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Common Business Cycles and Volatilities in US States and MSAs: The Role of Economic Uncertainty

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Abstract

This paper analyses the role of a news-based measure of economic policy uncertainty (EPU) in explaining time-varying co-movements in economic activity and volatility of 48 US states and 51 largest MSAs. In this regard, we, first, estimate a dynamic factor model with time-varying loadings and stochastic volatility (DFM-TV-SV). Then, in the second step, we use a quantile-on-quantile (QQ) predictive regression model to capture the effect of EPU on the common factor and stochastic volatility derived from the DFM-TV-SV for the states and MSAs. Our results show that EPU has a significant negative effect on the common economic activity of both the states and MASs, and it also significantly increases the common volatility. However, the impact of uncertainty varies substantially depending on the initial states (quantiles) of both common output or volatility and EPU. Thus, our results tend to suggest that policy design should be state-dependent.

Keywords: Common Business Cycles, Common Stochastic Volatility, Time-Varying Dynamic Factor Models, Quantile-on-Quantile Regressions.
JEL Codes: C11, C22, C32, E30, R10.

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1. Introduction

Following the recent global financial crisis, a burgeoning literature, both theoretical and empirical, has analysed the link between uncertainty and the macroeconomy. For instance, based on early works involving partial equilibrium models of Bernanke (1983) and, Dixit and Pindyck (1994), several researchers have recently developed dynamic stochastic general equilibrium models to capture the (negative) impact of uncertainty on macroeconomic variables (Bloom, 2009; Fernández-Villaverde et al., 2011, 2015; Gourio, 2012; Leduc and Liu, 2013; Johannsen, 2013; Mumtaz and Zanetti, 2013; Nakata, 2013; Basu and Bundick, 2014; Bloom et al., 2014; Christiano et al., 2014; and Carriero et al., 2015). At the same time, large amount of empirical research have also been undertaken to validate the predictions of these theoretical models (see for example, Karnizova and Li (2014), Carriero et al. (2015), Jurado et al. (2015), Rossi and Sekhposyan (2015), Baker et al. (2016), Balcilar et al. (2016, 2017, forthcoming), Cheng et al. (2016), Jones and Enders (2016), Scotti (2016), Stockhammar and Österholm (2016, 2017), Berger et al., (2017), Caggiano et al., (2017), Choi (2017), Mumtaz and Theodoridis (2017), Carriero et al., (forthcoming), Creal and Wu (forthcoming), Gupta and Jooste (forthcoming), Gupta et al., (forthcoming), and Segnon et al. (forthcoming).[1]

Uncertainty is a latent variable, but, in order to quantify the impact of uncertainty on the macroeconomy, one requires ways to measure uncertainty. In this regard, besides implied-volatility indices associated with financial market uncertainty (popularly called the VIX), a related strand in the literature has developed three broad approaches to quantify the effect of uncertainty on the economy: (1) The news-based approach proposed by Brogaard and Detzel (2015), Baker et al. (2016), and Larsen (2017).[2] The main idea behind this approach is to perform searches of newspapers for terms related to economic and policy uncertainty (EPU) and to use the results of this search to construct measures of uncertainty; (2) Mumtaz and Zanetti (2013), Mumtaz and Surico (2013), Alessandri and Mumtaz (2014), Carriero et al. (2015, forthcoming), Jurado et al. (2015), Ludvigson et al. (2015), Mumtaz et al., (2016), Shin and Zhong (2016), Chuliá et al. (2017), Mumtaz and Theodoridis (2017a, b) and Creal and Wu (forthcoming) recover measures of uncertainty from estimates of various types of small and large-scale structural models related to macroeconomics and finance, and; (3) Bali et al. (2015), Rossi and Sekhposyan (2015, 2017), Rossi et al. (2016), and Scotti (2016) construct measures of uncertainty based on dispersion of professional forecaster disagreement.

Against this backdrop, the objective of this paper is to analyze, for the first time, the role of uncertainty in explaining common business cycles and volatilities in the 48 contiguous US states and 51 largest metropolitan statistical areas (MSAs) separately, over the quarterly period of 1948:Q1 to 2014:Q4, and the monthly period of 1990:M1 to 2015:M12,

[1] For some earlier works and recent working papers, see also Alexopoulos and Cohen (2009), Knotek II and Khan (2011), Bachmann and Bayer (2011), Stock and Watson (2012), Bachmann et al. (2013), Benati (2013), Colombo (2013), Jones and Olson (2013, 2015), Alessandri and Mumtaz (2014), Born and Pfeifer (2014), Caggiano et al. (2014a, b, 2016), Foerster (2014), Furlanetto et al. (2014), Gilchrist et al. (2014), Kang et al. (2014), Nodari (2014), Pellegrino (2014, 2017), and Schüler (2014), Azzimonti (2015), Castelnuovo et al. (2015), Istrefi and Piloiu (2015), Ludvigson et al. (2015), Mecikovsky and Meier (2015), Caldara et al. (2016), Mumtaz et al. (2016), Rossi et al. (2016), Shin and Zhong (2016), Barrero et al., (2017), Junttila and Vataja (2017), and Pierdzioch and Gupta (2017).

[2] Using a similar approach based on newspaper articles, Azzimonti (2016), Caldara and Iacoviello (2016), and Manela and Moreira (2017) developed measures of partisan conflict, geopolitical risks and news-based VIX (NVIX).

respectively. For our purposeto capture potential time-varying co-movement among the output measures of US states and MSAs, we first estimate the dynamic factor model of Del Negro and Otrok (2008), which allows for time-varying loadings and stochastic volatility (DFM-TV-SV). In the second step, we use a quantile-on-quantile (QQ) predictive regression model of Sim and Zhou (2015) to try and capture the effect of uncertainty on the common factor and stochastic volatility derived from the DFM-TV-SV for the states and MSAs. The advantage of a quantile regression approach over a conditional mean-based model is that the former can study the entire conditional distribution of the dependent variable, i.e., it is inherently a time-varying approach capturing the various phases (low [lower quantiles], normal [median], high [higher quantiles]) of the common factor and stochastic volatility. The QQ regression goes even a step further because it renders it possible to analyze the response of the entire conditional distribution of common factor and stochastic volatility to various degrees uncertainty as well, as captured by its quantiles. As far as the metric of uncertainty is concerned, we use the news-based measure (economic policy uncertainty index; EPU) of Baker et al., (2016), primarily due to two reasons: (a) The measure does not require any complicated estimation of a large-scale model to generate it in the first place, and hence, is not model-specific, and; (2) While, the other measures of uncertainties, like those developed by Jurado et al. (2015), and Rossi and Sekhposyan (2015), are also available publicly like the EPU, their coverage only starts from early or late 1960s. The EPU data goes as far back as 1900, and thus allows us to analyze the output data of the US states which begins in 1947.

Our paper based on the QQ model applied to the common factor of output growth and stochastic volatility derived from the DFM-TV-SV model, extends the above-discussed empirical literature on uncertainty and national macroeconomic effects (in general) to regional-levels involving the US states and MSAs. In addition, unlike the literature, we also analyze the impact of uncertainty on volatility of output, i.e., we look at higher-order effects. The only study that is somewhat related to our paper is the work of Mumtaz et al., (2016), wherein the authors uses a FAVAR model with stochastic volatility to estimate the impact of uncertainty shocks on real income growth in US states. The results suggested that there is a large degree of heterogeneity in the magnitude and the persistence of the response to uncertainty shocks across states, with the magnitude of the decline in income being largest in states with a large share of manufacturing and construction industries, a larger share of small firms, a high fiscal deficit, a less rigid labor market and a more volatile housing market. But, in contrast, a higher share of mining industries and larger inter-governmental fiscal transfers is found to ameliorate the impact of uncertainty. Our paper is different from that of Mumtaz et al., (2016), in the sense that it makes a contribution to the understanding of the role played by uncertainty in explaining common business cycles and volatilities of not only US states but also largest MSAs over the entirety of their respective conditional distributions, following a change in uncertainty conditional on its current state. The QQ approach allows us to study the possible asymmetric impact of uncertainty on common growth and volatilities of the states and MSAs, given the current position of both the dependent variable and the predictor.

Note that our paper also adds to the literature on regional (restricted to primarily state-level) business cycle synchronization of the US economy (see for example, Carlino and DeFina (2004), Crone (2005), Partridge and Rickman (2005), Owyang et al., (2005, 2008, 2009); Artis et al., (2011); Aguiar-Conraria et al., (2017)) – an important issue for policy makers in devising appropriate economic policies. These studies tend to suggest that state-level business cycles are highly synchronized (Aguiar-Conraria et al., 2017), with the common factor explaining large proportion of the total variability in state-level business cycles (Owyang et

al., 2009)[3]. Understandably then, we not only analyze the role of this common factor for both US states and MSAs, but more importantly, we evaluate the importance of uncertainty in explaining the movement of this common factor as an explanatory variable for business cycle synchronization, besides already emphasized covariates like industry mix, agglomeration, and neighbor effects (Owyang et al., 2009; Aguiar-Conraria et al., 2017), and monetary policy (Owyang and Wall, 2009) respectively.[4] So from a policymaker's perspective, if indeed the common national factors of output and volatility drive regional business cycles and its fluctuations, with uncertainty in turn, affecting these factors, then national-level policies are likely to ameliorate the negative influence of uncertainty for the states and MSAs. Naturally, our paper has important policy implications. The remainder of the paper is organized as follows: Section 2 presents the data, while Section 3 lays out the basics of the DFM-TV-SV and QQ models. Section 4 discusses the results and Section 5 concludes.

2. Data

The DFM-TV-SV model is based on measures of economic activity for the 48 (barring Alaska and Hawaii) states, and 51 largest MSAs as listed in Table A1 of the Appendix. For the states, we use the growth rates of quarterly real personal income in the DFM-TV-SV model, as the model requires stationary data. We deflate the seasonally adjusted nominal state personal income by the seasonally adjusted consumer price index (CPI) of the overall US economy to obtain the real counterpart of the variable, given that state-level CPI is not available at quarterly frequency for the period under consideration. While the personal income data comes from the regional database of the Bureau of Economic Analysis (US Department of Commerce), the CPI data (with a base year of 1982-1984) is derived from the FRED database of Federal Reserve Bank of St. Louis. For the MSAs, we use the monthly economic activity indices as developed by Arias et al., (2016) and available for download from the FRED database. These authors derived each of these indices from a DFM based on twelve underlying variables capturing various aspects of metro area economic activity. Arias et al., (2016) estimates the DFM using a maximum-likelihood approach that allows for arbitrary patterns of missing data to accommodate mixed-frequency and differences in publication lags. These indices are stationary by design and hence, we apply the DFM-TV-SV directly on them without any further transformations.

The EPU indices used in this paper is derived from the work of Baker at al., (2016). To match the longer span of the state-level quarterly data on personal income, we use the historical version of the index, which dates as far back as 1900. Baker et al., (2016) uses two overlapping sets of newspapers, with the first spanning the period of 1900-1985, and comprising of the Wall Street Journal, the New York Times, the Washington Post, the Chicago Tribune, the LA Times, and the Boston Globe. From 1985 until 2014, the authors use USA Today, the Miami Herald, the Dallas Morning Tribune, and the San Francisco Chronicle, along with the previously mentioned newspapers. To construct the index, Baker et al., (2016) perform month-by-month searches of each paper, for terms in all three categories

[3] Unlike our work, Owyang et al., (2009) estimated three factors using a standard fixed-coefficient DFM for the 48 contiguous states based on the growth rates of real personal income and payroll employment, and the growth rates of the M1 and M2 money stocks, S&P 500 stock price index, and personal consumption expenditures (PCE) deflator; and first differences of the federal funds rate, 3-month Treasury bill yield, 10-year Treasury bond yield, and Moody's Seasoned Baa Corporate Bond yield. The authors then identified the first factor as the business cycle component in the data comprising of 106 state and national (financial) variables.

[4] In this regard also note that, the role of national housing market permit values have been shown to be driving MSA-level employment in Ghent and Owyang (2010).

pertaining to uncertainty, the economy and policy.[5] The data is available for download from: http://www.policyuncertainty.com/us_historical.html. Since the state-level data on real personal income is quarterly, the monthly EPU index is converted into its quarterly frequency by taking averages over three-months comprising a quarter. With the real personal income starting in 1947 and the historical EPU ending in 2014, the state-level analysis covers the period of 1947:Q1-2014:Q4. To capture the semi-elasticity and elasticity of the impact of EPU on common growth and volatility respectively, of the US states, we take natural logarithm of the EPU index (LEPU), given that the volatility is in its natural logarithmic form as well.

Given that the MSA economic activity indices start in 1990, the corresponding measure of uncertainty used is the benchmark EPU index developed by Baker et al., (2016), which in turn, starts in 1985. In this case, to measure policy-related economic uncertainty, Baker et al., (2016) construct the index from three types of underlying component: newspaper coverage of policy-related economic uncertainty; the number of federal tax code provisions set to expire in future years, and disagreement among economic forecasters. The data can be downloaded from: http://www.policyuncertainty.com/us_monthly.html. The first component is based on the search results for terms related to economic and policy uncertainty from 10 large newspapers, namely, USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the Houston Chronicle, and the Wall Street Journal.[6] The second component of the index uses reports of the Congressional Budget Office (CBO), which compiles lists of temporary federal tax code provisions. Temporary tax measures are a source of uncertainty for businesses and households, since Congress often extends them at the last minute; in the process, undermining stability in and certainty about the tax code. The third component draws on the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. Specifically, Baker et al., (2016) utilizes the individual-level quarterly forecasts one year in the future for CPI, purchase of goods and services by state and local governments, and the same by the federal government. The overall EPU index is then constructed by first normalizing each component by its own standard deviation prior to January 2012, and then computing the weighted (1/2 on the first component and 1/6 each on the second and third components) average value of the components. For the MSAs, our analysis covers the period of 1990:M1 to 2015:M12, with the start and end dates being purely driven by the availability of the economic activity indices at the time of writing this paper. As in the case of the states, the EPU index is converted into its natural logarithmic form (LEPU).

[5] In particular, the search is conducted for articles containing the term 'uncertainty' or 'uncertain', the terms 'economic', 'economy', 'business', 'commerce', 'industry', and 'industrial' as well as one or more of the following terms: 'congress', 'legislation', 'white house', 'regulation', 'federal reserve', 'deficit', 'tariff', or 'war'.

[6] In this case, Baker et al., (2016) search for articles containing the term 'uncertainty' or 'uncertain', the terms 'economic' or 'economy' and one or more of the following terms: 'congress', 'legislation', 'white house', 'regulation', 'federal reserve', or 'deficit'. Hence, compared to the historical EPU, the terms 'tariff', and 'war' are left out.

3. Econometric Frameworks

3.1. Dynamic Factor Model with Time-Varying Loadings and Stochastic Volatility (DFM-TV-SV):

To capture potential time-varying co-movement among multiple series, we estimate the extended dynamic factor model with time-varying loadings and stochastic volatility (or DFM-TV-SV) á la Del Negro and Otrok (2008). In the DFM-TV-SV framework, the growth rate in each state or the economic activity index in each MSA is decomposed into two components: national (common) factor and the regional (idiosyncratic) factor:

$$y_{i,t} = \lambda_{i,t} \cdot f_t + e_{i,t} . \tag{1}$$

Here $y_{i,t}$ is the growth rate (economic activity index) in state (MSA) i ($i = 1,2,\ldots,n$, where n is the total number of regions); f_t is the national (common) factor that affects all regions. The loading parameter for the common factor f_t is $\lambda_{i,t}$ for region i at time t. Finally, $e_{i,t}$ is the regional (idiosyncratic) factor. The common and idiosyncratic factors are assumed to be orthogonal for the identification purpose.
This factor model is dynamic in the sense that all factors follow simple time series dynamics. Specifically, the common factor follows a stationary AR(p) process with time-varying stochastic volatility:

$$f_t = \phi_1^f f_{t-1} + \phi_2^f f_{t-2} + \ldots + \phi_p^f f_{t-p} + \sqrt{\exp(h_t^f)} \cdot \varepsilon_t^f , \tag{2}$$

where $\varepsilon_t^f \sim i.i.d.N(0,\sigma_f^2)$. The time varying stochastic volatility is modeled as a random walk for the sake of parsimony:

$$h_t^f = h_{t-1}^f + \sigma_f^h \cdot v_t^f , v_t^f \sim i.i.d.N(0,1) , \tag{3}$$

where, σ_f^h is the so-called volatility of the volatility and measures the size of time variations of the stochastic volatility.
Similarly, each idiosyncratic factor follows a stationary AR(q) process:

$$e_{i,t} = \phi_{i,1} e_{i,t-1} + \phi_{i,2} e_{i,t-2} + \ldots + \phi_{i,q} e_{i,t-q} + \sqrt{\exp(h_{i,t})} \cdot \varepsilon_{i,t} , \tag{4}$$

where $\varepsilon_{i,t} \sim i.i.d.N(0,\sigma_i^2)$. The stochastic volatility is again modeled as a random walk:

$$h_{i,t} = h_{i,t-1} + \sigma_i^h \cdot v_{i,t} , v_{i,t} \sim i.i.d.N(0,1) , \tag{5}$$

where, σ_i^h is the volatility of the volatility for the idiosyncratic factor. The volatility shocks of all factors are assumed to be orthogonal to each other as it is standard in this literature.

To permit more general time-varying co-movement among multiple series, the loading parameters in the model are allowed to vary over time and are modeled as random walk processes to keep the model parsimonious:

$$\lambda_{i,t} = \lambda_{i,t-1} + \eta_{i,t}, \eta_{i,t} \sim i.i.d.N(0, \sigma^2_{\eta,i}) \tag{6}$$

We assume that the shocks to loading parameters are independent across series *i*. This assumption implies that the increasing or decreasing contribution of the common factor that are common to all series will be solely captured by the increasing or decreasing volatility of the common factor.

Once the model is estimated and conditional on knowing the time varying loading parameters at each time point, the variance decomposition is given by:

$$Var(y_{i,t}) = \lambda^2_{i,t} \cdot Var(f_t) + Var(e_{i,t}). \tag{7}$$

To separately identify the loading parameters and the variance of the common factor, we follow the literature and normalize the common factor shock variance $\sigma^2_f = 1$. The similar normalization applies to the time varying part of the factor volatility. Specifically, we set the initial values of the time-varying volatility *h*'s in eq. (3) and (5) all at zero in the beginning, i.e., $h^f_0 = h_{i,0} = 0$ for $i = 1,2,\ldots,n$. Finally, to reduce the number of parameters to be estimated, we first demean all growth rate data before estimating the model.

The above DFM-TV-SV model is estimated by Bayesian Markov Chain Monte Carlo (MCMC) due to its large dimension and the resulting complex log likelihood function. Our estimation strategy employs the Gibbs-sampling algorithm that builds upon Kim et al., (1998), Kim and Nelson (1999), Primiceri (2005), Koop and Korobilis (2010), Del Negro and Otrok (2008), and Del Negro and Primiceri (2015). Specifically, we take draws from the known posterior conditional density sequentially for each block of the model. Most blocks involve standard sampling algorithms as outlined in Kim and Nelson (1999), except for the part of the time-varying stochastic volatility that results in a non-Gaussian shock in the measurement equation of the relevant state-space model, for which the usual Kalman filter no longer applies. To deal with this, we employ the approach in Kim, et al., (1998) that uses a mixture of normal densities to approximate the resulting non-Gaussian density function in order to make draws of the stochastic volatility. Cogley and Sargent (2005) take a different approach that utilizes a Metropolis-Hasting algorithm to make draws of the stochastic volatility. The approach in Kim et al., (1998), can be embedded in the Gibbs-sampling algorithm and has been widely applied in the literature to make draws of the stochastic volatility. Stock and Watson (2007) and Primiceri (2005) are notable examples that show this approach has worked fairly well. After the MCMC algorithm converges, the joint density of parameters and states can be easily integrated numerically to yield the marginal distributions of parameters and states of interest. For further details of the estimation steps, readers are referred to the appendices of Bhatt, et al., (forthcoming).

With respect to the model parameters, we set *p*=*q*=2 for the common and all idiosyncratic factors to keep the model parsimonious and, at the same time, allow for sufficient time series dynamics for factors. Our results are based on the 8000 Monte Carlo simulation draws after the 2000 initial burn-in draws are discarded.

3.2. Quantile-on-Quantile (QQ) Predictive Regression

In order to study the predictive ability of the EPU for the common business cycle movements and stochastic volatilities of the US states and MSAs derived from the DFM-TV-SV model, we rely on a quantile-on-quantile (QQ) predictive regression model. Unlike a standard quantile regression which estimates the heterogeneous response of the common factor (of business cycle or volatility) to EPU at various points of the conditional distribution of the former, it overlooks the possibility that the change in EPU conditional on its current state could have varied influence on the common factor.

While there is also the triangular system of equations-based approach of Ma and Koenker (2006) for estimating QQ models, we use the single equation regression method of Sim and Zhou (2015) given that it can be easily estimated.

Let θ superscript denote the quantile of the common factor (*CF*) of economic activity ("Output") and logarithm of stochastic volatility ("LSV") under consideration. We first postulate a model for the θ-quantile of *CF* as a function of the first lag of EPU ("lagged LEPU"). We have:

$$CF_t = \beta^{\theta} EPU_{t-1} + \varepsilon_t^{\theta}, \tag{8}$$

where ε_t^{θ} is an error term that has a zero θ-quantile. We allow the relationship function $\beta^{\theta}(.)$ to be unknown, since we do not have a prior on how the *CF* and *EPU* changes are interlinked. To examine the linkage between the θ-quantile of *CF* and θ-quantile of *EPU*, denoted by EPU^{τ}, we linearize the function $\beta^{\theta}(.)$ by taking a first-order Taylor expansion of $\beta^{\theta}(.)$ around EPU^{τ}, which yields the following:

$$\beta^{\theta}(EPU_{t-1}) \approx \beta^{\theta}(EPU^{\tau}) + \beta^{\theta'}(EPU^{\tau})(EPU_{t-1} - EPU^{\tau}) \tag{9}$$

Based on Sim and Zhou's (2015) study, we can redefine $\beta^{\theta}(EPU^{\tau})$ and $\beta^{\theta'}(EPU^{\tau})$, respectively, as $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$. Then, equation (9) can be re-written as follows:

$$\beta^{\theta}(EPU_{t-1}) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(EPU_{t-1} - EPU^{\tau}). \tag{10}$$

Ultimately, we substitute equation (10) into equation (8) to obtain the following:

$$CF_t = \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(EPU_{t-1} - EPU^{\tau}) + \varepsilon_t^{\theta}. \tag{11}$$

Unlike a standard conditional quantile function, the expression

$$\beta_0(\theta,\tau) + \beta_1(\theta,\tau)(EPU_{t-1} - EPU^{\tau})$$

captures the relationship between the θ-quantile of the *CF* and τ-quantile of lagged *EPU*, given that β_0 and β_1 are doubly indexed in θ and τ. That is, this expression can capture the overall dependence structure between the *CF* and lagged *EPU* through the dependence between their respective distributions.

To estimate (11), we solve for:

$$\min_{\beta_0\beta_1} \sum_{i=1}^{n} \rho_\theta \left[CF_t - \beta_0 - \beta_1(EPU_{t-1} - EPU^\tau)\right] K\left(\frac{F_n(EPU_{t-1}) - \tau}{h}\right)$$

to obtain the estimates $\hat{\beta}_0(\theta,\tau)$ and $\hat{\beta}_1(\theta,\tau)$, where the function ρ_θ is the tilted absolute value function that provides the θ-conditional quantile of CF_t as the solution. Because we are interested in the effect exerted locally by the τ-quantile of lagged *EPU*, we employ a Gaussian kernel $K(.)$ to weight the observations in the neighbourhood of EPU^τ, based on bandwidth h (=0.05, following Sim and Zhou (2015)). The weights are inversely related to the distance of EPU_{t-1} from EPU^τ, or more conveniently, the distance of the empirical distribution function

$$F_n(EPU_{t-1}) = \frac{1}{n}\sum_{k=1}^{n} I(EPU_k < EPU_{t-1}) \tag{12}$$

from τ, where τ is the value of the distribution function that corresponds with EPU^τ.

4. Empirical Results

Figures 1 and 5 plot the extracted national factors using the MSAs economic activity indices and state level real personal income data, respectively. The point estimate is based on the median of the MCMC draws, and the dotted lines are the 95th and 5th percentiles as a way to gauge estimation accuracy. The much shorter sample in Figure 1 makes it easier to visualize the dramatic economic downtown during the recent "Great Recession" that plagued all the MSAs. Although the national factor is much more volatile in Figure 5, it still shows the economic downtown during the "Great Recession" for the states as well.

Figures 2 and 6 plot the variance contributions of the national factors using the MSA's economic activity indices and state-level real personal income data, respectively. These variance contributions vary substantially over time which justifies the necessity of estimating the DFM-TV-SV, which in turn, permits time-varying contributions. To better summarize the overall importance of the national factor to the regional economic activities over time, we compute the percentage contributions of the national factor to the state level real personal income in Table A2, and the corresponding quantities for the economic activity in 51 MSAs in Table A3. For the real personal income data that has a much longer sample span, the contributions of the national factor is over 50% across all states during the full sample period. This highlights the strong comovement of the economic activities across different regions overall and the importance of the national factor in explaining regional economic fluctuations. However, there is also a large amount of heterogeneity across different states. For example, states such as North Dakota and South Dakota appear to have the least amount of exposure to the national factor, while states such as Wisconsin and Ohio are more influenced by the national factor overall. Turning to the economic activity in 51 MSAs for a much shorter time span, the role of national factor seems to become smaller. But again, there is a lot of heterogeneity. Metropolitan areas such as Philadelphia and NY City have more than 70% contributions of the national factor overall. Interestingly, for both datasets, right before the recent "Great Recession", the contributions of the national factor all appear to have increased markedly, followed by a gradual decline. Both tables show the average percentage contributions of the national factor before and after 2007Q4, the start of the "Great Recession" as defined by the NBER. This highlights the severity of this recent recession that affects all states and regions across the board.

Figures 3 and 7 present the time varying stochastic volatility of the national factors using both datasets corresponding to the MSAs and the states. Notably, the stochastic volatility increased during the recent “Great Recession”. The increase of the stochastic volatility of the common factor tends to increase the contributions of the national factor, *ceteris paribus*.

The DFM-TV-SV model estimated here can conveniently document the potentially time-varying co-movement among multiple series, and therefore provide a straightforward way to summarize this useful statistical feature of the data. To this end, we compute and plot the implied average cross-correlations in the datasets for of all MSAs and states in Figures 4 and 8, respectively. To produce these time-varying average cross-correlations, we first compute all the pairwise correlations implied by the estimated factor model at each time point and then take the cross-sectional average. Consistent with the variance contributions results, the cross-correlation plots indicate that regional economic growth became more synchronized during the recent “Great Recession”.

After having recovered the common factors for measures of economic activity and stochastic volatilities for the MSAs and the states, we now use the QQ regressions to analyze the ability of LEPU to predict the movements in the common factors. The results are reported in Figures 9 to 12. As it can be seen from Figures 9 and 11, the impact of various quantiles of lagged LEPU, i.e., ($LEPU_{t-1}$) is negative and statistically significant over the quantiles of the common factor for economic activity of the MSAs and the real personal income growth of the states, respectively. For the MSAs, the impact is relatively stronger at moderately lower quantiles (i.e., 0.30-0.45) and upper quantiles (i.e., 0.80-0.85) as well, with the latter effect being the strongest, when the changes in uncertainty happens from its initial state corresponding to a high level (i.e., quantile range of 0.80-0.90). While for the states, qualitatively similar results are obtained in the sense that stronger effects are felt at lower and upper quantiles of the conditional distribution of the output growth, this tends to happen when the increases in EPU occurs from its initial state of low to normal, as given by the quantile range of 0.15 to 0.50. In Figures 10 and 12, we observe that EPU causes an increase in the common stochastic volatilities of both MSAs and states, respectively. In case of the MSAs, the strongest impact is felt at upper quantiles (i.e., 0.80-0.90) of the volatility corresponding to a change in EPU, given an initial state that represents its normal phase (i.e., quantile range of 0.45-0.50). For the common volatility of the states, results are qualitatively similar to that of the MSAs, i.e., stronger effects are observed at upper quantiles of the volatility (i.e., 0.85-0.90), when the changes in lagged EPU occurs from its normal phase, i.e., (quantiles of 0.50-0.60).

In sum, our results suggest that EPU negatively impact the common movements in economic activity in both MSAs and states, irrespective of whether the regional economies are in recession (lower quantiles) or expansion (upper quantiles). However, the initial state from where the uncertainty is changing is also important, with the effect being strongest for the MSAs when EPU is already quite high, while for the states, this is the case, with EPU being in a low to normal initial state-zone. In other words, to circumvent the negative influence of uncertainty on the co-movements of the MSAs and states, policymakers will need to implement state-dependent policies, which are aimed at removing tail risks, channel funds towards the private sector, and undo the "wait-and-see" attitudes by creating incentives to spend more strongly during periods of recession and expansion alike, following an uncertainty shock. But, to determine the strength of the stimulus, i.e., the degree of intervention, policymakers should also have knowledge about the existing levels of uncertainty, since as we show the negative effects are strongest for MSAs when uncertainty is

already quite high, while for states, this is the case at lower levels of the same. In other words, policymakers should have exact information about the current state of the economy-wide uncertainty, which in turn, would require accurate measures of this latent variable. Hence, importantly, it is not only the current state of the regional economies, but also the existing levels of uncertainty, that will determine not only the strength of the policies, but also whether, at that point in time, the emphasis should be on the MSAs or the states. Our results also suggest that, when changes in EPU occur from its initial normal phase, and if uncertainty of economic activity in the regional economies is already high, then this is likely to make the regional economies simultaneously highly volatile. Hence, if volatility is a concern for policymakers, policies will again need to be state-dependent, i.e., contingent on levels of volatility and uncertainty simultaneously.

5. Conclusion

In the wake of the "Great Recession", a large number of studies have analyzed the impact of uncertainty on national economies around the world. Given this, the objective of this paper is to analyze, for the first time, the role of a news-based measure of economic policy uncertainty (EPU) in explaining common business cycles and volatilities in the 48 contiguous US states and 51 largest MSAs separately, over the quarterly period of 1948:Q1 to 2014:Q4, and the monthly period of 1990:M1 to 2015:M12, respectively. In this regard, to capture potential time-varying co-movement among the output measures of US states and MSAs, we first estimate a dynamic factor model which allows for time-varying loadings and stochastic volatility (DFM-TV-SV). In the second step, we use a quantile-on-quantile (QQ) predictive regression model to capture the effect of uncertainty on the common factor and stochastic volatility derived from the DFM-TV-SV for the states and MSAs.

Our results from the DFM-TV-SV highlight the importance of the national factors in driving economic activity and stochastic volatility of the regional economies. The QQ model indicates that EPU negatively and, in a statistically significant fashion, affects the national factors of economic activity. Moreover, EPU also has a significant positive influence on the common factors of volatility for both the states and MSAs. While these results hold over the entire quantile range of both the dependent and independent variables, the size of the impact of EPU is contingent on the initial state of both the common factors and uncertainty. Therefore, policymakers should not only need to devise policies that are state-dependent, but also have appropriate measures of uncertainty to gauge its current level.

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Figure 1. National Factor of the Economic Activity Indices of the 51 MSAs

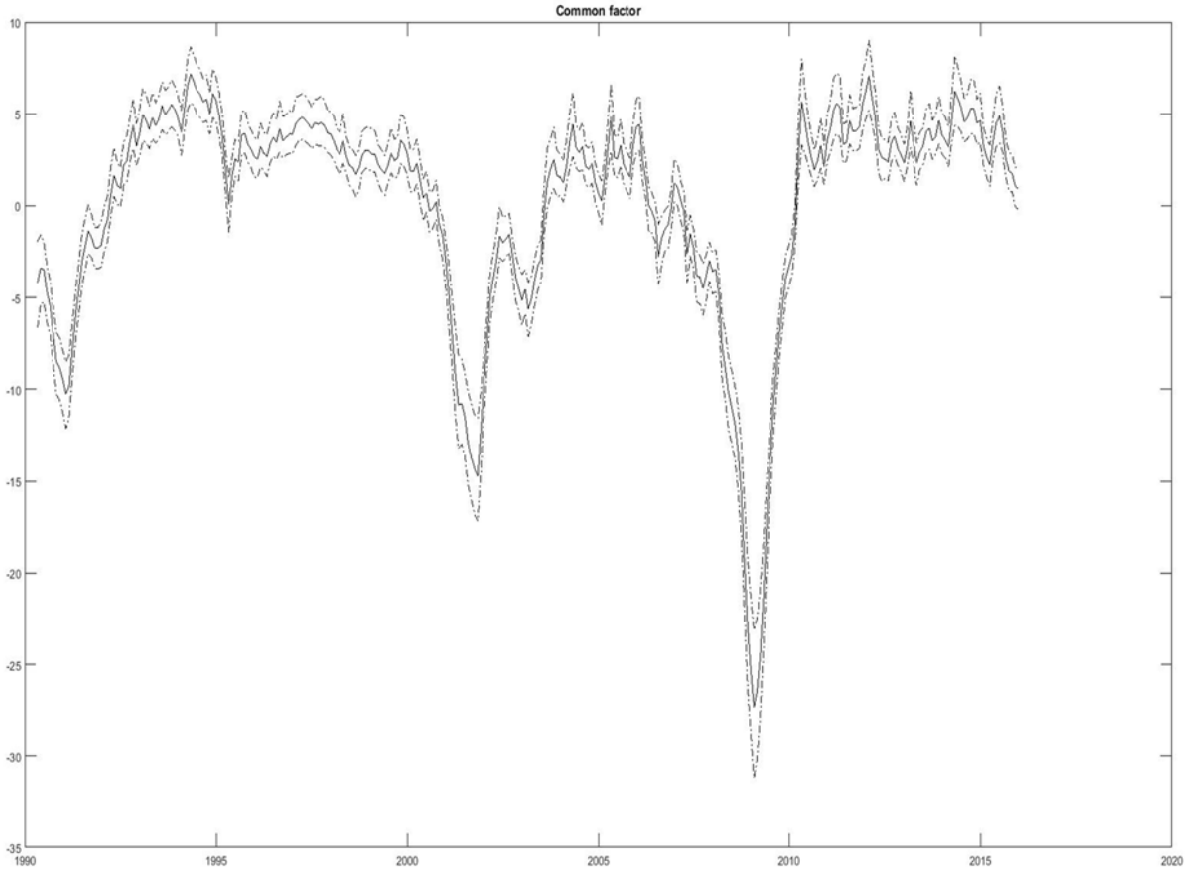


Figure 2. Variance Contributions of the National Factor for the 51 MSAs

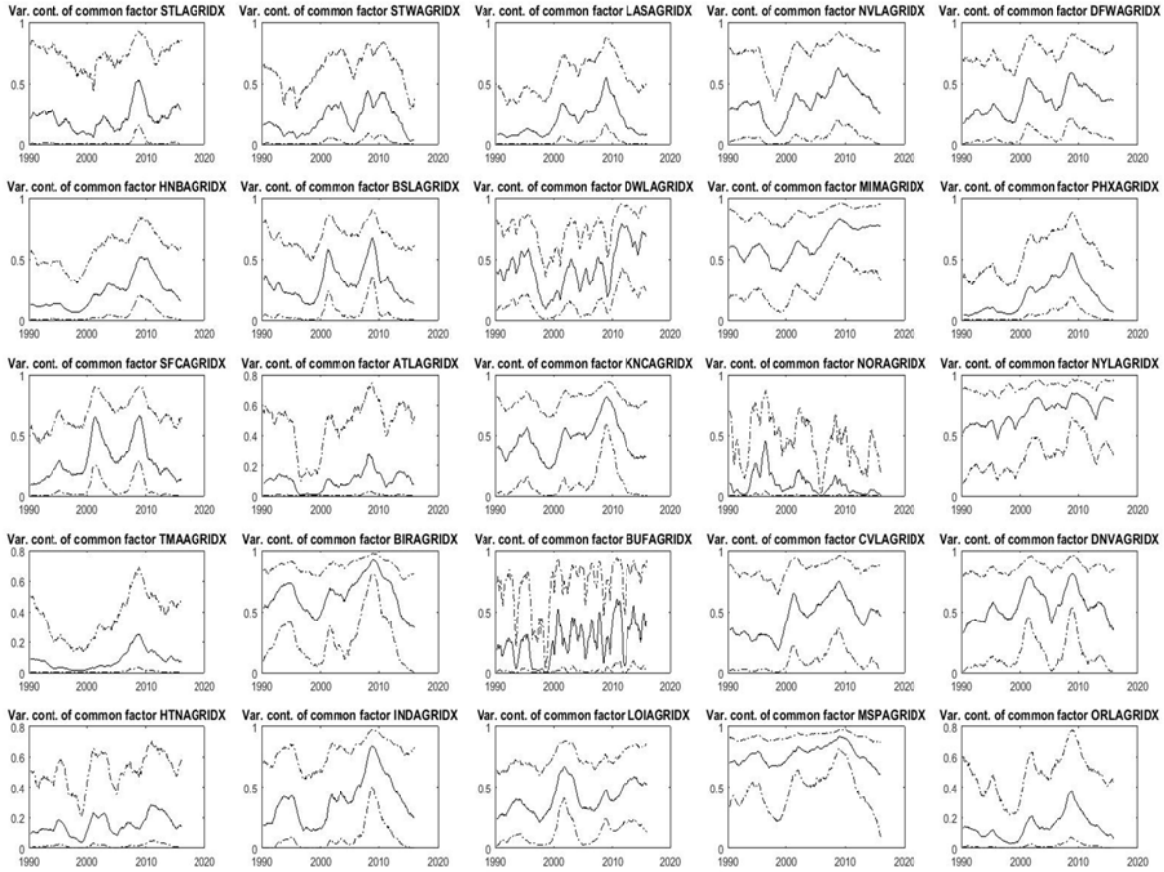


Figure 2. Variance Contributions of the National Factor for the 51 MSAs (Continued)

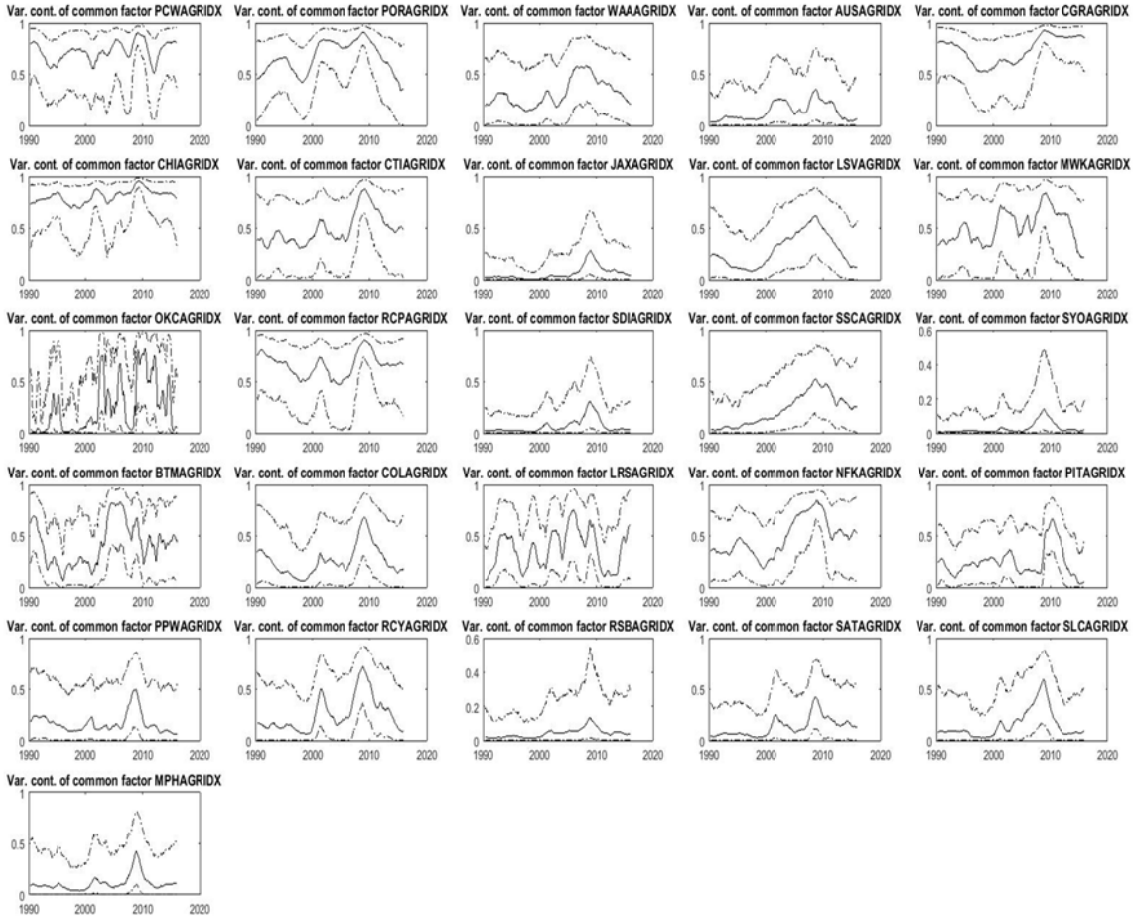


Figure 3. Stochastic Volatility of the National Factor for the 51 MSAs

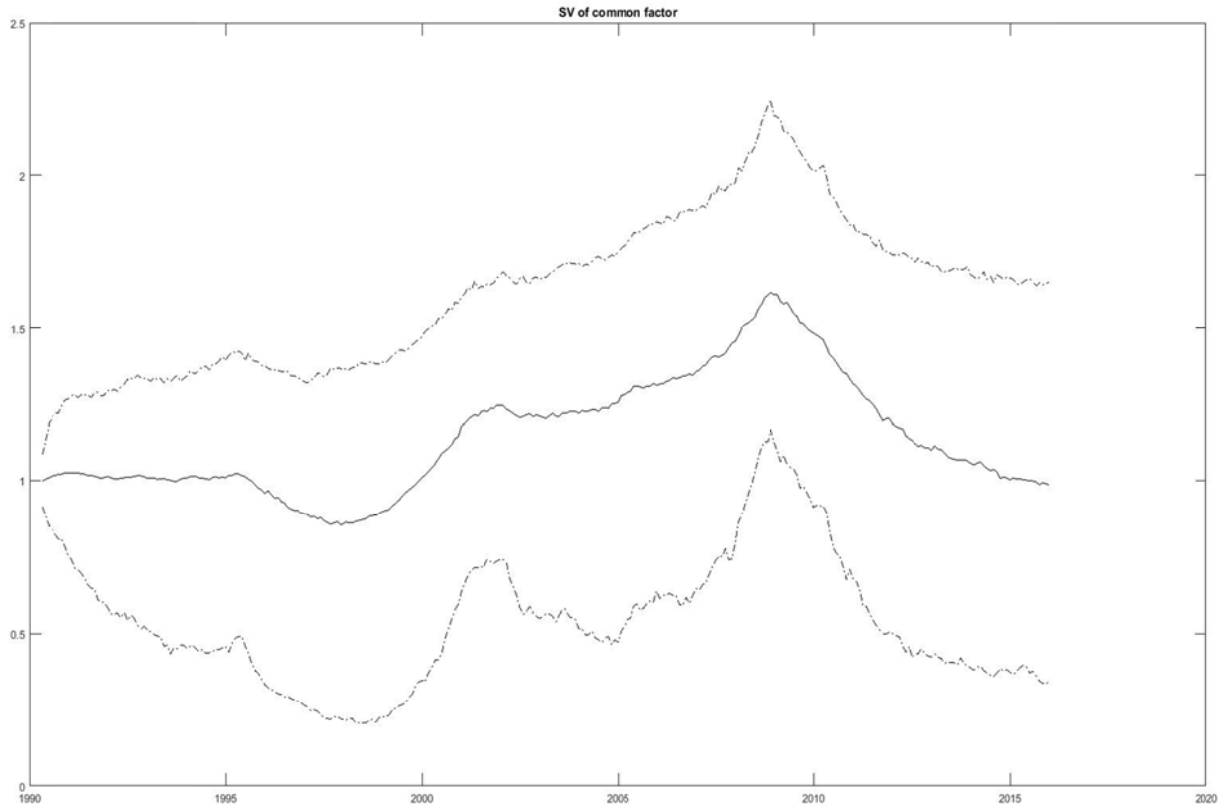


Figure 4. Average Cross-Correlation of Economic Activity Indices in 51 MSAs

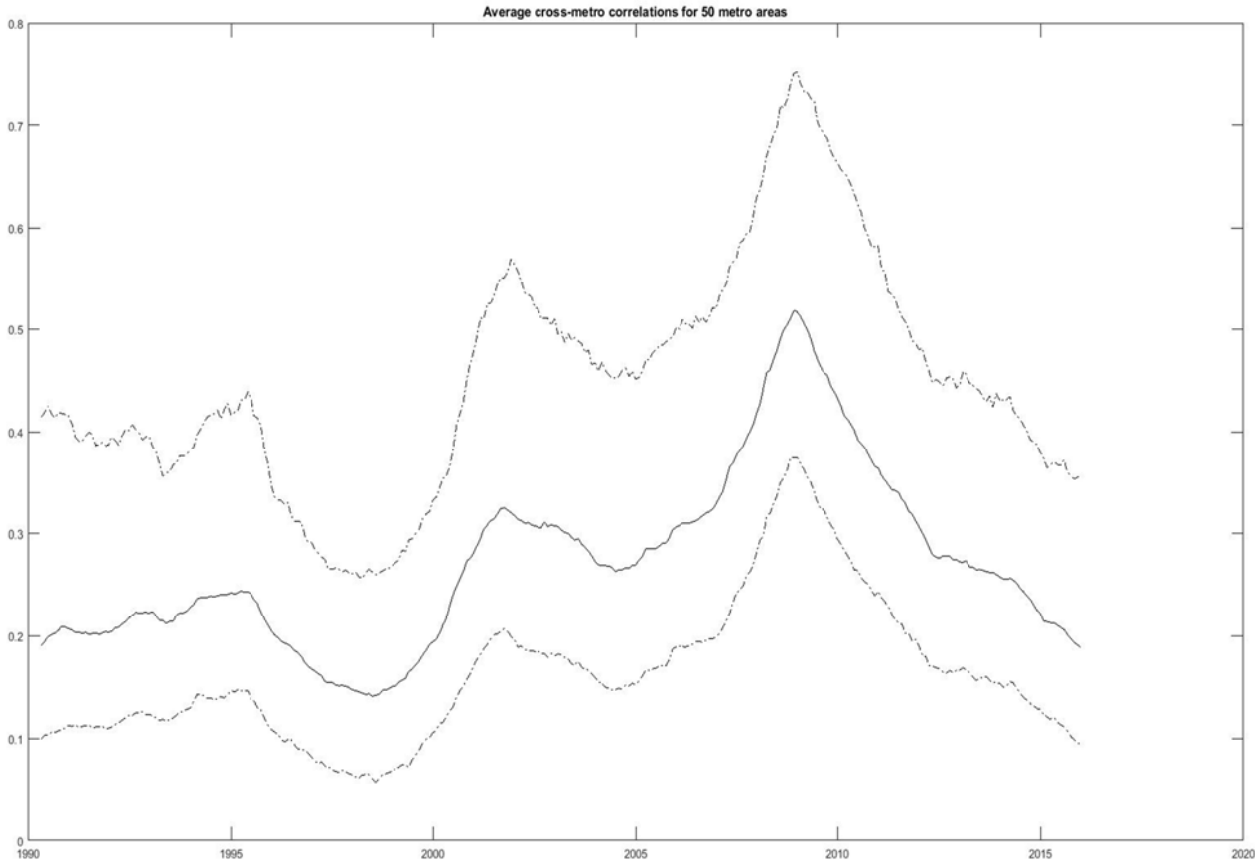


Figure 5. National Factor of Real Personal Income Growth for the 48 States

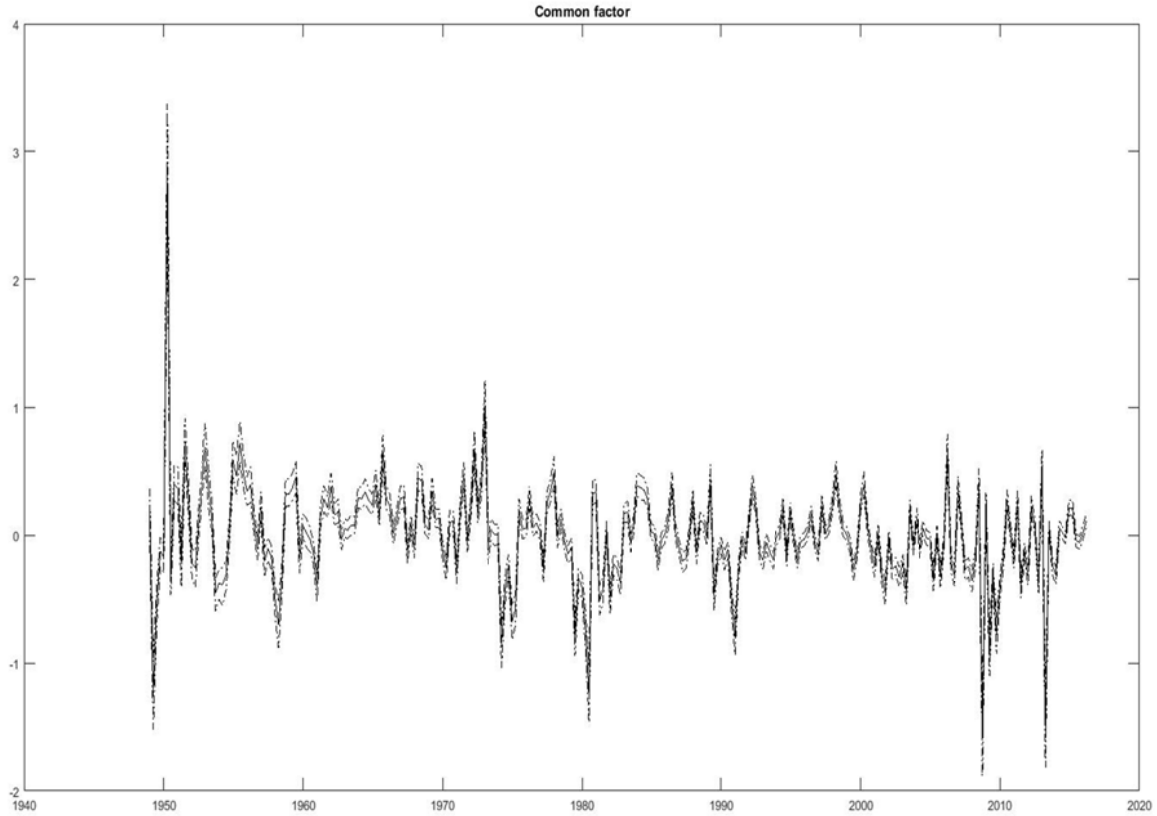


Figure 6. Variance Contributions of the National Factor for the 48 States

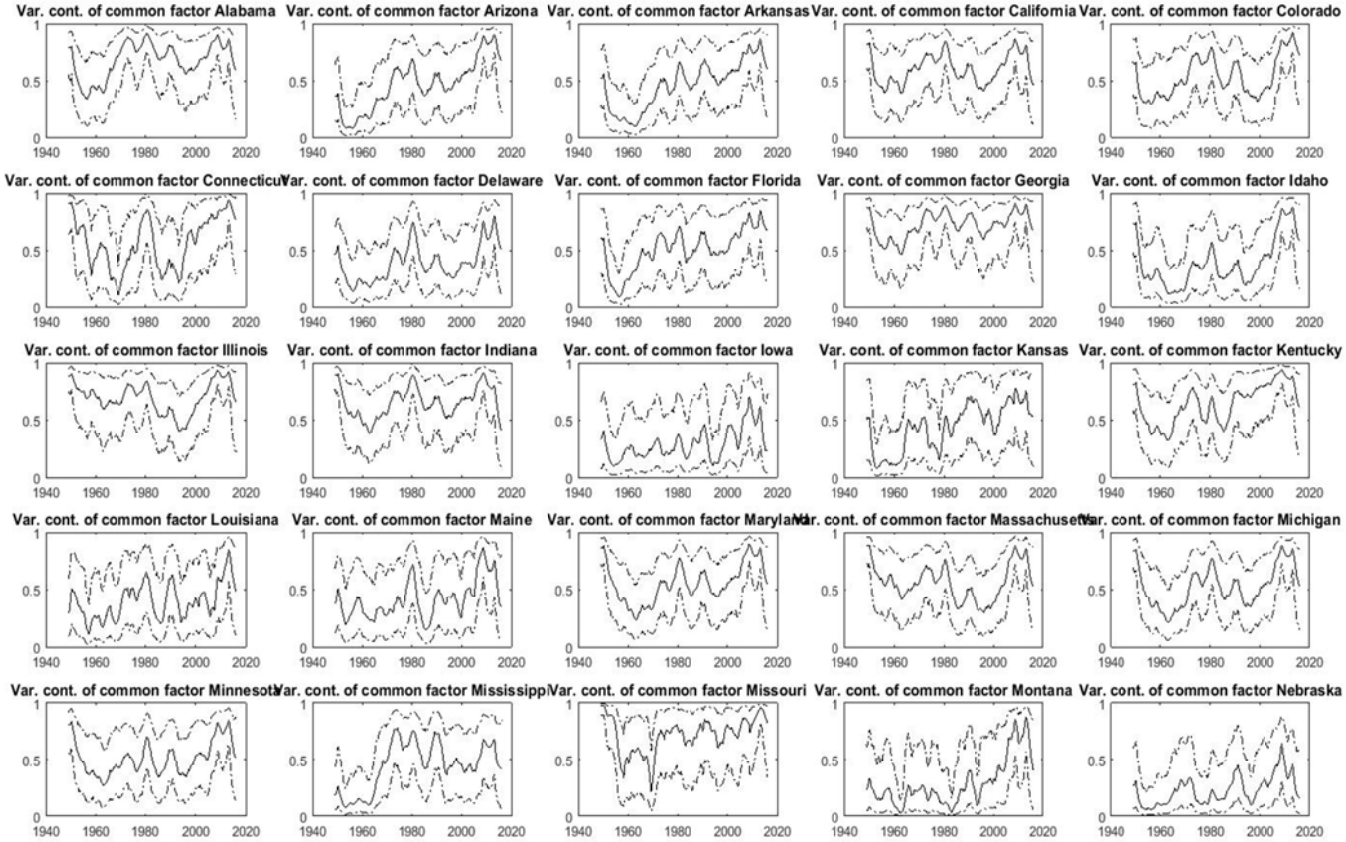


Figure 6. Variance Contributions of the National Factor for the 48 States (Continued)

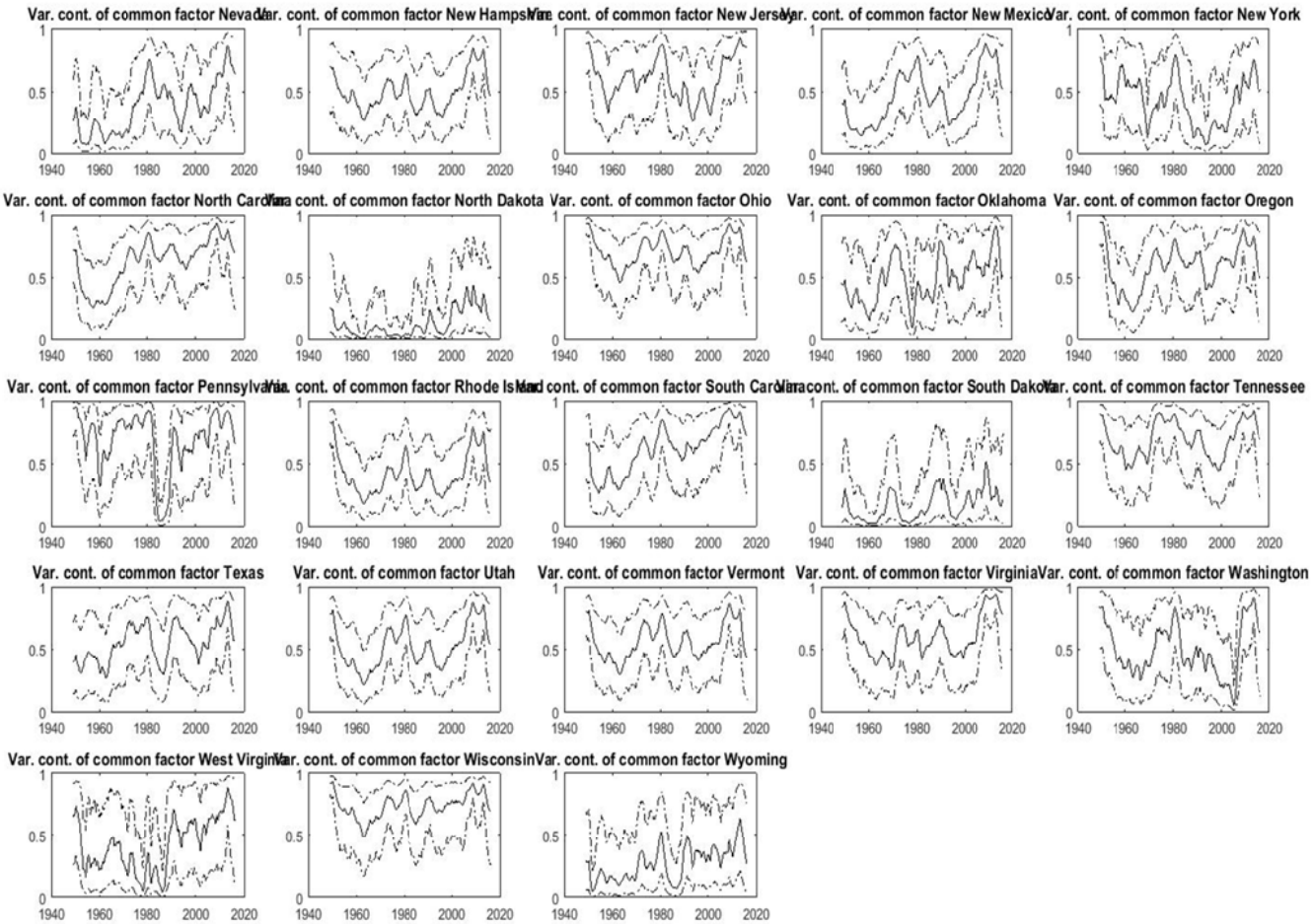


Figure 7. Stochastic Volatility of the National Factor for the 48 States

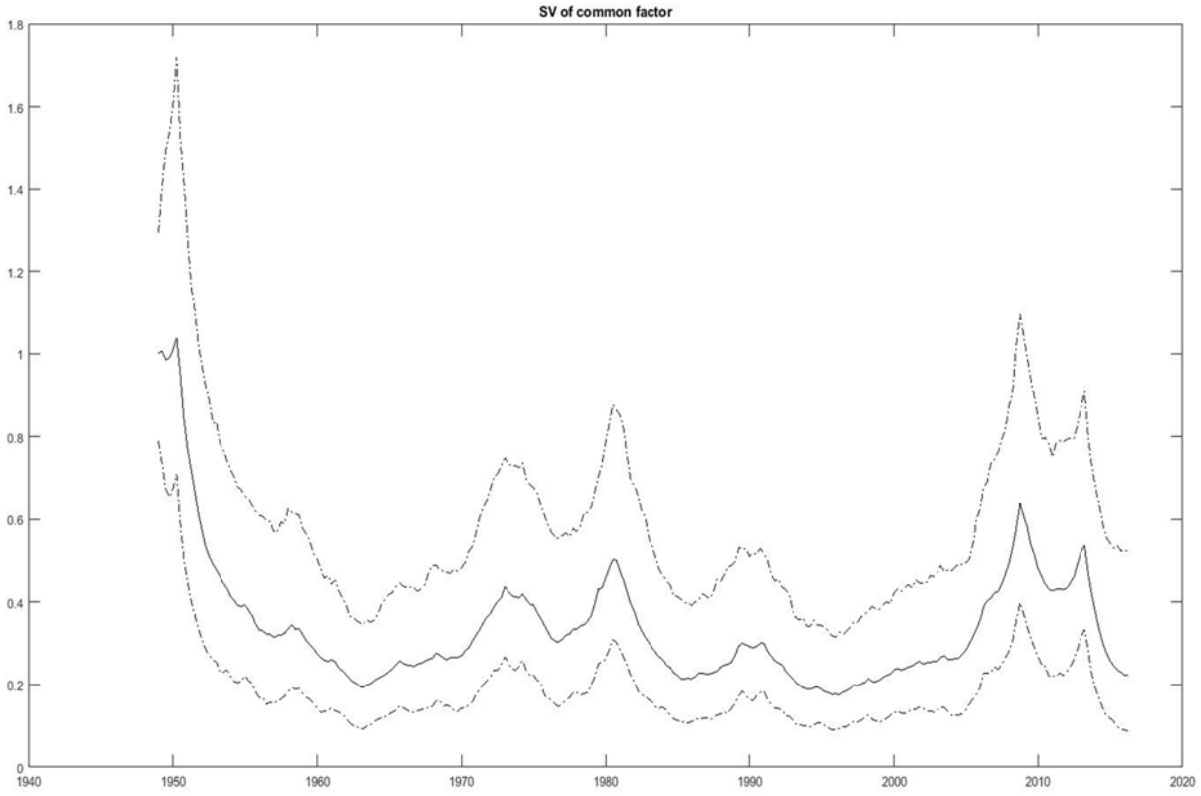


Figure 8. Average Cross-Correlation of Real Personal Income Growth in 48 States

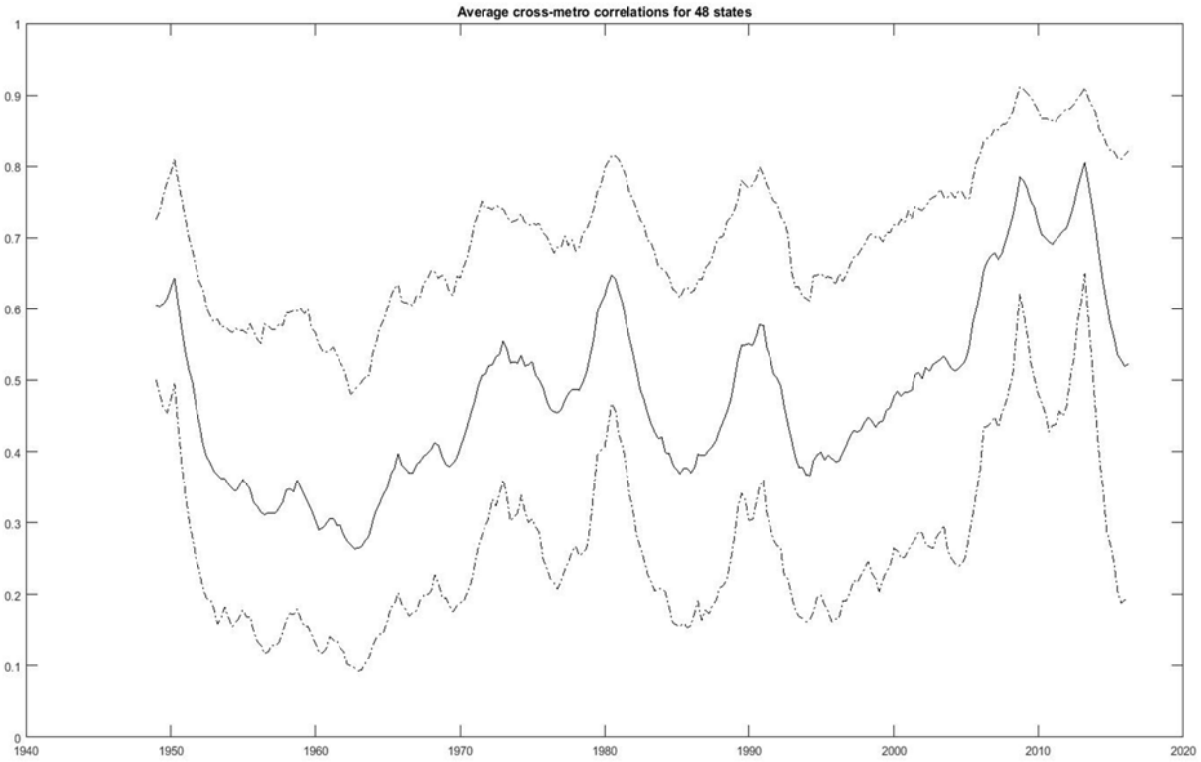


Figure 9. Impact of Uncertainty on the National Factor of the Economic Activity Indices of the MSAs

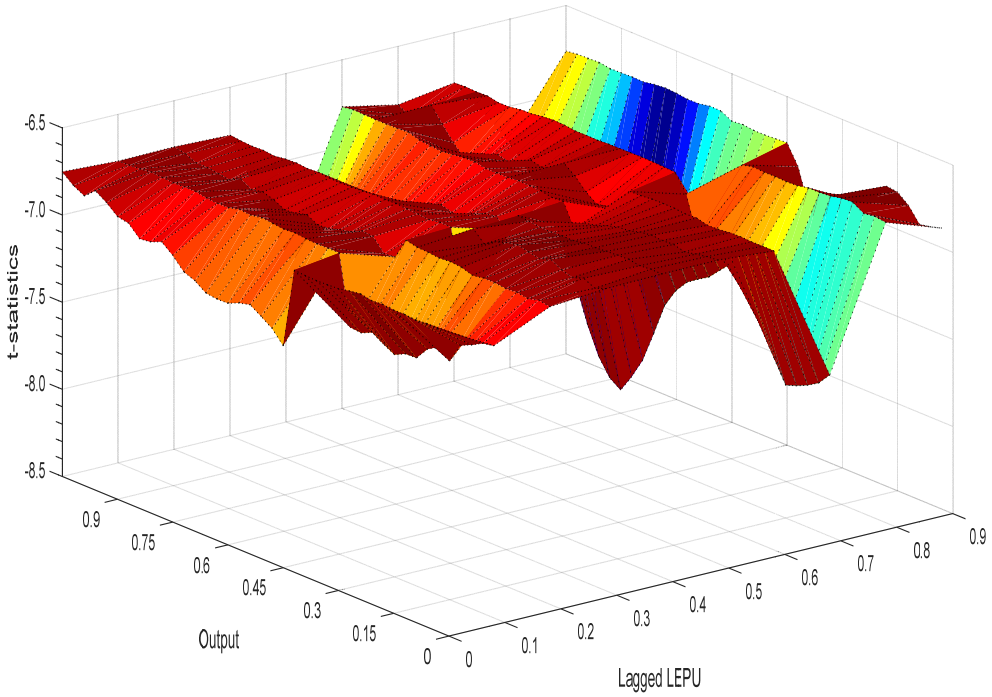


Figure 10. Impact of Uncertainty on the National Factor of the Stochastic Volatility of the MSAs

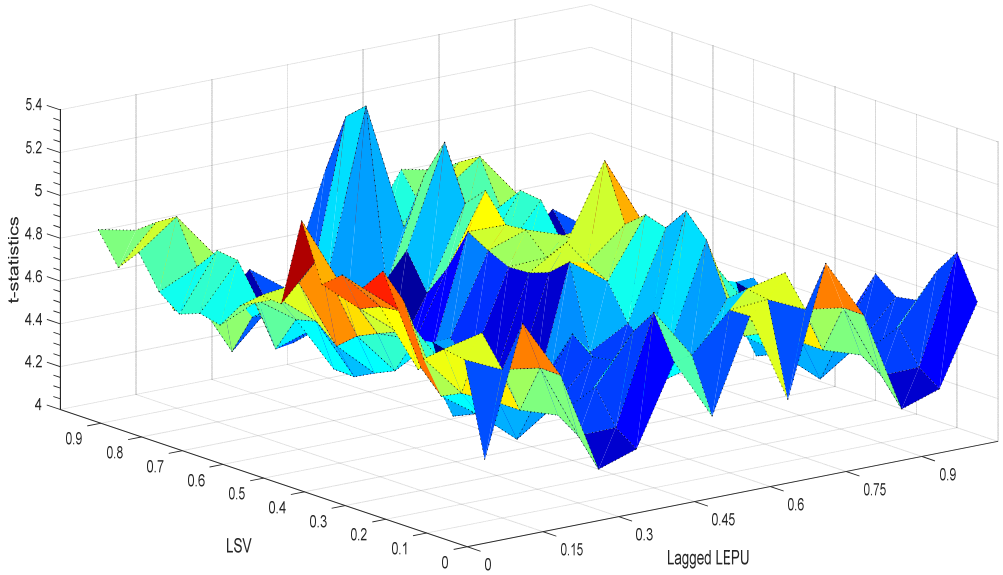


Figure 11. Impact of Uncertainty on the National Factor of Growth of Real Personal Income Growth of the States

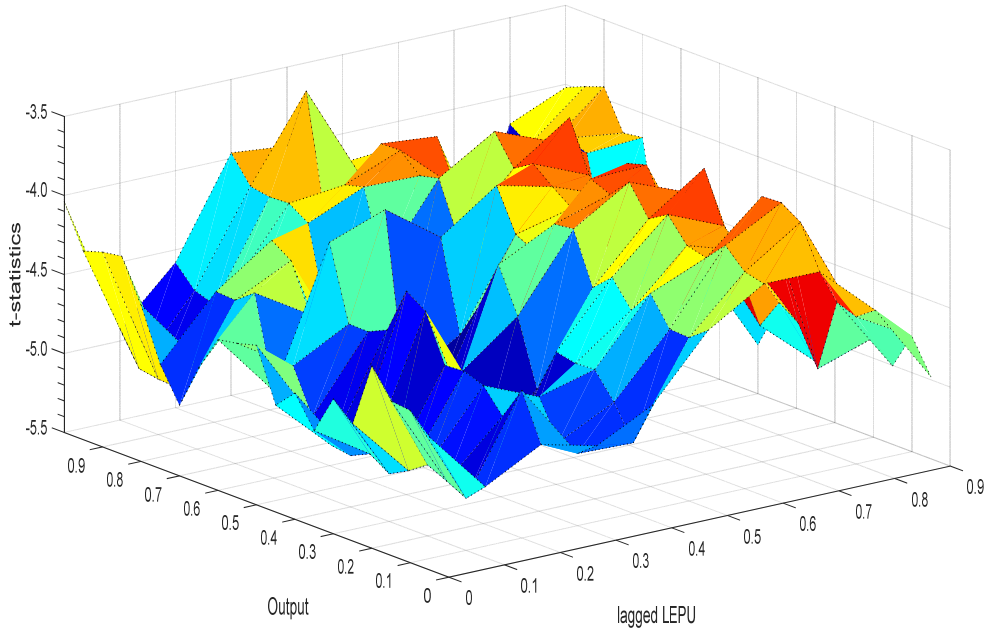
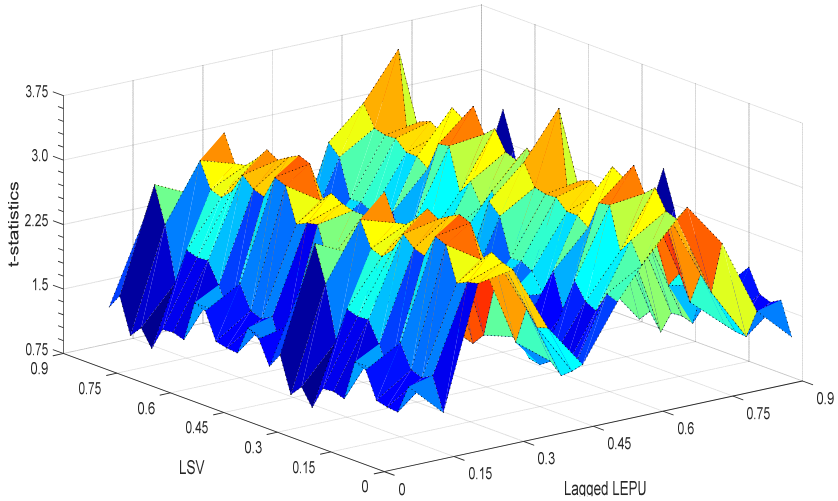


Figure 12. Impact of Uncertainty on the National Factor of Stochastic Volatility of Real Personal Income Growth of the States



APPENDIX:
Table A1. List of MSAs:

MSA Symbol	MSA Name
STLAGRIDX	St. Louis
STWAGRIDX	Seattle-Tacoma-Bellevue
LASAGRIDX	Los Angeles-Long Beach-Santa Ana
NVLAGRIDX	Nashville-Davidson--Murfreesboro--Franklin
DFWAGRIDX	Dallas-Fort Worth-Arlington
HNBAGRIDX	Hartford-West Hartford-East Hartford
BSLAGRIDX	Boston-Cambridge-Quincy
DWLAGRIDX	Detroit-Warren-Dearborn
MIMAGRIDX	Miami-Fort Lauderdale-West Palm Beach
PHXAGRIDX	Phoenix-Mesa-Scottsdale
SFCAGRIDX	San Francisco-Oakland-Hayward
ATLAGRIDX	Atlanta-Sandy Springs-Marietta
KNCAGRIDX	Kansas City
NORAGRIDX	New Orleans-Metairie
NYLAGRIDX	New York-Newark-Jersey City
TMAAGRIDX	Tampa-St. Petersburg-Clearwater
BIRAGRIDX	Birmingham-Hoover
BUFAGRIDX	Buffalo-Cheektowaga-Niagara Falls
CVLAGRIDX	Cleveland-Elyria
DNVAGRIDX	Denver-Aurora-Lakewood
HTNAGRIDX	Houston-The Woodlands-Sugar Land
INDAGRIDX	Indianapolis-Carmel-Anderson
LOIAGRIDX	Louisville/Jefferson County
MSPAGRIDX	Minneapolis-St. Paul-Bloomington
ORLAGRIDX	Orlando-Kissimmee-Sanford
PCWAGRIDX	Philadelphia-Camden-Wilmington
PORAGRIDX	Portland-Vancouver-Hillsboro
WAAAGRIDX	Washington-Arlington-Alexandria
AUSAGRIDX	Austin-Round Rock
CGRAGRIDX	Charlotte-Concord-Gastonia
CHIAGRIDX	Chicago-Naperville-Joliet
CTIAGRIDX	Cincinnati-Middletown
JAXAGRIDX	Jacksonville
LSVAGRIDX	Las Vegas-Henderson-Paradise
MWKAGRIDX	Milwaukee-Waukesha-West Allis
OKCAGRIDX	Oklahoma City
RCPAGRIDX	Richmond
SDIAGRIDX	San Diego-Carlsbad
SSCAGRIDX	San Jose-Sunnyvale-Santa Clara
SYOAGRIDX	Sacramento--Roseville--Arden-Arcade

BTMAGRIDX	Baltimore-Towson
COLAGRIDX	Columbus
LRSAGRIDX	Little Rock-North Little Rock-Conway
NFKAGRIDX	Virginia Beach-Norfolk-Newport News
PITAGRIDX	Pittsburgh
PPWAGRIDX	Providence-Warwick
RCYAGRIDX	Raleigh
RSBAGRIDX	Riverside-San Bernardino-Ontario
SATAGRIDX	San Antonio-New Braunfels
SLCAGRIDX	Salt Lake City
MPHAGRIDX	Memphis

Table A.2. Percentage Contribution of the National Factor to Real Personal Income of US States

	Full Sample Average	Average before 2007Q4	Average after 2007Q4
Alabama	68.11%	66.69%	78.08%
Arizona	46.62%	41.57%	81.95%
Arkansas	46.46%	42.37%	75.13%
California	60.67%	59.14%	71.38%
Colorado	54.04%	49.94%	82.71%
Connecticut	56.78%	52.73%	85.15%
Delaware	39.22%	35.48%	65.38%
Florida	50.94%	47.60%	74.30%
Georgia	72.33%	70.93%	82.11%
Idaho	39.28%	33.76%	77.89%
Illinois	69.91%	67.77%	84.94%
Indiana	65.92%	64.87%	73.29%
Iowa	29.26%	26.53%	48.38%
Kansas	44.32%	41.29%	65.51%
Kentucky	64.59%	62.00%	82.71%
Louisiana	39.98%	36.58%	63.80%
Maine	41.63%	38.28%	65.04%
Maryland	56.16%	53.10%	77.58%
Massachusetts	56.93%	54.22%	75.88%
Michigan	53.29%	49.98%	76.47%
Minnesota	51.60%	48.54%	73.04%
Mississippi	44.70%	42.79%	58.09%
Missouri	71.96%	69.80%	87.08%
Montana	29.34%	23.42%	70.78%
Nebraska	23.24%	21.18%	37.66%
Nevada	37.70%	33.17%	69.46%
New Hampshire	49.63%	46.43%	72.03%
New Jersey	60.66%	57.40%	83.45%
New Mexico	45.92%	41.74%	75.21%
New York	43.27%	40.85%	60.22%
North Carolina	62.60%	59.75%	82.56%
North Dakota	12.34%	10.20%	27.37%
Ohio	71.09%	69.40%	82.90%
Oklahoma	48.60%	45.72%	68.77%
Oregon	58.89%	56.76%	73.80%
Pennsylvania	69.45%	67.20%	85.20%
Rhode Island	42.25%	39.36%	62.51%
South Carolina	62.12%	58.66%	86.31%
South Dakota	16.54%	14.74%	29.19%
Tennessee	69.89%	67.76%	84.75%
Texas	55.23%	52.67%	73.10%

Utah	52.63%	49.30%	75.94%
Vermont	56.63%	54.57%	71.01%
Virginia	60.62%	56.58%	88.88%
Washington	49.75%	45.44%	79.88%
West Virginia	42.52%	38.25%	72.44%
Wisconsin	73.63%	72.20%	83.67%
Wyoming	27.31%	24.93%	43.95%
AVERAGE	50.97%	47.99%	71.81%

Table A.3. Percentage Contribution of the National Factor to Real Personal Income of US MSAs

	Full Sample Average	Average before 2007Q4	Average after 2007Q4
STLAGRIDX	21.83%	17.89%	30.27%
STWAGRIDX	20.51%	17.85%	26.21%
LASAGRIDX	18.95%	16.23%	24.79%
NVLAGRIDX	34.52%	29.33%	45.64%
DFWAGRIDX	35.67%	31.21%	45.23%
HNBAGRIDX	22.55%	16.74%	34.98%
BSLAGRIDX	30.29%	29.21%	32.60%
DWLAGRIDX	43.20%	35.88%	58.88%
MIMAGRIDX	63.02%	56.16%	77.70%
PHXAGRIDX	20.16%	16.44%	28.12%
SFCAGRIDX	29.23%	28.24%	31.33%
ATLAGRIDX	10.08%	8.09%	14.34%
KNCAGRIDX	46.18%	43.29%	52.37%
NORAGRIDX	9.34%	11.19%	5.38%
NYLAGRIDX	69.60%	65.56%	78.23%
TMAAGRIDX	8.05%	5.51%	13.50%
BIRAGRIDX	64.03%	62.52%	67.27%
BUFAGRIDX	26.40%	21.97%	35.89%
CVLAGRIDX	45.37%	40.77%	55.24%
DNVAGRIDX	55.22%	53.41%	59.10%
HTNAGRIDX	15.30%	13.16%	19.89%
INDAGRIDX	39.85%	32.53%	55.54%
LOIAGRIDX	41.36%	37.81%	48.96%
MSPAGRIDX	76.81%	75.94%	78.66%
ORLAGRIDX	14.33%	11.77%	19.83%
PCWAGRIDX	72.31%	70.35%	76.53%
PORAGRIDX	66.17%	65.74%	67.10%
WAAAGRIDX	31.59%	27.83%	39.65%
AUSAGRIDX	13.51%	11.84%	17.08%
CGRAGRIDX	74.00%	67.42%	88.10%
CHIAGRIDX	81.00%	78.43%	86.51%
CTIAGRIDX	49.16%	41.98%	64.54%
JAXAGRIDX	6.17%	3.14%	12.66%
LSVAGRIDX	28.81%	25.51%	35.88%
MWKAGRIDX	51.04%	47.48%	58.68%
OKCAGRIDX	25.24%	17.44%	41.93%
RCPAGRIDX	66.48%	62.83%	74.30%
SDIAGRIDX	6.61%	4.61%	10.89%
SSCAGRIDX	22.49%	15.65%	37.14%
SYOAGRIDX	2.70%	1.62%	5.00%
BTMAGRIDX	42.11%	40.73%	45.04%
COLAGRIDX	26.01%	21.05%	36.62%

LRSAGRIDX	36.71%	37.98%	33.99%
NFKAGRIDX	48.48%	42.35%	61.62%
PITAGRIDX	24.56%	21.74%	30.61%
PPWAGRIDX	16.96%	16.05%	18.92%
RCYAGRIDX	25.37%	19.58%	37.77%
RSBAGRIDX	4.23%	3.28%	6.29%
SATAGRIDX	13.33%	9.17%	22.26%
SLCAGRIDX	15.58%	12.94%	21.23%
MPHAGRIDX	11.21%	8.85%	16.27%
AVERAGE	33.80%	30.48%	40.91%