
$\sigma_{i,t}^{9\ purged}$	-7.29E-19	0.003	0.039	-0.005	3.388	27.301	3.34E+05	0.000
$\Delta Log(M_t)$	0.004	0.009	0.060	0.003	1.938	13.821	1447.777	0.000
H_t	1.18E-04	0.000	0.003	0.000	6.127	47.751	2.35E+04	0.000

Notes: * indicates variables in logarithms.

Table 3: Lilien Index ($\sigma_{i,t}^{9}$)

	AL	AZ	AR	CA	CO	CT	DE	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT
1990	0.0049	0.0055	0.0060	0.0034	0.0041	0.0061	0.0134	0.0044	0.0046	0.0083	0.0040	0.0051	0.0041	0.0060	0.0041	0.0050	0.0094	0.0065	0.0057	0.0060	0.0036	0.0068	0.0049	0.0091
2000	0.0037	0.0045	0.0042	0.0031	0.0037	0.0031	0.0098	0.0043	0.0052	0.0058	0.0030	0.0039	0.0050	0.0051	0.0050	0.0043	0.0091	0.0058	0.0055	0.0045	0.0035	0.0051	0.0046	0.0053
2011	0.0055	0.0047	0.0065	0.0024	0.0045	0.0047	0.0082	0.0032	0.0047	0.0066	0.0027	0.0042	0.0043	0.0060	0.0041	0.0058	0.0059	0.0058	0.0052	0.0053	0.0056	0.0046	0.0046	0.0070
1990-2011	0.0038	0.0047	0.0042	0.0035	0.0040	0.0044	0.0099	0.0039	0.0040	0.0061	0.0035	0.0040	0.0042	0.0050	0.0043	0.0051	0.0056	0.0041	0.0037	0.0049	0.0038	0.0054	0.0042	0.0062
	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
1990	0.0055	0.0075	0.0081	0.0053	0.0053	0.0041	0.0045	0.0054	0.0040	0.0055	0.0059	0.0035	0.0084	0.0055	0.0068	0.0054	0.0036	0.0043	0.0087	0.0046	0.0047	0.0071	0.0035	0.0085
2000	0.0050	0.0062	0.0046	0.0045	0.0047	0.0053	0.0036	0.0062	0.0034	0.0039	0.0034	0.0043	0.0090	0.0046	0.0069	0.0059	0.0023	0.0039	0.0106	0.0052	0.0066	0.0111	0.0034	0.0069
2011	0.0050	0.0054	0.0064	0.0048	0.0072	0.0050	0.0035	0.0072	0.0032	0.0050	0.0041	0.0029	0.0080	0.0042	0.0067	0.0047	0.0029	0.0051	0.0066	0.0040	0.0044	0.0061	0.0051	0.0074
1990-2011	0.0046	0.0062	0.0054	0.0038	0.0056	0.0033	0.0041	0.0061	0.0033	0.0044	0.0039	0.0031	0.0067	0.0045	0.0058	0.0052	0.0027	0.0046	0.0066	0.0037	0.0044	0.0060	0.0036	0.0068

Notes: See Table 1 for U.S. States Abbreviations.

Table 4: U.S. Regional Employment Structure

	AL	AZ	AR	CA	CO	CT	DE	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT
1990 (%)																								
Mining - Log - Constr	6.38	6.53	4.93	5.45	5.29	3.92	6.23	7.73	5.50	6.70	4.59	4.92	3.82	4.80	6.74	9.54	6.05	7.38	3.41	3.93	4.05	5.08	4.31	6.25
Manufacturing	22.20	11.90	23.70	15.70	11.20	18.60	13.20	9.46	17.50	13.60	17.30	24.00	17.90	16.30	18.30	11.10	17.40	9.14	16.10	21.30	16.00	24.50	16.70	6.57
Trade - Transportations	19.40	20.90	21.10	19.40	20.00	19.60	19.40	22.70	22.30	22.20	21.70	21.10	22.00	21.90	20.70	22.40	21.00	20.40	19.10	19.60	21.00	20.00	21.50	23.70
Information	1.83	2.20	1.92	3.14	3.43	2.60	1.44	2.38	2.85	1.97	2.48	1.78	2.44	2.79	1.81	1.69	1.91	2.18	2.93	1.77	2.54	1.39	2.85	2.16
Financial activities	4.90	6.65	4.34	6.55	6.88	9.47	10.60	7.17	5.32	4.98	7.08	5.17	5.67	5.48	4.35	5.47	4.96	6.32	6.73	4.88	6.05	4.40	5.95	4.65
Professional activities	7.20	9.63	6.22	12.00	11.80	10.40	14.50	5.80	9.50	8.50	10.80	6.20	5.63	7.70	6.70	7.30	6.29	11.90	11.50	10.10	10.00	5.48	9.30	5.24
Education - Health	7.90	9.12	9.88	8.97	8.50	12.20	9.50	11.30	8.20	8.40	10.20	9.90	12.00	9.60	11.50	10.30	12.40	10.40	15.40	10.40	11.30	8.00	10.90	11.80
Leisure - Hospitality	6.51	10.70	7.04	8.84	11.00	6.66	8.00	13.20	8.05	9.53	7.45	8.25	8.27	8.03	8.19	8.00	9.00	8.51	7.94	8.38	8.45	6.00	8.80	11.80
Other services	3.74	3.89	3.61	3.34	3.68	3.54	3.39	4.30	3.06	2.99	3.92	3.84	4.53	3.76	4.22	3.65	3.23	4.43	3.26	3.65	4.27	3.36	3.90	3.89
Government	20.00	18.40	17.20	16.60	18.20	13.00	13.80	15.80	17.80	21.10	14.50	14.90	17.90	19.60	17.50	20.50	17.90	19.40	13.70	16.00	16.30	21.70	15.80	24.00
Total (000s)	1635.7	1483.1	923.8	12500.2	1520.8	1619.6	347.5	5373.3	2991.8	385.3	5287.6	2522.0	1226.3	1091.9	1487.2	1587.6	535.1	2173.3	2988.2	3946.6	2135.9	936.5	2345.1	297.2

	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
1990 (%)																								
Mining - Log - Constr	3.98	10.20	4.59	4.16	8.04	4.02	5.59	5.20	4.31	6.68	5.34	4.91	4.13	6.58	4.87	4.61	7.16	5.02	6.05	6.87	6.03	9.87	4.01	14.40
Manufacturing	13.30	3.90	19.40	14.60	6.55	12.00	26.40	5.85	21.70	13.20	16.30	18.40	21.00	22.60	11.60	22.80	13.30	14.30	16.60	13.40	15.70	13.00	22.80	4.60
Trade - Transportations	23.00	17.90	21.50	22.90	20.30	19.10	20.30	24.30	19.70	20.90	21.10	20.20	17.10	19.70	22.30	22.00	22.20	21.20	19.80	19.90	20.20	21.50	20.00	21.00
Information	3.01	1.77	2.07	3.31	1.84	3.48	1.66	2.25	2.07	1.93	2.15	2.11	2.22	1.50	1.90	2.04	2.49	1.85	2.13	2.56	2.31	1.90	1.94	1.85
Financial activities	6.67	5.11	6.49	6.44	4.76	9.49	4.51	4.79	5.22	5.71	5.79	6.28	5.90	4.62	5.92	5.17	6.46	4.81	5.24	4.97	5.28	4.15	5.41	3.99
Professional activities	8.40	9.50	7.20	12.10	9.80	10.50	7.70	4.50	9.30	8.20	8.20	8.80	9.40	8.60	3.86	7.60	9.00	10.30	5.50	12.00	9.20	5.19	6.70	4.47
Education - Health	10.20	5.63	12.10	10.00	8.80	13.10	7.40	13.50	11.10	9.80	10.30	14.30	15.20	6.40	12.80	9.60	9.50	9.30	13.50	8.30	9.60	11.10	10.40	6.50
Leisure - Hospitality	8.19	31.00	8.90	7.42	10.40	6.99	7.70	9.19	8.19	8.02	8.70	7.42	7.90	8.60	10.10	8.10	8.36	8.74	11.20	8.08	8.90	7.59	8.69	12.00
Other services	3.52	2.70	3.48	3.29	3.76	3.39	3.25	4.88	3.64	3.55	3.68	4.06	3.54	3.08	4.82	2.12	3.70	3.53	3.07	4.03	4.18	5.42	5.09	3.37
Government	19.60	12.20	14.30	15.90	25.80	17.90	15.50	25.50	14.80	22.10	18.50	13.60	13.80	18.30	21.90	16.00	17.80	20.80	16.90	20.00	18.60	20.20	15.00	27.80
Total (000s)	730.8	620.9	508.2	3635.5	580.4	8214.6	3125.5	265.8	4882.3	1183.9	1255.6	5173.0	454.1	1541.9	288.5	2196.0	7101.0	723.6	257.7	2894.3	2142.9	630.0	2291.4	198.5

	AL	AZ	AR	CA	CO	CT	DE	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT
2011 (%)																								
Mining - Log - Constr	4.89	5.12	4.98	4.14	6.20	3.19	4.69	4.54	3.98	5.56	3.62	4.49	4.36	4.62	5.04	9.19	4.60	5.74	3.39	3.35	3.64	5.31	4.02	7.22
Manufacturing	12.70	6.20	13.60	8.90	5.70	10.30	6.10	4.28	9.00	9.10	10.10	16.40	14.00	12.00	11.90	7.30	8.50	4.44	7.90	12.90	11.20	12.30	9.30	3.94
Trade - Transportations	19.50	19.60	20.30	18.90	17.80	18.10	18.00	20.60	21.20	20.10	20.10	19.40	20.40	19.00	20.30	19.60	19.80	17.30	17.10	18.30	18.50	19.70	19.30	20.20
Information	1.25	1.52	1.26	3.07	3.17	1.94	1.38	1.85	2.51	1.55	1.77	1.21	1.89	2.08	1.49	1.25	1.38	1.66	2.58	1.36	1.97	1.09	2.20	1.70
Financial activities	4.96	6.90	4.15	5.42	6.37	8.31	10.20	6.64	5.38	4.84	6.39	4.64	6.80	5.47	4.71	4.98	5.34	5.60	6.41	4.91	6.51	4.11	6.01	4.88
Professional activities	11.40	14.30	10.20	15.10	15.10	12.00	13.30	14.50	14.10	12.30	14.60	10.10	8.37	11.20	10.50	10.30	9.61	15.60	14.80	14.00	12.30	8.62	12.50	9.56
Education - Health	11.60	14.80	14.40	13.00	12.10	19.40	16.00	15.20	12.90	14.30	15.00	15.10	14.60	13.80	14.30	14.80	20.30	16.10	20.90	15.80	17.50	12.40	15.70	15.00
Leisure - Hospitality	9.04	10.80	8.53	10.90	12.00	8.40	10.20	13.10	9.78	9.67	9.16	9.83	8.84	8.64	9.46	10.40	10.00	9.14	9.63	9.54	8.78	10.80	10.20	13.00
Other services	4.28	3.72	3.74	3.46	4.14	3.72	4.67	4.22	3.95	3.46	4.38	3.86	3.82	3.91	3.92	3.31	3.38	4.54	3.78	4.25	4.31	3.12	4.24	3.87
Government	20.40	17.10	18.90	17.10	17.40	14.70	15.40	15.10	17.20	19.20	14.80	15.00	16.90	19.30	18.40	18.90	17.10	19.90	13.50	15.70	15.20	22.60	16.50	20.60
Total (000s)	1866.6	2405.4	1160.0	14060.6	2255.3	1623.5	417.3	7271.5	3879.9	606.8	5663.1	2830.4	1477.8	1335.9	1790.4	1905.7	593.4	2548.0	3210.6	3935.6	2675.7	1090.0	2650.4	427.3

	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
2011 (%)																								
Mining - Log - Constr	4.35	5.90	3.64	3.39	7.94	3.59	4.62	10.20	3.65	7.69	4.68	4.49	3.44	4.38	5.13	4.12	7.53	6.37	4.81	5.15	5.08	8.82	3.41	16.80
Manufacturing	9.90	3.38	10.60	6.60	3.66	5.30	11.10	6.00	12.60	8.30	10.30	9.90	8.80	11.80	9.60	11.50	7.90	9.40	10.30	6.20	9.50	6.60	16.20	3.15
Trade - Transportations	20.70	18.90	21.30	21.20	16.50	17.10	18.50	21.80	18.80	18.10	19.30	19.20	15.90	19.10	20.20	21.00	19.90	19.30	18.80	17.10	18.60	17.90	18.60	18.40
Information	1.79	1.12	1.78	1.92	1.77	2.94	1.75	1.81	1.50	1.56	1.99	1.59	2.21	1.41	1.57	1.66	1.85	2.44	1.67	2.01	3.68	1.39	1.69	1.35
Financial activities	7.36	4.62	5.54	6.51	4.10	7.87	5.17	5.35	5.47	5.13	5.68	5.44	6.68	5.24	6.88	5.10	6.05	5.71	4.04	4.96	4.87	3.62	5.77	3.73
Professional activities	11.00	12.40	10.50	15.60	12.40	13.10	13.00	7.66	12.70	11.20	11.50	12.50	11.80	12.40	7.02	12.10	12.70	13.20	8.31	18.00	12.00	8.27	10.30	6.13
Education - Health	14.50	9.22	18.20	15.80	15.30	19.90	13.90	14.30	16.70	13.30	14.50	20.30	22.50	11.80	16.10	14.40	13.50	13.20	20.10	12.70	13.50	16.30	15.00	9.36
Leisure - Hospitality	8.71	28.20	10.10	8.68	10.50	8.82	10.20	8.86	9.40	9.17	10.20	8.96	10.70	11.40	10.40	10.00	9.88	9.41	10.90	9.45	9.64	9.67	9.10	11.30
Other services	3.88	2.96	3.63	4.24	3.41	4.26	3.97	3.95	4.13	3.86	3.56	4.47	4.79	3.76	3.83	3.82	3.50	2.81	3.28	5.07	3.80	7.27	4.95	4.14
Government	17.80	13.30	14.80	16.10	24.40	17.10	17.80	20.10	15.10	21.70	18.30	13.10	13.20	18.60	19.20	16.30	17.20	18.20	17.70	19.30	19.20	20.10	15.10	25.70
Total (000s)	944.0	1125.0	626.4	3856.1	804.1	8683.3	3922.4	394.2	5083.0	1550.3	1618.1	5687.0	460.2	1832.1	406.2	2656.2	10557.1	1208.0	299.6	3680.3	2820.4	753.8	2740.8	285.7

	AL	AZ	AR	CA	CO	CT	DE	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT
1990:01-2011:12 (%)																								
Mining - Log - Constr	-1.49	-1.41	0.05	-1.31	0.91	-0.73	-1.54	-3.19	-1.52	-1.14	-0.97	-0.43	0.54	-0.18	-1.70	-0.35	-1.45	-1.64	-0.02	-0.58	-0.41	0.23	-0.29	0.97
Manufacturing	-9.50	-5.70	-10.10	-6.80	-5.50	-8.30	-7.10	-5.18	-8.50	-4.50	-7.20	-7.60	-3.90	-4.30	-6.40	-3.80	-8.90	-4.70	-8.20	-8.40	-4.80	-12.20	-7.40	-2.63
Trade - Transportations	0.10	-1.30	-0.80	-0.50	-2.20	-1.50	-1.40	-2.10	-1.10	-2.10	-1.60	-1.70	-1.60	-2.90	-0.40	-2.80	-1.20	-3.10	-2.00	-1.30	-2.50	-0.30	-2.20	-3.50
Information	-0.58	-0.68	-0.66	-0.07	-0.26	-0.66	-0.06	-0.53	-0.34	-0.42	-0.71	-0.57	-0.55	-0.71	-0.32	-0.44	-0.53	-0.52	-0.35	-0.41	-0.57	-0.30	-0.65	-0.46
Financial activities	0.06	0.25	-0.19	-1.13	-0.51	-1.16	-0.40	-0.53	0.06	-0.14	-0.69	-0.53	1.13	-0.01	0.36	-0.49	0.38	-0.72	-0.32	0.03	0.46	-0.29	0.06	0.23
Professional activities	4.20	4.67	3.98	3.10	3.30	1.60	-1.20	8.70	4.60	3.80	3.80	3.90	2.74	3.50	3.80	3.00	3.32	3.70	3.30	3.90	2.30	3.14	3.20	4.32
Education - Health	3.70	5.68	4.52	4.03	3.60	7.20	6.50	3.90	4.70	5.90	4.80	5.20	2.60	4.20	2.80	4.50	7.90	5.70	5.50	5.40	6.20	4.40	4.80	3.20
Leisure - Hospitality	2.53	0.10	1.49	2.06	1.00	1.74	2.20	-0.10	1.73	0.14	1.71	1.58	0.57	0.61	1.27	2.40	1.00	0.63	1.69	1.16	0.33	4.80	1.40	1.20
Other services	0.54	-0.17	0.13	0.12	0.46	0.18	1.28	-0.08	0.89	0.47	0.46	0.02	-0.71	0.15	-0.30	-0.34	0.15	0.11	0.52	0.60	0.04	-0.24	0.34	-0.02
Government	0.40	-1.30	1.70	0.50	-0.80	1.70	1.60	-0.70	-0.60	-1.90	0.30	0.10	-1.00	-0.30	0.90	-1.60	-0.80	0.50	-0.20	-0.30	-1.10	0.90	0.70	-3.40
Total (000s)	230.8	922.3	236.2	1560.4	734.4	3.9	69.8	1898.2	888.1	221.5	375.5	308.3	251.5	244.1	303.2	318.1	58.2	374.6	222.5	-10.9	539.8	153.5	305.2	130.0

	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
1990:01-2011:12 (%)																								
Mining - Log - Constr	0.37	-4.30	-0.95	-0.77	-0.10	-0.43	-0.97	5.00	-0.66	1.01	-0.66	-0.42	-0.69	-2.20	0.26	-0.49	0.37	1.35	-1.24	-1.72	-0.95	-1.05	-0.60	2.40
Manufacturing	-3.40	-0.52	-8.80	-8.00	-2.89	-6.70	-15.30	0.15	-9.10	-4.90	-6.00	-8.50	-12.20	-10.80	-2.00	-11.30	-5.40	-4.90	-6.30	-7.20	-6.20	-6.40	-6.60	-1.45
Trade - Transportations	-2.30	1.00	-0.20	-1.70	-3.80	-2.00	-1.80	-2.50	-0.90	-2.80	-1.80	-1.00	-1.20	-0.60	-2.10	-1.00	-2.30	-1.90	-1.00	-2.80	-1.60	-3.60	-1.40	-2.60
Information	-1.22	-0.65	-0.29	-1.39	-0.07	-0.54	0.09	-0.44	-0.57	-0.37	-0.16	-0.52	-0.01	-0.09	-0.33	-0.38	-0.64	0.59	-0.46	-0.55	1.37	-0.51	-0.25	-0.50
Financial activities	0.69	-0.49	-0.95	0.07	-0.66	-1.62	0.66	0.56	0.25	-0.58	-0.11	-0.84	0.78	0.62	0.96	-0.07	-0.41	0.90	-1.20	-0.01	-0.41	-0.53	0.36	-0.26
Professional activities	2.60	2.90	3.30	3.50	2.60	2.60	5.30	3.16	3.40	3.00	3.30	3.70	2.40	3.80	3.16	4.50	3.70	2.90	2.81	6.00	2.80	3.08	3.60	1.66
Education - Health	4.30	3.59	6.10	5.80	6.50	6.80	6.50	0.80	5.60	3.50	4.20	6.00	7.30	5.40	3.30	4.80	4.00	3.90	6.60	4.40	3.90	5.20	4.60	2.86
Leisure - Hospitality	0.52	-2.80	1.20	1.26	0.10	1.83	2.50	-0.33	1.21	1.15	1.50	1.54	2.80	2.80	0.30	1.90	1.52	0.67	-0.30	1.37	0.74	2.08	0.41	-0.70
Other services	0.36	0.26	0.15	0.95	-0.35	0.87	0.72	-0.93	0.49	0.31	-0.12	0.41	1.25	0.68	-0.99	1.70	-0.20	-0.72	0.21	1.04	-0.38	1.85	-0.14	0.77
Government	-1.80	1.10	0.50	0.20	-1.40	-0.80	2.30	-5.40	0.30	-0.40	-0.20	-0.50	-0.60	0.30	-2.70	0.30	-0.60	-2.60	0.80	-0.70	0.60	-0.10	0.10	-2.10
Total (000s)	213.1	504.1	118.2	220.6	223.7	468.8	796.9	128.4	200.7	366.4	362.5	514.1	6.1	290.2	117.7	460.2	3456.1	484.5	41.8	786.0	677.5	123.9	449.4	87.2

Notes: See Table 1 for U.S. States Abbreviations.

Part B: Data Properties

Table 5: Panel Unit Root Tests

	$U_{i,t}^{Logistic}$		$U_{i,t}^{Logarithmic}$		$\sigma_{i,t}$		$\sigma_{i,t}^{purged}$	
	Statistic	Prob	Statistic	Prob	Statistic	Prob	Statistic	Prob
IPS	-3.654*	0.000	-3.423*	0.000	-52.395*	0.000	-53.100*	0.000
CIPS	-2.767*	0.003	-2.709*	0.003	-32.150*	0.000	-32.012*	0.000

Notes: * indicates rejection of the null hypothesis at 5% significance level. The 5% critical value for the IPS statistics is -1.645 and the 5% critical value for the CIPS statistics is -2.12.

Table 6: Cross-Sectional Dependence Tests

	$U_{i,t}^{Logistic}$	$U_{i,t}^{Logarithmic}$	$\sigma_{i,t}$	$\sigma_{i,t}^{purged}$
CD-test	413.35*	412.36*	150.54*	138.57*
P-value	0.000	0.000	0.000	0.000
Corr	0.759	0.757	0.276	0.254

Notes: * indicates rejection of the null hypothesis at *5%* significance level.

Table 7: Poolability Tests

	$U_{i,t}^{Logistic}$		$U_{i,t}^{Logarithmic}$	
	Regions	Time	Regions	Time
Chow test	3.530*	5.591*	3.446*	5.397*
P-value	0.000	0.000	0.000	0.000

Notes: * indicates rejection of the null hypothesis at *5%* significance level.

Part C: Estimation Tables

Table 8: Assumptions about Panel Estimators

		Parameter Heterogeneity	
		Homogeneity	Heterogeneity
Cross-Sectional Correlation	Independence	POLS, FE, AB GMM, BB GMM, PMG	MG
	Dependence	FE-DK, CCEP	CCEMG, AMG

Notes: POLS – Pooled OLS, FE – Fixed Effects, AB GMM – Arellano and Bond (1991), BB GMM – Blundell and Bond (1998), PMG – Pesaran *et al.*'s (1999) Pooled Mean Group, MG – Pesaran and Smith's (1995) Mean Group, FE-DK – Driscoll and Kraay's (1998) Fixed Effects, CCEP – Pesaran's (2006) Pooled Common Correlated Effects, CCEMG – Pesaran's (2006) Mean Group Common Correlated Effects, AMG – Bond and Eberhardt's (2009) Augmented Mean Group.

Table 9: Lilien's Index and Sectoral Shifts: Aggregate Estimates

	$U_t^{Logistic}$								$U_t^{Logarithmic}$							
	OLS	GMM	OLS	GMM	OLS	GMM	OLS	GMM	OLS	GMM	OLS	GMM	OLS	GMM	OLS	GMM
$U_{t-1}^{Logistic}$	0.987**	0.989**	0.986**	0.987**	0.987**	0.989**	0.986**	0.987**								
	(162.04)	(159.29)	(148.42)	(144.52)	(162.04)	(159.29)	(148.42)	(144.52)								
$U_{t-1}^{Logarithmic}$									0.987**	0.989**	0.986**	0.987**	0.987**	0.989**	0.986**	0.987**
									(161.66)	(159.41)	(148.61)	(145.19)	(161.66)	(159.41)	(148.61)	(145.19)
σ_t^9	6.296**	5.889**							5.817**	5.507**						
	(2.68)	(2.72)							(2.65)	(2.72)						
σ_t^{13}			3.915**	2.794*							3.648**	2.685*				
			(2.14)	(1.73)							(2.15)	(1.78)				
$\sigma_t^{9\ purged}$					6.296**	5.889**							5.817**	5.507**		
					(2.68)	(2.72)							(2.65)	(2.72)		
$\sigma_t^{13\ purged}$							3.915**	2.794*							3.648**	2.685*
							(2.14)	(1.73)							(2.15)	(1.78)
$\Delta Log(M_t)$	0.654	0.509	0.766*	0.709*	0.843**	0.685*	0.870**	0.783*	0.616	0.466	0.718*	0.649	0.790**	0.631	0.814**	0.720*
	(1.56)	(1.22)	(1.82)	(1.68)	(2.10)	(1.68)	(2.12)	(1.88)	(1.56)	(1.19)	(1.81)	(1.63)	(2.09)	(1.64)	(2.11)	(1.83)
H_t	108.632**	97.610**	124.876**	118.708**	151.694**	137.887**	153.013**	138.789**	101.985**	91.359**	116.757**	110.605**	141.766**	129.024**	142.974**	129.904**
	(2.67)	(2.43)	(2.94)	(2.65)	(4.45)	(3.84)	(4.07)	(3.29)	(2.68)	(2.45)	(2.96)	(2.67)	(4.46)	(3.89)	(4.10)	(3.35)

Notes: t-statistics in parentheses. All estimations were carried out using Newey-West HAC robust standard errors. * and ** denotes significance at the 10% and 5% significance levels, respectively.

Table 10: Lilien's Index and Sectoral Shifts: Pooled & Heterogeneous Parameter Estimates

	$U_{i,t}^{Logistic}$										$U_{i,t}^{Logarithmic}$									
	POLS	FE	DK FE	AB GMM	BB GMM	PMG	MG	CCEP	CCEMG	AMG	POLS	FE	DK FE	AB GMM	BB GMM	PMG	MG	CCEP	CCEMG	AMG
$U_{i,t-1}^{Logistic}$	0.993**	0.988**	0.988**	0.990**	0.990**	0.987**	0.989**	0.986**	0.983**	0.968**										
	(984.34)	(817.13)	(208.88)	(540.08)	(534.57)	(655.80)	(1159.56)	(344.70)	(369.07)	(190.84)										
$U_{i,t-1}^{Logarithmic}$											0.993**	0.988**	0.988**	0.990**	0.990**	0.987**	0.989**	0.986**	0.983**	0.968**
											(994.27)	(829.04)	(208.34)	(549.13)	(540.20)	(673.34)	(1160.11)	(354.52)	(374.14)	(191.14)
$\sigma_{i,t}$	0.630**	0.846**	0.846**	0.694**	1.022**	1.055**	0.859**	0.504	0.435**	0.902**	0.584**	0.787**	0.787**	0.649**	0.952**	0.982**	0.805**	0.467	0.404**	0.843**
	(2.40)	(2.71)	(2.21)	(3.08)	(5.00)	(5.18)	(5.59)	(1.39)	(2.28)	(5.75)	(2.41)	(2.72)	(2.21)	(3.12)	(5.02)	(5.21)	(5.61)	(1.39)	(2.28)	(5.72)
$\Delta Log(M_t)$	0.414**	0.459**	0.459**	0.475**	0.594**	0.459**	0.436**			0.344**	0.392**	0.434**	0.434**	0.450**	0.561**	0.433**	0.411**			0.323**
	(8.77)	(9.53)	(2.54)	(9.27)	(11.00)	(9.67)	(14.97)			(11.76)	(8.74)	(9.49)	(2.56)	(9.26)	(10.93)	(9.62)	(15.07)			(11.85)
H_t	24.415**	25.102**	25.102**	26.996**	28.643**	24.742**	23.678**			21.320**	22.907**	23.561**	23.561**	25.321**	26.862**	23.222**	22.127**			19.850**
	(17.95)	(17.66)	(2.60)	(18.27)	(19.73)	(17.16)	(17.23)			(12.64)	(17.76)	(17.47)	(2.62)	(18.10)	(19.59)	(16.98)	(17.27)			(12.59)

Notes: t-statistics in parentheses. All estimations were carried out using White heteroskedasticity robust standard errors. * and ** denotes significance at the 10% and 5% significance levels, respectively.

Table 11: Purged Lilien's Index and Sectoral Shifts: Pooled & Heterogeneous Parameter Estimates

	$U_{i,t}^{Logistic}$										$U_{i,t}^{Logarithmic}$									
	POLS	FE	DK FE	AB GMM	BB GMM	PMG	MG	CCEP	CCEMG	AMG	POLS	FE	DK FE	AB GMM	BB GMM	PMG	MG	CCEP	CCEMG	AMG
$U_{i,t-1}^{Logistic}$	0.993**	0.988**	0.988**	0.990**	0.990**	0.987**	0.989**	0.986**	0.983**	0.968**										
	(984.34)	(817.13)	(208.88)	(540.08)	(534.57)	(655.80)	(1159.56)	(336.77)	(369.07)	(190.84)										
$U_{i,t-1}^{Logarithmic}$											0.993**	0.988**	0.988**	0.990**	0.990**	0.987**	0.989**	0.986**	0.983**	0.968**
											(994.27)	(829.04)	(208.34)	(549.13)	(540.20)	(673.34)	(1160.11)	(346.28)	(374.14)	(191.14)
$\sigma_{i,t}^{purged}$	0.630**	0.846**	0.846**	0.694**	1.022**	1.055**	0.859**	0.493	0.435**	0.902**	0.584**	0.787**	0.787**	0.649**	0.952**	0.982**	0.805**	0.456	0.404**	0.843**
	(2.40)	(2.71)	(2.21)	(3.08)	(5.00)	(5.18)	(5.59)	(1.34)	(2.28)	(5.75)	(2.41)	(2.72)	(2.21)	(3.12)	(5.02)	(5.21)	(5.61)	(1.34)	(2.28)	(5.72)
$\Delta Log(M_t)$	0.416**	0.461**	0.461**	0.477**	0.596**	0.461**	0.439**			0.346**	0.393**	0.436**	0.436**	0.451**	0.562**	0.435**	0.414**			0.325**
	(8.79)	(9.55)	(2.55)	(9.31)	(11.04)	(9.71)	(14.94)			(11.82)	(8.75)	(9.51)	(2.57)	(9.30)	(10.97)	(9.65)	(15.04)			(11.90)
H_t	25.246**	26.220**	26.220**	27.912**	29.992**	26.135**	25.014**			22.433**	23.679**	24.599**	24.599**	26.178**	28.119**	24.518**	23.343**			20.920**
	(19.01)	(18.94)	(2.69)	(19.07)	(20.40)	(18.85)	(19.21)			(13.23)	(18.82)	(18.73)	(2.71)	(18.89)	(20.25)	(18.64)	(19.39)			(13.32)

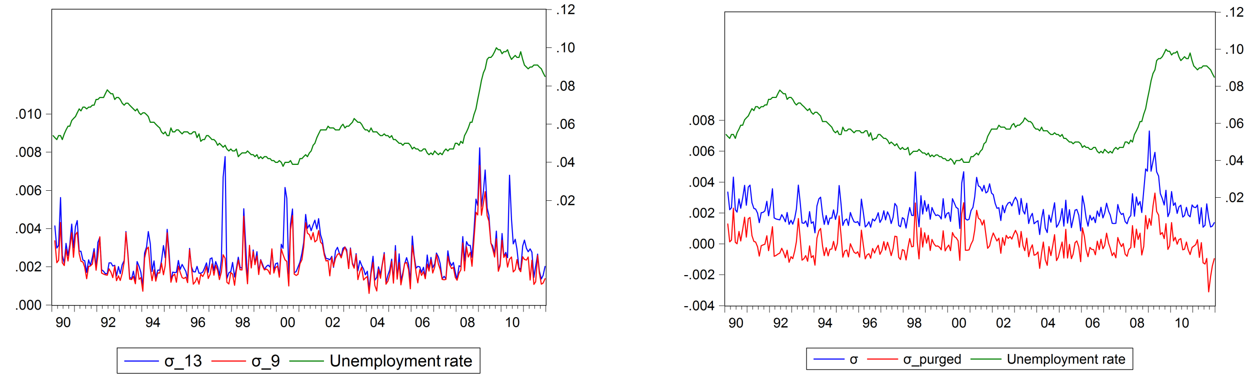
Notes: t-statistics in parentheses. All estimations were carried out using White heteroskedasticity robust standard errors. * and ** denotes significance at the 10% and 5% significance levels, respectively.

Table 12: Purged Index and Sectoral Shifts: Alternative Sectoral Decomposition

	$U_{i,t}^{Logistic}$										$U_{i,t}^{Logarithmic}$									
	$\sigma_{i,t}^{13\ purged}$		$\sigma_{i,t}^{10\ purged}$		$\sigma_{i,t}^{9\ purged}$		$\sigma_{i,t}^{7\ purged}$		$\sigma_{i,t}^{4\ purged}$		$\sigma_{i,t}^{13\ purged}$		$\sigma_{i,t}^{10\ purged}$		$\sigma_{i,t}^{9\ purged}$		$\sigma_{i,t}^{7\ purged}$		$\sigma_{i,t}^{4\ purged}$	
	DK FE	CCEMG	DK FE	CCEMG	DK FE	CCEMG	DK FE	CCEMG	DK FE	CCEMG	DK FE	CCEMG	DK FE	CCEMG	DK FE	CCEMG	DK FE	CCEMG	DK FE	CCEMG
$U_{i,t-1}^{Logistic}$	0.988**	0.983**	0.988**	0.983**	0.988**	0.983**	0.988**	0.983**	0.988**	0.982**										
	(207.69)	(348.69)	(208.22)	(354.00)	(208.88)	(369.07)	(209.21)	(370.71)	(211.26)	(348.82)										
$U_{i,t-1}^{Logarithmic}$											0.988**	0.983**	0.988**	0.983**	0.988**	0.983**	0.988**	0.983**	0.988**	0.982**
											(207.21)	(353.83)	(207.74)	(359.07)	(208.34)	(374.14)	(208.64)	(375.53)	(210.60)	(354.42)
$\sigma_{i,t}^{purged}$	0.484*	0.354**	0.703**	0.381**	0.846**	0.435**	0.884**	0.429**	1.277**	0.654**	0.450*	0.328**	0.655**	0.352**	0.787**	0.404**	0.821**	0.399**	1.189**	0.606**
	(1.75)	(2.01)	(1.97)	(2.15)	(2.21)	(2.28)	(2.79)	(2.62)	(3.41)	(2.24)	(1.75)	(2.01)	(1.98)	(2.15)	(2.21)	(2.28)	(2.80)	(2.61)	(3.42)	(2.25)

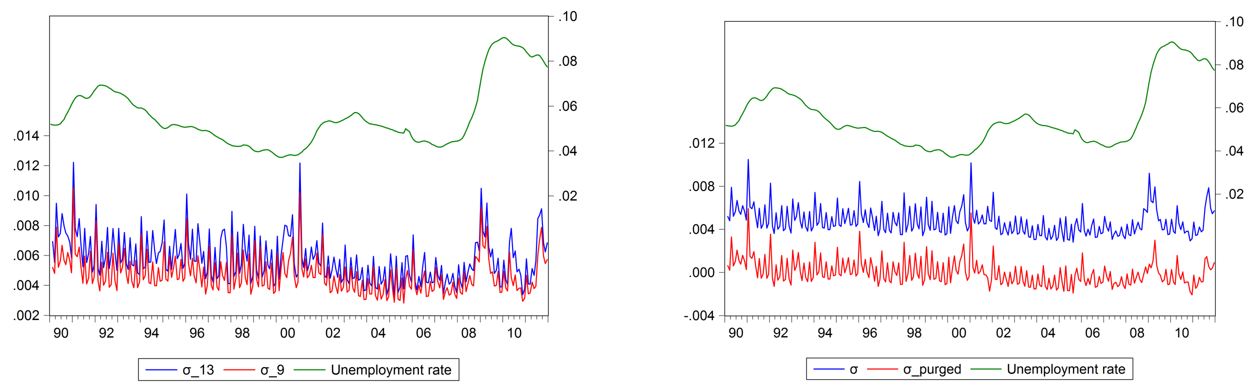
Notes: t-statistics in parentheses. All estimations were carried out using White heteroskedasticity robust standard errors. * and ** denotes significance at the 10% and 5% significance levels, respectively.

Part D: Figures



(a) σ_t^{13} *and* σ_t^9 (b) σ_t^9 *and* $\sigma_{t\ purged}^9$

Figure 1: Unemployment Rate and Lilien's σ_t for the U.S. Agregate, 1990:M1–2011:M12.



(a) $\sigma_{i,t}^{13}$ *and* $\sigma_{i,t}^9$ (b) $\sigma_{i,t}^9$ *and* $\sigma_{i,t\ purged}^9$

Figure 2: Unemployment rate and Lilien's $\sigma_{i,t}$ for the 48 U.S. States Average, 1990:M1–2011:M12.

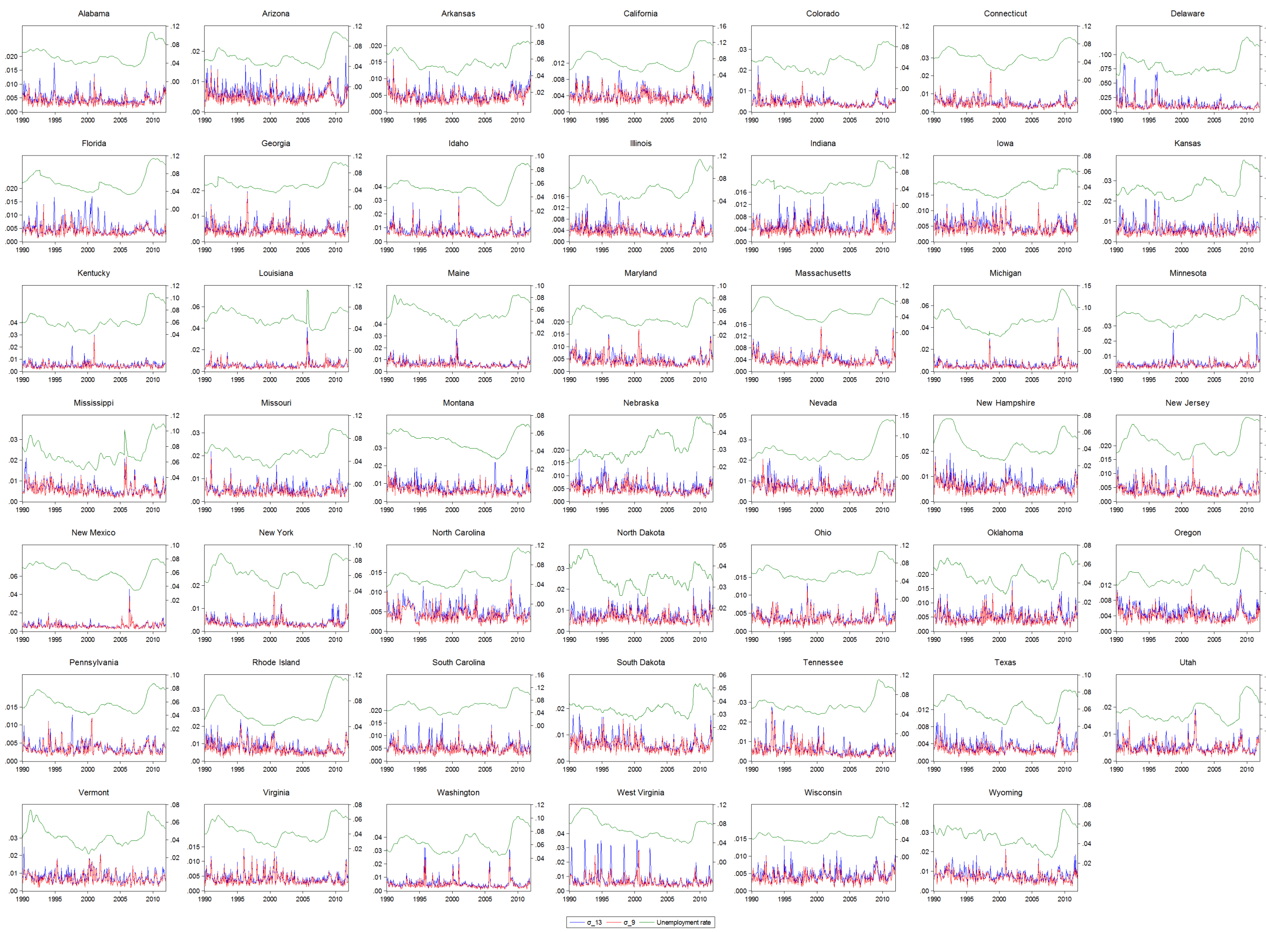


Figure 3: *Unemployment rate and Lilien's $\sigma^{13}_{i,t}$ and $\sigma^{9}_{i,t}$ for the 48 U.S. States, 1990:M1–2011:M12.*

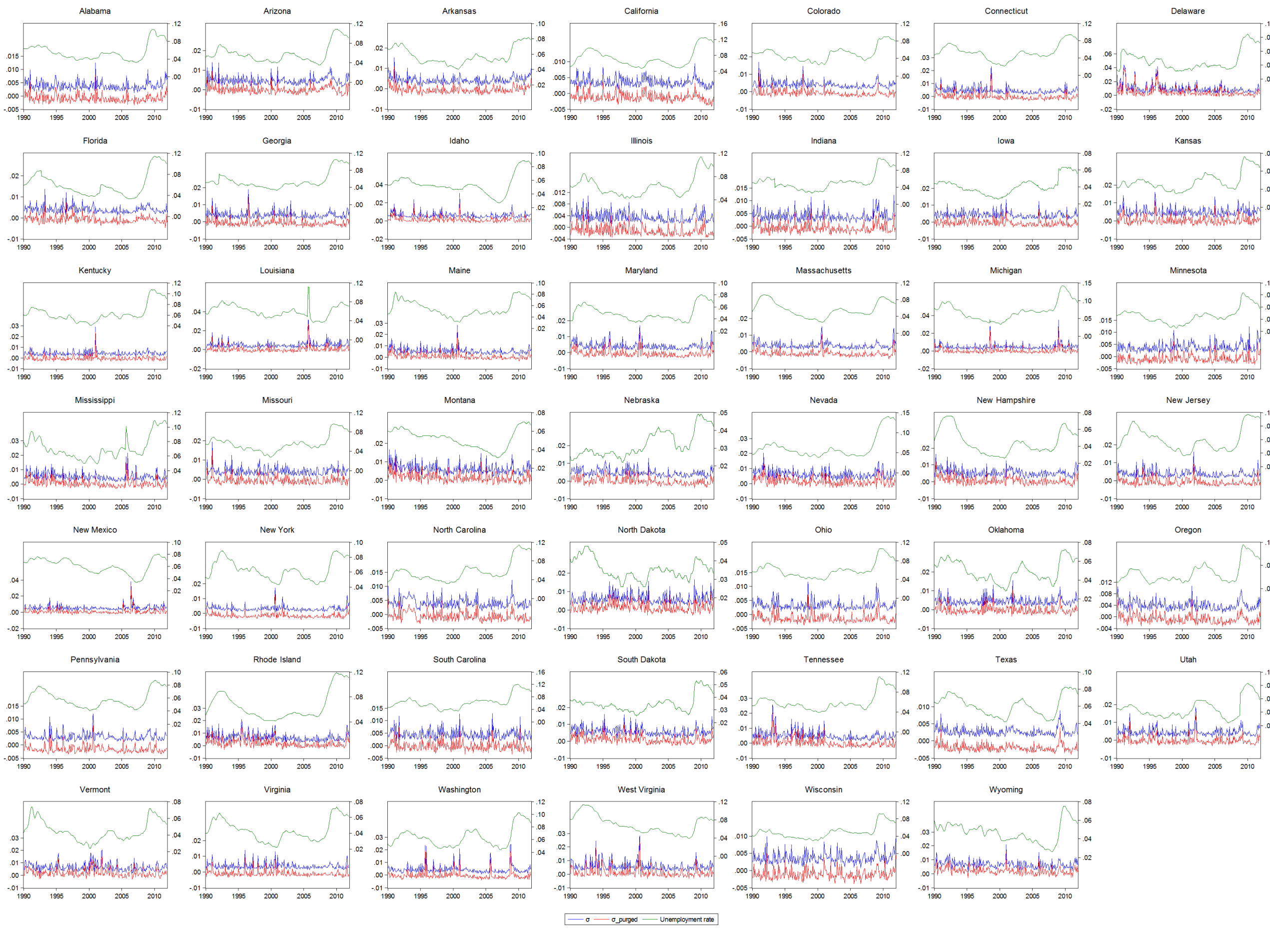


Figure 4: *Unemployment rate and Lilien's $\sigma^9_{i,t}$ and $\sigma^9_{i,t\ purged}$ for the 48 U.S. States, 1990:M1–2011:M12.*