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Metro Business Cycles

Abstract

We construct monthly economic activity indices for the 50 largest U.S. metropolitan statistical areas (MSAs) beginning in 1990. Each index is derived from a dynamic factor model based on twelve underlying variables capturing various aspects of metro area economic activity. To accommodate mixed-frequency data and differences in data-publication lags, we estimate the dynamic factor model using a maximum-likelihood approach that allows for arbitrary patterns of missing data. Our indices highlight important similarities and differences in business cycles across MSAs. While a number of MSAs experience sizable recessions during the national recessions of the early 1990s and early 2000s, other MSAs escape recessions altogether during one or both of these periods. Nearly all MSAs suffer relatively deep recessions near the recent Great Recession, but we still find significant differences in the depth of recent metro recessions. We relate the severity of metro recessions to a variety of MSA characteristics and find that MSAs with less-educated populations and less elastic housing supplies experience significantly more severe recessions. After controlling for national economic activity, we also find significant evidence of dynamic spillover effects in economic activity across MSAs.

JEL classifications: C38, E32, R11, R31

Keywords: Economic activity index; Metropolitan statistical area; Recession; Dynamic factor model; Latent variable; EM algorithm; Mixed regressive, spatial autoregressive model; Dynamic spillovers

1. Introduction

The grand tradition of Burns and Mitchell (1946) views business cycles as common fluctuations in a host of economic variables. Beginning with Geweke (1977) and Sargent and Sims (1977), and continuing with Stock and Watson (1989, 1991), researchers have formalized this notion by developing dynamic factor models that allow for the estimation of a latent common factor—an index of economic activity—underlying the comovements in multiple variables. For example, Stock and Watson (1989, 1991) specify a dynamic factor model for four national variables (industrial production, personal income, manufacturing and retail sales, and employment) to estimate a monthly economic activity index for the United States. Subsequently, a sizable literature uses dynamic factor models to construct economic activity indices for the United States and other countries based on a larger number of individual economic variables; see, for example, Arouba et al. (2009) for the Unites States and Altissimo et al. (2001) for the Euro area.[1]

Although the bulk of the literature focuses on national activity indices, a few studies construct monthly indices for individual U.S. states. For example, adopting the approach of Stock and Watson (1989, 1991), Crone and Clayton-Matthews (2005) estimate an economic activity index for each of the 50 individual U.S. states using a dynamic factor model and four state-level labor-market variables (payroll employment, the unemployment rate, average hours worked in manufacturing, and real wage and salary disbursements), while Bram et al. (2009) develop indices for New York and New Jersey using a similar approach.[2] State indices allow researchers to compare state business cycles to the national cycle (e.g., Owyang et al., 2005; Crone, 2006) and to link differences in state business cycles to state characteristics (e.g., Owyang et al., 2009). Along the lines of Wall and Zoega (2002)

[1] Marcellino (2006) and Stock and Watson (2011) provide extensive surveys of dynamic factor models.

[2] Indices based on these studies are reported regularly by the Federal Reserve Banks of Philadelphia (available at http://www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident/) and New York (available at http://www.ny.frb.org/research/regional_economy/coincident_summary.html), respectively.

and Nakamura and Steinsson (2014), they also provide researchers with more information for estimating economic relations that are typically estimated using national data. Of course, state indices supply state governments with important information for formulating appropriate policies in light of economic conditions, and state indices also inform national policymakers of regional differences in economic conditions when setting national economic policies.[3]

While national and state indices of monthly economic activity are now widely available, monthly economic activity indices are currently only available for a small number of U.S. metropolitan statistical areas (MSAs), despite their potential value. Metro indices allow for an even more disaggregated geographical comparison of business cycles, thus permitting researchers to identify significant differences in economic activity that are masked by existing state indices. In this vein—and similarly to Ghent and Owyang (2010), Mian et al. (2013), Kiley (2014), and Mian and Sufi (2014)—metro indices provide a rich source of variation in economic activity that can be exploited to analyze important economic relations with greater precision. Metro indices are also clearly valuable to local governments for setting policy, and they provide state and national governments with a more complete picture of differences in local economic activity when deciding on appropriate policies at the state and national levels, respectively.

In this paper, we develop monthly economic activity indices for the 50 largest MSAs (by population) in the United States.[4] In the spirit of Burns and Mitchell (1946), our goal is to measure economic activity by incorporating information from a wide array of metro variables. Data issues, however, present keen challenges for achieving this goal; most pressingly, we need to accommodate mixed-frequency data, different starting dates for some variables, and different publication lags across variables. To this end, we construct each metro index via a dynamic factor model based on twelve underlying metro variables, where we estimate the

[3]Regional economic conditions appear relevant for the Federal Reserve's monetary policy decisions, as exemplified by the Beige Book.

[4]Table 1 provides a complete list of the 50 largest MSAs and their populations in 2014.

model using the recently developed maximum-likelihood approach of Bańbura and Modugno (2014). Their approach relies on the Expectation Maximization (EM) algorithm of Dempster et al. (1977) to implement maximum-likelihood estimation and is explicitly designed to handle arbitrary patterns of missing data, including mixed-frequency data and missing data for some variables at the beginning and/or end of the sample. The Bańbura and Modugno (2014) procedure allows us to compute monthly metro economic activity indices based on a large number of local variables in a timely manner.

To the best of our knowledge, the only extant monthly economic activity indices at the MSA level are for New York City and nine MSAs in Texas, which are produced by the Federal Reserve Banks of New York and Dallas, respectively.[5] The New York City index is based on four labor-market variables, while the indices for the Texas MSAs are based on three labor-market variables and retail sales. Our study is thus the first to construct consistent monthly economic activity indices based on a broad array of local economic variables for a large number of U.S. metro areas.

We calibrate our monthly metro indices to annual gross metropolitan product (GMP) growth. This strategy is analogous to Clayton-Matthews and Stock (1998), who calibrate an economic activity index for Massachusetts to gross state product (GSP) growth. By calibrating our metro indices to GMP growth, we create economically meaningful scales, so that we can compare business-cycle fluctuations across MSAs. In conjunction with a nonparametric algorithm, our indices' meaningful scales allow us to identify a complete set of monthly business-cycle peaks and troughs for the 50 MSAs.

Our economic activity indices reveal important similarities and differences in business cycles across MSAs. Important differences are evident around the national recessions of the early 1990s and early 2000s. Although many MSAs experience sizable recessions during these periods, others manage to escape recessions altogether during one or both of these periods. Indeed, we even find marked differences in business cycles across MSAs within the

[5] Available at http://www.newyorkfed.org/research/regional_economy/coincident_summary.html and http://www.dallasfed.org/research/econdata/mbci.cfm, respectively.

same state. For example, San Jose and San Francisco endure deep recessions during the early 2000s, while Riverside, San Diego, and Sacramento do not experience recessions at all during this period. There are greater similarities across MSAs near the recent Great Recession, as nearly all MSAs suffer relatively deep recessions in the late 2000s. Nevertheless, our indices still indicate substantive differences in the depth of recent recessions across some MSAs.

To gain insight into the underlying sources of differences in business-cycle fluctuations across MSAs, we relate the severity of metro recessions to a variety of MSA characteristics. We present robust cross-sectional evidence that MSAs with less-educated populations and less elastic housing supplies experience more severe recessions. The negative relation between housing supply elasticity and recession severity across MSAs lines up well with recent findings reported in Glaeser et al. (2008), Mian et al. (2013), and Mian and Sufi (2014). The first study finds that areas with lower housing supply elasticities are more susceptible to "boom-bust" housing cycles, while the latter two studies detect large consumption responses to housing net worth shocks. In conjunction, these studies indicate that areas with less elastic housing supply are more likely to suffer large declines in housing net worth and sharp concomitant decreases in consumption spending, making areas with inelastic housing supply more vulnerable to recessions. Our results confirm that such a pattern exists across MSAs. In the context of a mixed regressive, spatial autoregressive (MRSAR) model, we also detect significant spatial effects in the severity of metro recessions.

Finally, we test for dynamic spillover effects using the infinite-dimensional vector autoregression (IVAR) approach and cross-section augmented least squares (CALS) estimation procedure recently developed by Chudik and Pesaran (2011). Their methodology allows us to parsimoniously estimate dynamic spillovers between MSAs, while controlling for national economic activity. The CALS estimation results provide significant evidence of dynamic spillover effects across a number of MSAs.

The rest of the paper is organized as follows. Section 2 specifies the dynamic factor model and outlines maximum-likelihood estimation of the model. Section 3 describes the MSA data underlying the metro economic activity indices. Section 4 presents economic activity indices for the 50 largest MSAs in the United States for 1990:02 to 2015:06 and identifies a set of business-cycle peaks and troughs for each MSA. Section 5 reports cross-sectional results relating the severity of metro recession to a variety of MSA characteristics, while Section 6 reports estimates of dynamic spillover effects. Section 7 contains concluding remarks. The paper includes three appendices: Appendix A details maximum-likelihood estimation of the dynamic factor model via the EM algorithm, Appendix B explains the calibration of the metro indices, and Appendix C describes the updating and regular reporting of the indices on the Federal Reserve Economic Data (FRED) website maintained by the Federal Reserve Bank of St. Louis.[6] With respect to mathematical notation, we use bold lowercase and uppercase letters to signify vectors and matrices, respectively.

2. Econometric methodology

A factor model provides our basic framework:

$$\Delta \boldsymbol{y}_t = \boldsymbol{\lambda} \, \Delta f_t + \boldsymbol{\varepsilon}_t \quad \text{for} \quad t = 1, \ldots, T, \tag{1}$$

where $\Delta \boldsymbol{y}_t = (\Delta y_{1,t}, \ldots, \Delta y_{N,t})'$ is an N-vector of variables for a given MSA in month t, Δf_t is a latent common factor, $\boldsymbol{\lambda} = (\lambda_1, \ldots, \lambda_N)'$ is an N-vector of factor loadings, and $\boldsymbol{\varepsilon}_t = (\varepsilon_{1,t}, \ldots, \varepsilon_{N,t})'$ is an N-vector of idiosyncratic components corresponding to the individual variables in $\Delta \boldsymbol{y}_t$. We specify Eq. (1) in terms of $\Delta \boldsymbol{y}_t$ to emphasize that we take the first difference of $\boldsymbol{y}_t = (y_{1,t}, \ldots, y_{N,t})'$ to render each of its elements stationary (since each element of $\boldsymbol{y}_t$ is expressed in levels or log levels, as described in Section 3). Following convention, and without loss of generality, we standardize each element in $\Delta \boldsymbol{y}_t$ to have zero mean and unit variance before estimating Eq. (1).

[6] Available at http://research.stlouisfed.org/fred2/.

The factor model becomes dynamic by assuming that Δf_t and each of the idiosyncratic components follow stationary autoregressive processes:

$$\Delta f_t = a\,\Delta f_{t-1} + u_{f,t}, \quad u_{f,t} \sim \text{ i.i.d. } N(0, \sigma_f^2), \tag{2}$$

$$\varepsilon_{i,t} = \alpha_i\,\varepsilon_{i,t-1} + e_{i,t}, \quad e_{i,t} \sim \text{ i.i.d. } N(0, \sigma_i^2) \text{ for } i = 1, \ldots, N, \tag{3}$$

where $|a| < 1$ and $|\alpha_i| < 1$ for $i = 1, \ldots, N$.[7] Using the standard dynamic factor model specification, we also assume that $E(e_{i,t}\,e_{j,t}) = 0$ for $i \neq j$ and $E(u_{f,t}\,e_{i,t}) = 0$ for all i. The common factor Δf_t is thus solely responsible for the common fluctuations in the elements of $\Delta \boldsymbol{y}_t$, so that Δf_t is naturally interpreted as an index of economic activity.[8]

Based on Eqs. (1) through (3), we can write the log-likelihood function for the dynamic factor model and estimate the model via maximum likelihood. However, because Δf_t is unobserved, closed-form estimates are generally not available. In addition, to construct metro economic activity indices based on a broad array of local variables, we need to address missing-data issues relating to mixed-frequency data and differences in data-publication lags (the "ragged-edge" problem). We thus estimate Δf_t using the recently developed approach of Bańbura and Modugno (2014), who extend Shumway and Stoffer (1982) and Watson and Engle (1983) and show how the EM algorithm of Dempster et al. (1977) can be used to estimate dynamic factor models via maximum likelihood when $\Delta \boldsymbol{y}_t$ contains arbitrary patterns of missing data. Bańbura and Modugno (2014) use the procedure of Mariano and Murasawa (2003) to accommodate mixed-frequency data (monthly and quarterly) and build on Durbin and Koopman (2012) to accommodate the ragged-edge problem (as well as

[7] We follow Bańbura and Modugno (2014) by specifying that the shocks in Eqs. (2) and (3) are homoskedastic. Allowing for time-varying volatility would significantly increase the computational complexity of maximum-likelihood estimation of the dynamic factor model and is beyond the scope of the present paper. It is an interesting avenue for future research.

[8] The assumption that $E(e_{i,t}\,e_{j,t}) = 0$ for $i \neq j$ means that Eq. (1) represents an exact (dynamic) factor model. An approximate factor model in the sense of Chamberlain and Rothschild (1983) allows for a limited degree of cross-sectional correlation in the idiosyncratic components. If we permit such cross-sectional correlation, Doz et al. (2012) show that the common factor can be consistently estimated by quasi-maximum likelihood; in this case, our economic activity index corresponds to the quasi-maximum-likelihood estimate of the common factor.

differences in starting dates for some variables). Appendix A provides a detailed description of maximum-likelihood estimation of our dynamic factor model via the EM algorithm.[9]

Since we employ mixed-frequency data and a broad array of metro variables, the dimension of the state vector needed to implement the EM algorithm is quite large (see Appendix A). Nevertheless, Bańbura and Modugno (2014) find that the EM algorithm converges relatively quickly for high-dimensional state vectors in applications involving dynamic factor models and a large number of macroeconomic and financial variables to nowcast Euro-area real GDP growth. We also find that the EM algorithm converges reasonably rapidly (and is not sensitive to initial values) when estimating our metro indices.

Because Δf_t is an index, its sign and scale are arbitrary.[10] We set the sign of the index based on fluctuations in employment growth so that an increase in the index naturally corresponds to stronger economic growth. With respect to the scale, we calibrate each index to the log growth rate of real GMP based on annual GMP data available at the time of index construction; each index thus has the same annualized mean and standard deviation as its real GMP log growth rate (over the sample period for which data on real GMP growth are available). Our calibration is analogous to Clayton-Matthews and Stock (1998), who construct a monthly state index of economic activity for Massachusetts and calibrate it to annual real GSP growth.[11] The calibration to GMP growth gives each of our indices an economically meaningful scale. Appendix B details the calibration process, and we denote the calibrated index by $\Delta \tilde{f}_t$.

To measure the uncertainty in the indices, we also compute 95% confidence bands for each metro index. The Kalman filter and smoother are components of the EM algorithm, so that we can straightforwardly compute the variance of the latent factor at each point in time

[9] An alternative estimation approach is principal component analysis (adjusted to account for missing data), where the estimated common factor is the first principal component extracted from the set of local variables. This approach, however, is inefficient; accordingly, it generally produces more volatile index estimates.

[10] Multiplying Δf_t by $-k$ and dividing λ by $-k$ in Eq. (1) produces the same model.

[11] The 50 monthly U.S. state indices reported regularly by the Federal Reserve Bank of Philadelphia are similarly calibrated to individual GSP growth rates.

using the familiar Kalman recursions after plugging in the maximum-likelihood parameter estimates (as detailed in Appendix A). However, this approach does not account for the sampling uncertainty in the parameter estimates. To account for parameter estimation uncertainty, we use the parametric bootstrap approximation of Pfeffermann and Tiller (2005) to compute 95% confidence bands for our indices. Appendix A describes the construction of the confidence bands.

3. Data

To increase the number and scope of the local variables used to estimate the metro indices, we employ both monthly and quarterly data. As indicated in Section 2, our estimation procedure is designed to handle mixed-frequency data. Table 2 lists the twelve metro variables used to compute each metro index and the data sources. Seven (five) of the variables are monthly (quarterly). The variables include seven labor-market measures (average weekly hours worked, unemployment rate, private sector goods-producing employment, private sector services-producing employment, government sector employment, real average hourly earnings, real average quarterly wages), building permits, real personal income per capita, and three financial metrics (return on average assets, net interest margin, loan loss reserve ratio).[12] Our new metro indices are thus based on a much broader set of variables than the few existing metro indices (as well as the state indices reported by the Federal Reserve Bank of Philadelphia, which are based on four labor-market variables). The fourth column of Table 2 indicates how each variable is transformed to render it stationary.

After transforming the variables, our sample begins in 1990:02 and extends through 2015:06. Data for ten of the twelve series (in levels) are available for all 50 MSAs beginning in

[12] We convert nominal average hourly earnings, average quarterly wages, and personal income per capita to real variables using the national consumer price index (CPI). MSA personal income data are available annually, and we interpolate a quarterly personal income series for each metro area using a cubic spline. The banking data used for the financial metrics are for banks with total assets of less than $5 billion. The Federal Deposit Insurance Corporation (FDIC) uses this threshold to identify community banks (i.e., banks that operate in a limited geographical area).

1990:01. Data for two of the series, average weekly hours worked and average hourly earnings, are not available until 2007:01 for all MSAs. Our estimation procedure accommodates missing data due to series that begin at later dates, so that we use the series when they become available.

The monthly MSA variables are available from the Bureau of Labor Statistics (BLS) and U.S. Census Bureau with a one-month lag. With the exceptions of average quarterly wages per employee and personal income, the quarterly variables are released by various agencies within the first or second month after the end of a quarter. Average quarterly wages per employee (personal income) is available with a nine-month (eleven-month) lag. The annual real GMP data used to calibrate the indices begin in 2001 and are available with a nine-month lag. Based on these publication lags, the last column of Table 2 gives the last observation for each variable used to compute the monthly indices for 1990:02 to 2015:06 reported in this paper. Our estimation procedure also accommodates missing data at the end of the sample created by the different publication lags.

4. Economic activity indices

Fig. 1 shows the estimated economic activity indices for the 50 largest U.S. MSAs. The solid line in each panel depicts the index itself, while the dotted lines delineate 95% confidence bands. Recall that each metro index is scaled to have the same annualized mean and standard deviation as its real GMP log growth rate, and we report the monthly indices in annualized log growth rates (multiplied by 100) in Fig. 1. Overall, the indices appear relatively smooth, so that the dynamic factor model approach successfully filters out much of the noise in the underlying series and generates informative measures of broad economic activity. Furthermore, the 95% confidence bands indicate that the indices are generally estimated with substantial precision. However, the indices for some MSAs—including Detroit, Baltimore, Pittsburgh, Oklahoma City, Louisville, and Buffalo—exhibit greater higher-frequency volatility. This greater volatility apparently stems from differences in the quality of the underlying data for certain MSAs.[13]

The vertical bars in Fig. 1 delineate business-cycle recessions for each MSA, while Table 3 reports the complete set of cyclical peaks and troughs defining the recessions. We identify the peaks and troughs using a nonparametric algorithm designed to reflect the decision-making process of the National Bureau of Economic Research (NBER) Business Cycle Dating Committee, the committee that "officially" dates cyclical peaks and troughs for the U.S. economy. We use the following procedure to identify business-cycle peaks:

- Condition P1: find months where $\Delta \tilde{f}_t > 0$ and $\Delta \tilde{f}_{t+1} < 0$.
- Condition P2: if Condition P1 holds, confirm that $\sum_{s=0}^{2} \Delta \tilde{f}_{t-s} > 0$.
- Condition P3: if Conditions P1 and P2 hold, confirm that $\sum_{s=1}^{3} \Delta \tilde{f}_{t+s} < 0$ and $\sum_{s=4}^{6} \Delta \tilde{f}_{t+s} < 0$.
- If Conditions P1 through P3 hold, then month t is a business-cycle peak.

Condition P1 locates local maxima, Condition P2 filters noise from the two months before and month of a potential peak, and Condition P3 incorporates the rule of thumb that two consecutive quarters of negative growth signify a recession. We use an analogous procedure to identify business-cycle troughs:

- Condition T1: find months where $\Delta \tilde{f}_t < 0$ and $\Delta \tilde{f}_{t+1} > 0$.
- Condition T2: if Condition T1 holds, confirm that $\sum_{s=0}^{2} \Delta \tilde{f}_{t-s} < 0$.
- Condition T3: if Conditions T1 and T2 hold, confirm that $\sum_{s=1}^{3} \Delta \tilde{f}_{t+s} > 0$ and $\sum_{s=4}^{6} \Delta \tilde{f}_{t+s} > 0$.

[13]Based on inspection of the underlying series, the greater high-frequency volatility for these MSAs appears primarily due to greater measurement error in the underlying employment series, as the underlying employment growth series are substantially more volatile for Detroit, Baltimore, Pittsburgh, Oklahoma City, Louisville, and Buffalo relative to the remaining MSAs.

- If Conditions T1 through T3 hold, then month t is a business-cycle trough.

Because the committee approach of the NBER relies on judgment, it is not replicable for research purposes. Nevertheless, Harding and Pagan (2002, 2003) and Chauvet and Piger (2008) show that nonparametric algorithms like ours pinpoint cyclical turning points similar to those identified by the NBER.

The results in Fig. 1 and Table 3 highlight important similarities and differences in business cycles across MSAs.[14] For example, only 26 of the 50 MSAs experience a recession around the time of the national recession in the early 1990s corresponding to the NBER-dated peak (trough) in 1990:07 (1991:03).[15] Los Angeles sustains the longest recession for this period, spanning 37 months. A number of MSAs in the upper Midwest and Northeast suffer relatively long and deep recessions during the early 1990s, including New York, Boston, Detroit, Cleveland, Providence, and Hartford; Washington, Miami, Riverside, Tampa, and Orlando also experience sizable recessions in the early 1990s. In contrast, a number of western MSAs, including Seattle, Denver, Portland, San Antonio, Austin, and Salt Lake City, realize positive growth throughout this period and completely avoid a recession.

Closer to the middle of the sample, 32 of the 50 MSAs experience recessions near the national recession in the early 2000s; the NBER dates the peak (trough) for this recession in 2001:03 (2001:11). Many MSAs in the upper Midwest and Northeast—for example, Boston, Detroit, Cleveland, and Hartford—again experience sizable recessions during this period. Other MSAs displaying sizable downturns during the early 2000s include Dallas, San Francisco, Denver, Portland, Orlando, San Jose, and Austin. In contrast, Philadelphia, Washington, Riverside, San Diego, Sacramento, and Virginia Beach display positive growth throughout the early 2000s.

[14]The set of cyclical turning points in Table 3 complements Owyang et al. (2005), who use Hamilton's (1989) Markov-switching model to identify cyclical peaks and troughs for individual U.S. states for 1979 to 2002. Chauvet and Piger (2008) show that nonparametric algorithms and Markov-switching models identify similar turning points for the U.S. business cycle.

[15]The complete set of NBER-dated cyclical peaks and troughs for the U.S. economy is available at http://www.nber.org/cycles.html.

An interesting pattern emerges with respect to MSAs within the state of California during the early 2000s. Consistent with the collapse of the technology stock-price bubble, San Francisco and, especially, San Jose—two areas with particularly high concentrations of high-tech firms—suffer severe recessions in the early 2000s. However, Riverside, San Diego, and Sacramento—areas less dependent on the high-tech industry—avoid recessions altogether during this period. During the recessions experienced by San Francisco and San Jose during the early 2000s, the 95% confidence bands for the indices for Riverside, San Diego, and Sacramento do not overlap those for San Francisco and San Jose, so that our analysis identifies statistically significant differences in economic activity for MSAs within the same state. State indices necessarily mask such differences in economic activity across MSAs within the same state, so that our metro economic activity indices clearly add value relative to state indices.

There is greater uniformity across MSAs during the recent Great Recession, with an NBER-dated peak (trough) in 2007:12 (2009:06): 49 of the 50 MSAs experience sizable recessions around this time; the exception is Oklahoma City.[16] In this sense, the Great Recession appears to be a national phenomenon. Nevertheless, important differences in the length and depth of recessions across MSAs are evident in Fig. 1 and Table 3 during the late 2000s. MSAs such as Miami, Riverside, Detroit, Las Vegas, Tampa, Orlando, Sacramento, and Jacksonville suffer long-lived and deep recessions in the late 2000s, while the corresponding recessions for MSAs such as Denver, San Antonio, and Austin are substantially shorter and less severe. There are also significant differences across MSAs within the same state during this period. For example, although both Houston and Austin experience recessions during the late 2000s, the 95% confidence bands for Houston do not overlap those for Austin during a number of months in 2009, so that the contraction in economic activity is significantly greater in Houston than Austin during part of 2009.

[16]Indeed, our algorithm does not identify any recessions for Oklahoma City over our sample period. In accord with this finding, annual GMP growth for Oklahoma City as reported by the BEA is positive for each year for 2001 to 2014.

Fig. 4 shows the diffusion of the Great Recession across individual MSAs. The figure indicates MSAs that are in recession according to Table 3 for various months surrounding the Great Recession: 2007:06 (two quarters before the national peak), 2007:09 (one quarter before the national peak), 2007:12 (national peak), 2008:09 (middle of the national recession), 2009:06 (national trough), 2009:09 (one quarter after the national trough), and 2009:12 (two quarters after the national trough).[17] Even six months before the national cyclical peak in 2007:12, a number of MSAs in the Southeast (Jacksonville, Tampa, and Orlando) and West (Riverside, Sacramento, and Las Vegas) are in recession. Highlighting the central role of housing in the Great Recession, these are among the MSAs that experienced the largest increases in housing prices in the early-to-mid 2000s as well as the sharpest declines beginning around 2006. Detroit is also part of the first group of MSAs to fall into recession, consistent with the severe consequences of the Global Financial Crisis for the auto industry. At the time of the national cyclical peak in 2007:12, recessionary conditions remain largely limited to these areas. However, only nine months later, nearly all MSAs are in recession, and all MSAs (with the exception of Oklahoma City) are still in recession at the national cyclical trough in 2009:06. The last panel of Fig. 4 shows that a significant number of MSAs remain in recession six months after the national trough, including the MSAs in the Southeast and West that were among the first to enter into recessions in the late 2000s.

Table 4 provides additional perspective on the relation between national and MSA business cycles for the 305 months comprising the 1990:02 to 2015:06 sample period. For each MSA, the columns with the E/E (R/R) heading report the number of months when both the national and MSA economies are in expansion (recession); the columns with the E/R (R/E) heading report the number of months when the national economy is in expansion (recession) and an MSA economy is in recession (expansion). Table 4 also reports the percentage of months when the business-cycle phases of the national and MSA economies match (E/E plus R/R divided by 305).

[17] Fig. 4 is similar to Figs. 2 through 4 in Owyang et al. (2005), which show the diffusion of national recessions across individual U.S. states.

The matching frequencies in the sixth and twelfth columns of Table 4 show that the business cycles of many MSAs are reasonably well synchronized with the national cycle. Atlanta has the highest matching frequency of 96.07%, followed by Charlotte with a matching frequency of 95.08%, and then St. Louis, Portland, and Columbus with matching frequencies of 94.75%. Nevertheless, MSAs typically spend many months out of phase with the national cycle. Comparing the fourth and tenth columns with the fifth and twelfth columns, the discrepancies are primarily due to months when an MSA economy is contracting while the national economy is expanding. Leading examples include Los Angeles, Houston, Detroit, Cleveland, Jacksonville, Memphis, New Orleans, and Hartford, all of which spend 30 months or more in recession while the national economy is in expansion. New Orleans is an extreme case, as it spends 197 months in recession while the national economy is expanding, which is likely due to the low average growth rate of New Orleans over the sample and the effects of Hurricane Katrina.

5. MSA characteristics and recessions

Section 4 identifies important differences in the length and depth of MSA recessions over our 1990:02 to 2015:06 sample period. In this section, we relate differences in the severity of recessions across MSAs to a variety of MSA characteristics, thereby shedding light on the underlying sources of the differences in metro business cycles. We begin by defining the total depth of recession (TDR) for each MSA:

$$\text{TDR} = \left| \sum_{t=1}^{T} \mathcal{I}(t = \text{recession}) \Delta \tilde{f}_t \right|, \tag{4}$$

where $\mathcal{I}(t = \text{recession})$ is an indicator function that takes a value of one if the MSA is in recession in month t according to our dating algorithm in Section 4 and zero otherwise. TDR measures the total contraction in economic activity during recessions for the 1990:02 to 2015:06 period, so that it provides an overall measure of the severity of recessions in an

MSA. Fig. 2 depicts the TDR (divided by 100) for each of the 50 MSAs. The figure clearly shows the substantial differences in the severity of recessions across numerous MSAs. MSAs with relatively large TDRs include Miami, Riverside, Detroit, Orlando, Las Vegas, San Jose, Jacksonville, and Hartford; MSAs such as Philadelphia, Baltimore, Denver, Pittsburgh, San Antonio, Kansas City, Austin, Virginia Beach, Oklahoma City, Raleigh, and Buffalo have much smaller TDRs.

We relate the TDR for each MSA to the following set of metro characteristics:

- *Northeast region*: dummy variable equal to one if the MSA is in the Census Bureau's Northeast region and zero otherwise.

- *Midwest region*: dummy variable equal to one if the MSA is in the Census Bureau's Midwest region and zero otherwise.

- *South region*: dummy variable equal to one if the MSA is in the Census Bureau's South region and zero otherwise.

- *Average population (in millions)*: based on population data from the Census Bureau for 1990 to 2014.

- *Average private sector service-producing employment share*: based on private sector service-producing employment and total nonfarm employment data from the BLS for 1990:02 to 2015:06.

- *Average government sector employment share*: based on government sector employment and total nonfarm employment data from the BLS for 1990:02 to 2015:06.

- *Share of population 25 and older with a high school diploma*: based on five-year estimates (2009 to 2013) from the American Community Survey.

- *Share of population 25 and older with a bachelor's degree or higher*: based on five-year estimates (2009 to 2013) from the American Community Survey.

- *Housing supply elasticity*: estimated housing supply elasticity from Table 6 in Saiz (2010); the elasticity is based on MSA land-availability fundamentals.

- *Average establishment size*: based on data for the number of employees by establishment from the Census Bureau for 1990 to 2013.

We estimate the following cross-sectional regression for the 50 MSAs:

$$\mathrm{TDR}_j = \beta_0 + \sum_{k=1}^{K} \beta_k \, x_{k,j} + v_j \quad \text{for} \quad j = 1, \ldots, 50, \tag{5}$$

where TDR_j is the total depth of recession measure for MSA j, $x_{k,j}$ is characteristic k for MSA j, $K = 10$, and v_j is a zero-mean disturbance term. We estimate Eq. (5) via ordinary least squares (OLS) and compute White (1980) t-statistics that are robust to cross-sectional heteroskedasticity in v_j. The second column of Table 5 reports the results.[18] The positive coefficient estimates on the regional dummy variables indicate that recessions are typically more severe in the Northeast, Midwest, and South (relative to the West, the excluded region). However, the regional effects are not significant at conventional levels. We also fail to find significant effects for population, employment share, and establishment size. In contrast, the educational attainment measures and housing supply elasticity are significant determinants of recession severity in the second column of Table 5. The estimated coefficients on these variables are all negative, so that increases in the share of the population with high school diplomas and college degrees as well as more elastic housing supply correspond to significantly less severe recessions.

This significant cross-sectional relations between the educational attainment measures and recession severity are consistent with Elsby et al. (2010), who show that less educated workers are substantially more likely to become unemployed during recessions. Furthermore, the significant cross-sectional relation between housing price elasticity and recession severity

[18] To prevent perfect collinearity in the data matrix for the cross-sectional regression, we exclude the dummy variable for the Census Bureau's West region and the average private sector goods-producing employment share from the set of regressors in Eq. (5).

accords well with recent results reported in Glaeser et al. (2008), Mian et al. (2013), and Mian and Sufi (2014). Glaeser et al. (2008) find that MSAs with lower housing price elasticities experience larger housing price fluctuations, which make these MSAs more susceptible to "boom-bust" housing cycles. Mian et al. (2013) and Mian and Sufi (2014) estimate large household consumption responses to changes in housing net worth, and they find limited evidence of consumption risk sharing across households. Taking these findings together, MSAs with lower housing price elasticities are more susceptible to sharp decreases in housing prices and corresponding declines in housing net worth and household consumption spending; sharp decreases in consumption spending presumably make an MSA more vulnerable to recessions. We would thus expect MSAs with lower housing supply elasticity to experience more severe recessions on average, which is precisely what we find in Table 5.

Next, we test for spatial effects in recession severity across MSAs. To this end, we include a spatial term in Eq. (5) to specify a mixed regressive, spatial autoregressive (MRSAR) model, which can be expressed in matrix form as

$$\boldsymbol{y} = \delta\, \boldsymbol{S}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{v}, \tag{6}$$

where $\boldsymbol{y} = (\mathrm{TDR}_1\,,\,\ldots\,,\,\mathrm{TDR}_J)'$, $\boldsymbol{X} = (\boldsymbol{\iota}_J\,,\,\boldsymbol{x}_1\,,\,\ldots\,,\,\boldsymbol{x}_K)$, $\boldsymbol{\iota}_J$ is a J-vector of ones, $\boldsymbol{x}_k = (x_{k,1}\,,\,\ldots\,,\,x_{k,J})'$, $\boldsymbol{\beta} = (\beta_0\,,\,\beta_1\,,\,\ldots\,,\,\beta_K)'$, $\boldsymbol{v} = (v_1\,,\,\ldots\,,\,v_J)'$, $\boldsymbol{S}$ is a J-by-J spatial weighting matrix with zeros along the main diagonal, δ is the spatial effect coefficient measuring the average influence of neighboring observations, and $J = 50$. We use inverse squared distances and l nearest neighbors to define the non-diagonal elements of the spatial weighting matrix. Specifically, the (j, m) element of $\boldsymbol{S}$ equals $d_{j,m}^{-2}$ if MSA m is one of MSA j's l nearest neighbors and zero otherwise, where $d_{j,m}$ is the distance between j and m. The distance between j and m is based on the longitudes and latitudes for j and m and the Euclidean distance measure. Following convention, we row-standardize $\boldsymbol{S}$, so that we expect the spatial effect coefficient δ to lie within $(-1, 1)$. We estimate Eq. (6) using the robust generalized method of moments (RGMM) procedure of Lin and Lee (2010), which allows for valid inferences in the presence of general forms of cross-sectional heteroskedaticity.

The RGMM estimation results for Eq. (6) are reported in the third through fifth columns of Table 5 for l values of two, four, and six, respectively. The estimates of the spatial effect coefficient in the penultimate row are similar across the three specifications, ranging from 0.38 to 0.40. The estimates are economically sizable, and those for $l = 2$ and $l = 4$ are significant at conventional levels. We thus find significant evidence of spatial effects across MSAs with respect to the severity of recessions. The inclusion of the spatial effect component in the regression model has relatively little impact on the estimated effects of the MSA characteristics: the regional dummies and employment shares remain insignificant, while the educational attainment shares and housing supply elasticity are again significant at conventional levels, in the last three columns of Table 5. The only qualitative change in the results is for the average establishment size, which becomes significant at conventional levels in the last three columns. Overall, the MRSAR results in Table 5 reinforce the relevance of educational attainment and housing supply elasticity for the severity of MSA recessions; furthermore, the results point to the pertinence of average establishment size and spatial effects for the severity of metro recessions.

6. Dynamic spillovers

Chudik and Pesaran (2011) propose an infinite-dimensional vector autoregression (IVAR) framework and corresponding cross-section augmented least squares (CALS) estimation procedure for analyzing dynamic spillover effects. They apply their methodology to the U.S. state-level data from Holly et al. (2010) and find significant evidence of dynamic spillovers in housing prices across neighboring states. In a similar spirit, and as a final empirical exercise, we use the Chudik and Pesaran (2011) approach to test for dynamic spillovers in economic activity across MSAs. Specifically, we estimate the following dynamic model via least squares for each MSA ($j = 1, \ldots, 50$):

$$\Delta \tilde{f}_{j,t} = \phi_{j,0} + \phi_{j,1} \Delta \tilde{f}_{j,t-1} + \psi_j \boldsymbol{S}_{j,\cdot} \Delta \tilde{\boldsymbol{f}}_{t-1} + \delta_{j,0} \Delta \bar{\tilde{f}}_t + \delta_{j,1} \Delta \bar{\tilde{f}}_{t-1} + u_{j,t}, \tag{7}$$

where $\Delta \tilde{\boldsymbol{f}}_t = (\Delta \tilde{f}_{1,t}, \ldots, \Delta \tilde{f}_{50,t})'$, $\boldsymbol{S}_{j,\cdot}$ is the jth row of $\boldsymbol{S}$, and $\Delta \bar{\tilde{f}}_t = (1/50) \sum_{j=1}^{50} \Delta \tilde{f}_{j,t}$.

There are two key aspects to note for the specification in Eq. (7). First, as suggested by Chudik and Pesaran (2011), we use spatial weights to parsimoniously parameterize dynamic spillover effects, as captured by the $\psi_j \boldsymbol{S}_{j,\cdot} \Delta \tilde{\boldsymbol{f}}_{t-1}$ term on the right-hand-side of Eq. (7). To avoid a plethora of parameters, this single term replaces the 49 terms that would represent the dynamic spillover effects in a typical equation from an unrestricted vector autoregression (VAR) specification. By exploiting the spatial weights in $\boldsymbol{S}$, we can use ψ_j to conveniently measures dynamic spillover effects from non-j MSAs to j in a tractable manner.

Second, the terms involving the cross-sectional averages, $\Delta \bar{\tilde{f}}_t$ and $\Delta \bar{\tilde{f}}_{t-1}$, on the right-hand-side of Eq. (7) control for contemporaneous cross-sectional dependence in the metro indices. In this way, we control for the effects of the national business cycle when estimating dynamic spillover effects: Pesaran (2006) shows that including a cross-sectional average is akin to assuming that the cross-sectional units follow a common factor structure, and such a common factor structure for the elements of $\Delta \tilde{\boldsymbol{f}}_t$ is a natural way to account for national economic activity.

Fig. 3 displays estimates of ψ_j in Eq. (7) for each MSA, along with 95% confidence bands, when the spatial weighting matrix is based on the inverse squared distances and $l = 4$ nearest neighbors.[19] A clear majority (33) of the estimates are positive in Fig. 3, so that increased economic activity in nearby MSAs typically leads to increased future economic activity in an MSA, even after controlling for changes in national activity (as well as an MSA's own lagged activity). Just over half (17) of the positive estimates in Fig. 3 are significant according to the 95% confidence bands. A number of MSAs in the Northeast and upper Midwest experience some of the strongest spillover effects, including New York

[19]The results are similar for l values of two and six.

Chicago, Detroit, Baltimore, Pittsburgh, Columbus, Hartford, and Buffalo.[20] Interestingly, the estimated spillover effects are negative for a number of MSAs, and the estimates are significantly negative for Washington, Austin, and Providence. Negative spillovers point to a substantive degree of substitution in economic activity across neighboring MSAs.

7. Conclusion

We construct monthly economic activity indices for the 50 largest U.S. MSAs for 1990:02 to 2015:06. We compute each metro index in the context of a dynamic factor model. To incorporate information from a wide variety of local economic variables and accommodate arbitrary patterns of missing data, we estimate the dynamic factor model using the recently developed maximum-likelihood approach of Bańbura and Modugno (2014). By calibrating each index to average GMP growth, we provide each index with a meaningful economic scale for comparing business cycles across MSAs. Applying a nonparametric algorithm to the indices, we generate a complete set of business-cycle peaks and troughs for each MSA.

Our economic activity indices reveal important similarities and differences in business cycles across MSAs. A number of MSAs experience sizable recessions during the national recessions of the early 1990s and early 2000s; however, other MSAs completely avoid recessions during one or both of these periods. Around the recent Great Recession, almost all MSAs suffer relatively deep recessions, although significant differences are still evident in the depth of recent metro recessions.

We also link the severity of metro recessions to MSA characteristics. Our results show that MSAs with less-educated populations and less elastic housing supplies tend to experience significantly more severe recessions. Furthermore, we detect significant evidence of dynamic spillovers in economic activity across MSAs, even after controlling for national economic activity.

[20] The estimate of ψ_j for Detroit is clearly an outlier in Fig. 3. (Indeed, the point estimate lies above the upper limit of the vertical axis in the second panel of Fig. 3.) The extreme estimate for Detroit is potentially an artifact of the significant volatility and uncertainty in Detroit's economic activity index in Fig. 1.

As indicated in Section 1, the metro economic activity indices developed in the present paper are regularly updated and available on the FRED website. We hope that the indices provide researchers with a rich new source of information on metro economic activity for investigating a variety of topics.

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Appendix A. Maximum-likelihood estimation

This appendix describes maximum-likelihood estimation of our dynamic factor model via the EM algorithm. The implementation of the EM algorithm for our dynamic factor model utilizes results from Watson and Engle (1983), Harvey (1989), Mariano and Murasawa (2003), Bańbura et al. (2011), Durbin and Koopman (2012), and Bańbura and Modugno (2014).

We begin with the model's state-space representation. The measurement equation is given by

$$\Delta \boldsymbol{y}_t = \boldsymbol{H}\boldsymbol{x}_t + \boldsymbol{\xi}_t, \quad \boldsymbol{\xi}_t \sim N(\boldsymbol{0}_{N_M+N_Q}, \boldsymbol{R}), \tag{A.1}$$

where

$$\begin{aligned}
\boldsymbol{x}_t &= (\Delta f_t\,, \Delta f_{t-1}\,, \Delta f_{t-2}\,, \Delta f_{t-3}\,, \Delta f_{t-4}\,, \boldsymbol{\varepsilon}_t^{M\,\prime}\,, \boldsymbol{\varepsilon}_t^{Q\,\prime}\,, \boldsymbol{\varepsilon}_{t-1}^{Q\,\prime}\,, \boldsymbol{\varepsilon}_{t-2}^{Q\,\prime}\,, \boldsymbol{\varepsilon}_{t-3}^{Q\,\prime}\,, \boldsymbol{\varepsilon}_{t-4}^{Q\,\prime})^\prime, \\
\boldsymbol{H} &= \begin{pmatrix} \boldsymbol{\lambda}_M & \boldsymbol{0}_{N_M} & \boldsymbol{0}_{N_M} & \boldsymbol{0}_{N_M} & \boldsymbol{0}_{N_M} & \boldsymbol{I}_{N_M} & \underset{N_M\times N_Q}{\boldsymbol{0}} & \underset{N_M\times N_Q}{\boldsymbol{0}} & \underset{N_M\times N_Q}{\boldsymbol{0}} & \underset{N_M\times N_Q}{\boldsymbol{0}} & \underset{N_M\times N_Q}{\boldsymbol{0}} \\ \boldsymbol{\lambda}_Q & 2\boldsymbol{\lambda}_Q & 3\boldsymbol{\lambda}_Q & 2\boldsymbol{\lambda}_Q & \boldsymbol{\lambda}_Q & \underset{N_Q\times N_M}{\boldsymbol{0}} & \boldsymbol{I}_{N_Q} & 2\boldsymbol{I}_{N_Q} & 3\boldsymbol{I}_{N_Q} & 2\boldsymbol{I}_{N_Q} & \boldsymbol{I}_{N_Q} \end{pmatrix}, \\
\boldsymbol{\xi}_t &= (\boldsymbol{\xi}_t^{M\,\prime}\,, \boldsymbol{\xi}_t^{Q\,\prime})^\prime, \\
\boldsymbol{R} &= \kappa \boldsymbol{I}_{N_M+N_Q},
\end{aligned}$$

$\boldsymbol{x}_t$ is the state vector, $\boldsymbol{\varepsilon}_t^M$ ($\boldsymbol{\varepsilon}_t^Q$) is the N_M-vector (N_Q-vector) of elements in $\boldsymbol{\varepsilon}_t = (\boldsymbol{\varepsilon}_t^{M\,\prime}, \boldsymbol{\varepsilon}_t^{Q\,\prime})^\prime$ corresponding to the N_M (N_Q) monthly (quarterly) variables in $\Delta\boldsymbol{y}_t$, $N = N_M + N_Q$, $\boldsymbol{\xi}_t^M$ ($\boldsymbol{\xi}_t^Q$) is the N_M-vector (N_Q-vector) of elements in $\boldsymbol{\xi}_t = (\boldsymbol{\xi}_t^{M\,\prime}, \boldsymbol{\xi}_t^{Q\,\prime})^\prime$ corresponding to the monthly (quarterly) variables, $\boldsymbol{\lambda}_M$ ($\boldsymbol{\lambda}_Q$) is the N_M-vector (N_Q-vector) of factor loadings corresponding to the monthly (quarterly) variables, and κ is a small number.[21]

We accommodate mixed-frequency monthly and quarterly data in the measurement equation using the approach of Mariano and Murasawa (2003). Let $\Delta\tilde{\boldsymbol{y}}_t^Q = \tilde{\boldsymbol{y}}_t^Q - \tilde{\boldsymbol{y}}_{t-1}^Q$ denote the vector of

[21] We use $\boldsymbol{0}_n$ and $\underset{n\times m}{\boldsymbol{0}}$ to denote an n-vector of zeros and $n \times m$ matrix of zeros, respectively. The particular form of $\boldsymbol{R}$ in Eq. (A.1) is needed to write the likelihood function analogously to the exact factor model specification; see the Appendix in Bańbura and Modugno (2014).

actual (but unobservable) values for the quarterly variables for month t. According to Eq. (1),

$$\Delta \tilde{\boldsymbol{y}}_t^Q = \boldsymbol{\lambda}_Q \Delta f_t + \boldsymbol{\varepsilon}_t^Q. \tag{A.2}$$

For the quarterly variables, we assume that we observe

$$\Delta \boldsymbol{y}_t^Q = \boldsymbol{y}_t^Q - \boldsymbol{y}_{t-3}^Q \tag{A.3}$$

for end-of-quarter months only, where

$$\boldsymbol{y}_t^Q = \tilde{\boldsymbol{y}}_t^Q + \tilde{\boldsymbol{y}}_{t-1}^Q + \tilde{\boldsymbol{y}}_{t-2}^Q. \tag{A.4}$$

Based on Eqs. (A.2) and (A.4), we can write Eq. (A.3) as

$$\begin{aligned} \Delta \boldsymbol{y}_t^Q &= (\tilde{\boldsymbol{y}}_t^Q + \tilde{\boldsymbol{y}}_{t-1}^Q + \tilde{\boldsymbol{y}}_{t-2}^Q) - (\tilde{\boldsymbol{y}}_{t-3}^Q + \tilde{\boldsymbol{y}}_{t-4}^Q + \tilde{\boldsymbol{y}}_{t-5}^Q) \\ &= \Delta \tilde{\boldsymbol{y}}_t^Q + 2\Delta \tilde{\boldsymbol{y}}_{t-1}^Q + 3\Delta \tilde{\boldsymbol{y}}_{t-2}^Q + 2\Delta \tilde{\boldsymbol{y}}_{t-3}^Q + \Delta \tilde{\boldsymbol{y}}_{t-4}^Q \\ &= \boldsymbol{\lambda}_Q \Delta f_t + 2\boldsymbol{\lambda}_Q \Delta f_{t-1} + 3\boldsymbol{\lambda}_Q \Delta f_{t-2} + 2\boldsymbol{\lambda}_Q \Delta f_{t-3} + \boldsymbol{\lambda}_Q \Delta f_{t-4} + \\ &\quad \boldsymbol{\varepsilon}_t^Q + 2\boldsymbol{\varepsilon}_{t-1}^Q + 3\boldsymbol{\varepsilon}_{t-2}^Q + 2\boldsymbol{\varepsilon}_{t-3}^Q + \boldsymbol{\varepsilon}_{t-4}^Q, \end{aligned} \tag{A.5}$$

which explains the structure of $\boldsymbol{H}$ in Eq. (A.1).

The transition equation of the state-space representation is given by

$$\boldsymbol{x}_t = \boldsymbol{F}\boldsymbol{x}_{t-1} + \boldsymbol{u}_t, \quad \boldsymbol{u}_t \sim N(\mathbf{0}_{5+N_M+5N_Q}, \boldsymbol{Q}), \tag{A.6}$$

where

$$
\boldsymbol{F} = \begin{pmatrix}
a & 0 & 0 & 0 & 0 & \mathbf{0}'_{N_M} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} \\
1 & 0 & 0 & 0 & 0 & \mathbf{0}'_{N_M} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} \\
0 & 1 & 0 & 0 & 0 & \mathbf{0}'_{N_M} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} \\
0 & 0 & 1 & 0 & 0 & \mathbf{0}'_{N_M} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} \\
0 & 0 & 0 & 1 & 0 & \mathbf{0}'_{N_M} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{N_Q} \\
\mathbf{0}_{N_M} & \mathbf{0}_{N_M} & \mathbf{0}_{N_M} & \mathbf{0}_{N_M} & \mathbf{0}_{N_M} & \mathrm{diag}(\boldsymbol{\alpha}_M) & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} \\
\mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \underset{N_Q\times N_M}{\mathbf{0}} & \mathrm{diag}(\boldsymbol{\alpha}_Q) & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} \\
\mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \underset{N_Q\times N_M}{\mathbf{0}} & \boldsymbol{I}_{N_Q} & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} \\
\mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \underset{N_Q\times N_M}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} & \boldsymbol{I}_{N_Q} & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} \\
\mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \underset{N_Q\times N_M}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} & \boldsymbol{I}_{N_Q} & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} \\
\mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \mathbf{0}_{N_Q} & \underset{N_Q\times N_M}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} & \underset{N_Q\times N_Q}{\mathbf{0}} & \boldsymbol{I}_{N_Q} & \underset{N_Q\times N_Q}{\mathbf{0}}
\end{pmatrix},
$$

$$
\boldsymbol{u}_t = (u_{f,t}\,,\, \mathbf{0}'_4\,,\, \boldsymbol{e}_t^{M\,\prime}\,,\, \boldsymbol{e}_t^{Q\,\prime}\,,\, \mathbf{0}'_{4N_Q})',
$$

$$
\boldsymbol{Q} = \begin{pmatrix}
\sigma_f^2 & \mathbf{0}'_4 & \mathbf{0}'_{N_M} & \mathbf{0}'_{N_Q} & \mathbf{0}'_{4N_Q} \\
\mathbf{0}_4 & \underset{4\times 4}{\mathbf{0}} & \underset{4\times N_M}{\mathbf{0}} & \underset{4\times N_Q}{\mathbf{0}} & \underset{4\times 4N_Q}{\mathbf{0}} \\
\mathbf{0}_{N_M} & \underset{N_M\times 4}{\mathbf{0}} & \boldsymbol{\Sigma}_M & \underset{N_M\times N_M}{\mathbf{0}} & \underset{N_M\times 4N_Q}{\mathbf{0}} \\
\mathbf{0}_{N_Q} & \underset{N_Q\times 4}{\mathbf{0}} & \underset{N_Q\times N_M}{\mathbf{0}} & \boldsymbol{\Sigma}_Q & \underset{N_Q\times 4N_Q}{\mathbf{0}} \\
\mathbf{0}_{4N_Q} & \underset{4N_Q\times 4}{\mathbf{0}} & \underset{4N_Q\times N_M}{\mathbf{0}} & \underset{4N_Q\times N_Q}{\mathbf{0}} & \underset{4N_Q\times 4N_Q}{\mathbf{0}}
\end{pmatrix},
$$

$\boldsymbol{\alpha}_M$ ($\boldsymbol{\alpha}_Q$) is the N_M-vector (N_Q-vector) of autoregressive coefficients for the idiosyncratic component processes for the monthly (quarterly) variables, and $\boldsymbol{\Sigma}_M$ ($\boldsymbol{\Sigma}_Q$) is the diagonal covariance matrix for the elements in $\boldsymbol{e}_t = (\boldsymbol{e}_t^{M\,\prime}\,,\, \boldsymbol{e}_t^{Q\,\prime})'$ corresponding to the monthly (quarterly) variables.

Denote the vector of the dynamic factor model parameters by

$$
\boldsymbol{\theta} = (a\,,\, \boldsymbol{\lambda}'_M\,,\, \boldsymbol{\lambda}'_Q\,,\, \boldsymbol{\alpha}'_M\,,\, \boldsymbol{\alpha}'_Q\,,\, \mathrm{diag}(\boldsymbol{\Sigma}_M)'\,,\, \mathrm{diag}(\boldsymbol{\Sigma}_Q)')'. \tag{A.7}
$$

The vector $\boldsymbol{\theta}$ defines the $\boldsymbol{H}$ and $\boldsymbol{R}$ matrices in Eq. (A.1) and $\boldsymbol{F}$ and $\boldsymbol{Q}$ matrices in Eq. (A.6). Suppose that we have an estimate of $\boldsymbol{\theta}$ ($\hat{\boldsymbol{\theta}}$) and corresponding estimates of $\boldsymbol{H}$, $\boldsymbol{R}$, $\boldsymbol{F}$ and $\boldsymbol{Q}$ ($\hat{\boldsymbol{H}}$,

$\hat{\boldsymbol{R}}$, $\hat{\boldsymbol{F}}$ and $\hat{\boldsymbol{Q}}$, respectively). Together with $\Delta \boldsymbol{y}_t$ for $t = 1, \ldots, T$, we use these estimates to generate estimates of $\boldsymbol{x}_t$ for $t = 1, \ldots, T$ via a modified version of the Kalman filter that handles missing data (Durbin and Koopman, 2012).

Starting with the initial values $\hat{\boldsymbol{x}}_{0|0}$ and $\hat{\boldsymbol{P}}_{0|0}$,[22] the recursive prediction equations of the modified Kalman filter for $t = 1, \ldots, T$ are given by

$$\hat{\boldsymbol{x}}_{t|t-1} = \hat{\boldsymbol{F}} \hat{\boldsymbol{x}}_{t-1|t-1}, \tag{A.8}$$

$$\hat{\boldsymbol{P}}_{t|t-1} = \hat{\boldsymbol{F}} \hat{\boldsymbol{P}}_{t-1|t-1} \hat{\boldsymbol{F}}' + \hat{\boldsymbol{Q}}, \tag{A.9}$$

$$\hat{\boldsymbol{\xi}}^*_{t|t-1} = \Delta \boldsymbol{y}^*_t - \hat{\boldsymbol{H}}^*_t \hat{\boldsymbol{x}}_{t|t-1},, \tag{A.10}$$

$$\hat{\boldsymbol{L}}^*_{t|t-1} = \hat{\boldsymbol{H}}^*_t \hat{\boldsymbol{P}}_{t|t-1} \hat{\boldsymbol{H}}^{*\prime}_t + \hat{\boldsymbol{R}}^*_t, \tag{A.11}$$

where $\hat{\boldsymbol{x}}_{t|t-1}$ ($\hat{\boldsymbol{x}}_{t|t}$) is the one-step-ahead (filtered) estimate of the state vector $\boldsymbol{x}_t$, $\hat{\boldsymbol{P}}_{t|t-1}$ ($\hat{\boldsymbol{P}}_{t|t}$) is the estimated variance-covariance matrix for $\hat{\boldsymbol{x}}_{t|t-1}$ ($\hat{\boldsymbol{x}}_{t|t}$), $\hat{\boldsymbol{\xi}}^*_{t|t-1}$ is the N^*-vector of one-step-ahead prediction errors corresponding to the $N^* \leq N$ variables in $\Delta \boldsymbol{y}_t$ with available observations for month t, $\Delta \boldsymbol{y}^*_t$ is the N^*-vector of available $\Delta y_{i,t}$ observations, $\hat{\boldsymbol{H}}^*_t$ is a matrix comprised of the N^* rows of $\hat{\boldsymbol{H}}$ corresponding to the available $\Delta y_{i,t}$ observations, $\hat{\boldsymbol{L}}^*_{t|t-1}$ is the estimated variance-covariance matrix for $\hat{\boldsymbol{\xi}}^*_{t|t-1}$, and $\hat{\boldsymbol{R}}^*_t$ is a matrix comprised of the N^* rows and columns of $\hat{\boldsymbol{R}}$ corresponding to the available $\Delta y_{i,t}$ observations. The recursive updating equations for the modified Kalman filter for $t = 1, \ldots, T$ are given by

$$\hat{\boldsymbol{x}}_{t|t} = \hat{\boldsymbol{x}}_{t|t-1} + \hat{\boldsymbol{K}}_t \hat{\boldsymbol{\xi}}^*_{t|t-1}, \tag{A.12}$$

$$\hat{\boldsymbol{P}}_{t|t} = \hat{\boldsymbol{P}}_{t|t-1} - \hat{\boldsymbol{K}}_t \hat{\boldsymbol{H}}^*_t \hat{\boldsymbol{P}}_{t|t-1}, \tag{A.13}$$

where

$$\hat{\boldsymbol{K}}_t = \hat{\boldsymbol{P}}_{t|t-1} \hat{\boldsymbol{H}}^*_t \hat{\boldsymbol{L}}^{*\,-1}_{t|t-1}$$

[22] Following convention, we use $\hat{\boldsymbol{x}}_{0|0} = \boldsymbol{0}_{5+N_M+5N_Q}$ and $\text{vec}(\hat{\boldsymbol{P}}_{0|0}) = (\boldsymbol{I}_{5+N_M+5N_Q} - \hat{\boldsymbol{F}} \otimes \hat{\boldsymbol{F}})^{-1} \text{vec}(\hat{\boldsymbol{Q}})$.

is the Kalman gain. Using $\hat{\boldsymbol{\xi}}^*_{t|t-1}$, $\hat{\boldsymbol{L}}^*_{t|t-1}$, and the prediction error decomposition, the value of the log-likelihood function evaluated at $\hat{\theta}$ is given by

$$l(\hat{\theta}) = \sum_{t=1}^{T} \left[-(N/2)\log(2\pi) - 0.5\log(|\hat{\boldsymbol{L}}^*_{t|t-1}|) - 0.5\hat{\boldsymbol{\xi}}^{*\prime}_{t|t-1}\hat{\boldsymbol{L}}^{*-1}_{t|t-1}\hat{\boldsymbol{\xi}}^*_{t|t-1} \right]. \tag{A.14}$$

The Kalman fixed-interval smoother (see Harvey, 1989, p. 154) subsequently provides smoothed estimates of the state vector and its variance-covariance matrix, $\hat{\boldsymbol{x}}_{t|T}$ and $\hat{\boldsymbol{P}}_{t|T}$, respectively, for $t = 1, \ldots, T$. The filtered estimates from the last iteration of the Kalman filter, $\hat{\boldsymbol{x}}_{T|T}$ and $\hat{\boldsymbol{P}}_{T|T}$, coincide with the smoothed estimates for period T. Proceeding in reverse order, the recursive equations for Kalman smoother for $t = T-1, \ldots, 1$ are given by

$$\hat{\boldsymbol{x}}_{t|T} = \hat{\boldsymbol{x}}_{t|t} + \hat{\boldsymbol{P}}_{t|t}\hat{\boldsymbol{F}}'\hat{\boldsymbol{P}}^{-1}_{t+1|t}(\hat{\boldsymbol{x}}_{t+1|T} - \hat{\boldsymbol{F}}\hat{\boldsymbol{x}}_{t|t}), \tag{A.15}$$

$$\hat{\boldsymbol{P}}_{t|T} = \hat{\boldsymbol{P}}_{t|t} + \hat{\boldsymbol{P}}_{t|t}\hat{\boldsymbol{F}}'\hat{\boldsymbol{P}}^{-1}_{t+1|t}(\hat{\boldsymbol{P}}_{t+1|T} - \hat{\boldsymbol{P}}_{t+1|t})\hat{\boldsymbol{P}}^{-1\prime}_{t+1|t}\hat{\boldsymbol{F}}\hat{\boldsymbol{P}}'_{t|t}. \tag{A.16}$$

Maximum-likelihood estimation via the EM algorithm proceeds as follows. Starting with an initial $\hat{\boldsymbol{\theta}}$ estimate, we run the modified Kalman filter and compute the value of the log likelihood function evaluated at the initial estimate, $l(\hat{\theta})$. We then run the Kalman smoother to compute the smoothed estimates $\hat{\boldsymbol{x}}_{t|T}$, $\hat{\boldsymbol{P}}_{t|T}$, and $\tilde{\boldsymbol{P}}_{t|T}$ for $t = 1, \ldots, T$. Next, we generate updated estimates of the elements in $\boldsymbol{\theta}$. The updated estimate of a based on all of the available data in the sample (denoted by Ω_T) is given by

$$\hat{a}^{\text{new}} = \left[\sum_{t=1}^{T} E_{\hat{\boldsymbol{\theta}}}(\Delta f_t \Delta f_{t-1}|\Omega_T)\right] \left[\sum_{t=1}^{T} E_{\hat{\boldsymbol{\theta}}}(\Delta f_{t-1}^2|\Omega_T)\right]^{-1}, \tag{A.17}$$

where the formulas for the expectational terms in Eq. (A.17) and subsequent equations are given in Watson and Engel (1983), Section 4.

The updated estimate of $\boldsymbol{\lambda}_M$ is given by

$$\hat{\boldsymbol{\lambda}}_M^{\text{new}} = \left[\sum_{t=1}^{T} E_{\hat{\boldsymbol{\theta}}}(\Delta f_t^2|\Omega_T)\boldsymbol{W}_t^M\right]^{-1} \left[\sum_{t=1}^{T} \boldsymbol{W}_t^M \Delta\boldsymbol{y}_t^M E_{\hat{\boldsymbol{\theta}}}(\Delta f_t|\Omega_T) - \boldsymbol{W}_t^M E_{\hat{\boldsymbol{\theta}}}(\boldsymbol{\varepsilon}_t^M \Delta f_t|\Omega_T)\right], \tag{A.18}$$

where $\boldsymbol{W}_t^M$ is an N_M-by-N_M diagonal matrix with the ith diagonal element equal to one (zero) if the ith monthly variable is observed (missing) during month t and $\Delta \boldsymbol{y}_t^M$ is the N_M-vector of monthly variables for month t, so that $\boldsymbol{W}_t^M$ acts as a selector matrix.

The updated estimate of each element of $\boldsymbol{\alpha}_M$ is given by

$$\hat{\alpha}_{i,M}^{\text{new}} = \left[\sum_{t=1}^{T} E_{\hat{\boldsymbol{\theta}}}(\varepsilon_{i,t}^M \varepsilon_{i,t-1}^M | \Omega_T)\right] \left[\sum_{t=1}^{T} E_{\hat{\boldsymbol{\theta}}}((\varepsilon_{i,t-1}^M)^2 | \Omega_T)\right]^{-1} \text{ for } i = 1, \dots, N_M, \tag{A.19}$$

while the updated estimate of each element of the main diagonal of $\boldsymbol{\Sigma}_M$ is given by

$$\hat{\sigma}_{i,M}^{2,\text{new}} = (1/T)\left[\sum_{t=1}^{T} E_{\hat{\boldsymbol{\theta}}}((\varepsilon_{i,t}^M)^2) - \hat{\alpha}_{i,M}^{\text{new}} \sum_{t=1}^{T} E_{\hat{\boldsymbol{\theta}}}(\varepsilon_{i,t}^M \varepsilon_{i,t-1}^M | \Omega_T)\right] \text{ for } i = 1, \dots, N_M. \tag{A.20}$$

Turning to $\boldsymbol{\lambda}_Q$, we first compute

$$\text{vec}(\hat{\gamma}_Q^{\text{new}}) = \left[\sum_{t=1}^{T} E_{\hat{\boldsymbol{\theta}}}(\Delta \boldsymbol{f}_{t-4:t} \Delta \boldsymbol{f}'_{t-4:t} | \Omega_T) \otimes \boldsymbol{W}_t^Q\right]^{-1} \times$$

$$\text{vec}\left[\sum_{t=1}^{T} \boldsymbol{W}_t^Q \Delta \boldsymbol{y}_t^Q E_{\hat{\boldsymbol{\theta}}}(\Delta \boldsymbol{f}'_{t-4:t} | \Omega_T) - \boldsymbol{W}_t^Q E_{\hat{\boldsymbol{\theta}}}(\tilde{\boldsymbol{\varepsilon}}_t^Q \Delta \boldsymbol{f}'_{t-4:t} | \Omega_T)\right], \tag{A.21}$$

where

$$\begin{aligned} \Delta \boldsymbol{f}_{t-4:t} &= (\Delta f_t\,, \Delta f_{t-1}\,, \Delta f_{t-2}\,, \Delta f_{t-3}\,, \Delta f_{t-4})', \\ \tilde{\boldsymbol{\varepsilon}}_t^Q &= \boldsymbol{\varepsilon}_t^Q + 2\boldsymbol{\varepsilon}_{t-1}^Q + 3\boldsymbol{\varepsilon}_{t-2}^Q + 2\boldsymbol{\varepsilon}_{t-3}^Q + \boldsymbol{\varepsilon}_{t-4}^Q, \end{aligned}$$

$\boldsymbol{W}_t^Q$ is an N_Q-by-N_Q diagonal matrix with the ith diagonal element equal to one (zero) if the ith quarterly variable is observed (missing) during month t, and $\Delta \boldsymbol{y}_t^Q$ is the N_Q-vector of quarterly variables for month t. We then impose a set of restrictions consistent with $\boldsymbol{H}$ in Eq. (A.1):

$$\text{vec}(\tilde{\hat{\boldsymbol{\lambda}}}_Q^{\text{new}}) = \text{vec}(\hat{\gamma}_Q^{\text{new}}) - D^{-1}C'[CD^{-1}C']^{-1}C\,\text{vec}(\hat{\gamma}_Q^{\text{new}}), \tag{A.22}$$

where

$$
\begin{aligned}
D &= E_{\hat{\boldsymbol{\theta}}}(\Delta \boldsymbol{f}_{t-4:t}\Delta \boldsymbol{f}'_{t-4:t}|\Omega_T), \\
C &= \boldsymbol{I}_{N_Q} \otimes \begin{pmatrix} 1 & -1/2 & 0 & 0 & 0 \\ 1 & 0 & -1/3 & 0 & 0 \\ 1 & 0 & 0 & -1/2 & 0 \\ 1 & 0 & 0 & 0 & -1 \end{pmatrix}.
\end{aligned}
$$

The $\hat{\boldsymbol{\lambda}}_Q^{\text{new}}$ estimate is then elements one, N_Q+1, $2N_Q+1$, $3N_Q+1$, and $4N_Q+1$ of $\text{vec}(\tilde{\hat{\boldsymbol{\lambda}}}_Q^{\text{new}})$. The $\hat{\boldsymbol{\alpha}}_Q^{\text{new}}$ and $\hat{\boldsymbol{\Sigma}}_Q^{\text{new}}$ estimates are computed analogously to Eq. (A.19) and Eq. (A.20) using $\boldsymbol{\varepsilon}_t^Q$.

Based on the updated parameter estimates, we rerun the Kalman filter and smoother to generate updated smoothed estimates of the state vector, and we again evaluate the log-likelihood function at the updated parameter estimates. The EM algorithm guarantees that the value of the log-likelihood function increases for the updated parameter estimates. Using the updated estimates of the smoothed state vector, we then compute another set of updated parameter estimates using Eq. (A.17) through Eq. (A.22), rerun the Kalman filter and smoother, and compute the value of the log-likelihood function. We continue iterating in this manner until the increase in the log-likelihood function is very small. The converged estimate of $\boldsymbol{\theta}$ corresponds to the maximum-likelihood estimate, which we denote by $\hat{\boldsymbol{\theta}}_{\text{ML}}$. Finally, we run the Kalman filter and smoother based on $\hat{\boldsymbol{\theta}}_{\text{ML}}$ to produce smoothed estimates of the the state vector and its variance-covariance matrix, $\hat{\boldsymbol{x}}_{t|T}(\hat{\boldsymbol{\theta}}_{\text{ML}})$ and $\hat{\boldsymbol{P}}_{t|T}(\hat{\boldsymbol{\theta}}_{\text{ML}})$, respectively, for $t = 1, \dots, T$. The maximum-likelihood estimate of Δf_t, $\Delta \hat{f}_t(\hat{\boldsymbol{\theta}}_{\text{ML}})$, corresponds to the first element of $\hat{\boldsymbol{x}}_{t|T}(\hat{\boldsymbol{\theta}}_{\text{ML}})$.

We use the bootstrap approximation of Pfeffermann and Tiller (2005) to generate 95% confidence bands for the monthly indices that account for parameter estimation uncertainty. The three-step process in Pfeffermann and Tiller (2005), Section 3.1 proceeds as follows:

1. Using the measurement and transition equations given by Eqs. (A.1) and (A.6), respectively, and $\hat{\boldsymbol{\theta}}_{\text{ML}}$, build up a large number B of pseudo samples of length T for the vector of observable variables; denote the bth pseudo sample by $\{\Delta \boldsymbol{y}_t^b\}_{t=1}^T$ for $b = 1, \dots, B$.

2. For each $\{\Delta \boldsymbol{y}_t^b\}_{t=1}^T$, generate the maximum-likelihood estimate of $\boldsymbol{\theta}$ using the same procedure applied to the original sample; denote the vector of maximum-likelihood parameter estimates corresponding to bth pseudo sample by $\hat{\boldsymbol{\theta}}_{\mathrm{ML}}^b$ for $b = 1, \ldots, B$.

3. The bootstrap approximation to the variance-covariance of the state vector is given by

$$\hat{\boldsymbol{P}}_{t|T}^{\mathrm{boot}} = \frac{1}{B}\sum_{b=1}^{B}\left[\hat{\boldsymbol{x}}_{t|T}^b(\hat{\boldsymbol{\theta}}_{\mathrm{ML}}^b) - \hat{\boldsymbol{x}}_{t|T}^b(\hat{\boldsymbol{\theta}}_{\mathrm{ML}})\right]^2 + 2\hat{\boldsymbol{P}}_{t|T}(\hat{\boldsymbol{\theta}}_{\mathrm{ML}}) - \frac{1}{B}\sum_{b=1}^{B}\hat{\boldsymbol{P}}_{t|T}(\hat{\boldsymbol{\theta}}_{\mathrm{ML}}^b) \tag{A.23}$$

for $t = 1, \ldots, T$, where $\hat{\boldsymbol{x}}_{t|T}^b(\hat{\boldsymbol{\theta}}_{\mathrm{ML}}^b)$ and $\hat{\boldsymbol{x}}_{t|T}^b(\hat{\boldsymbol{\theta}}_{\mathrm{ML}})$ are the estimated smoothed state vectors for the bth pseudo sample based on the maximum-likelihood estimate of $\boldsymbol{\theta}$ for the bth pseudo sample and original sample, respectively, and $\hat{\boldsymbol{P}}_{t|T}(\hat{\boldsymbol{\theta}}_{\mathrm{ML}}^b)$ is the estimated variance-covariance matrix for the smoothed state vector for the original sample based on $\hat{\boldsymbol{\theta}}_{\mathrm{ML}}^b$. Finally, the bootstrap approximation to the 95% confidence band for Δf_t is given by

$$\Delta \hat{f}_t(\hat{\boldsymbol{\theta}}_{\mathrm{ML}}) \pm 1.96\left\{\left[\hat{\boldsymbol{P}}_{t|T}^{\mathrm{boot}}\right]_{1,1}\right\}^{0.5} \quad \text{for} \quad t = 1, \ldots, T. \tag{A.24}$$

Appendix B. Calibration

The calibration process follows Clayton-Matthews and Stock (1998). We transform the original index using

$$\Delta\tilde{f}_t = a + b\Delta f_t, \tag{B.1}$$

where we select a and b so that $\Delta\tilde{f}_t$ has the same annualized mean and standard deviation for 2002:01 to 2014:12 as annual real GMP log growth for 2002 to 2014 (the available sample for GMP log growth at the time of index construction). Let μ and σ be the annualized mean and standard deviation of Δf_t for 2002:01 to 2014:12. We standardize Δf_t to have zero mean and unit variance for 2002:01 to 2013:12:

$$\Delta\ddot{f}_t = (\Delta f_t - \mu)/\sigma. \tag{B.2}$$

We then specify $\Delta\tilde{f}_t$ so that it has the same mean and variance as annual real GMP log growth for 2002 to 2014:

$$\Delta\tilde{f}_t = \mu_{\mathrm{GMP}} + \sigma_{\mathrm{GMP}}\Delta\ddot{f}_t = \mu_{\mathrm{GMP}} + \sigma_{\mathrm{GMP}}[(\Delta f_t - \mu)/\sigma], \tag{B.3}$$

where μ_{GMP} (σ_{GMP}) is the mean (standard deviation) of annual real GMP log growth for 2002 to 2013. Finally, we use Eq. (B.3) to compute a and b in Eq. (B.1):

$$a = \mu_{\mathrm{GMP}} - \mu(\sigma_{\mathrm{GMP}}/\sigma) \tag{B.4}$$

and

$$b = \sigma_{\mathrm{GMP}}/\sigma. \tag{B.5}$$

Appendix C. Updating and regular reporting

To provide timely measures of economic activity for a large number of U.S. MSAs and provide researchers with a useful resource, we will regularly report updated metro indices on the FRED website. Based on the timing of data availability, we plan to release updates for each metro index on the second Tuesday of each quarter. The release will include initial estimates of each metro index for the sixth, fifth, and fourth months prior to the release date. For example, on the second Tuesday of January, we will release preliminary estimates of each metro index for July, August, and September of the previous year; on the second Tuesday of April, we will release preliminary estimates of each index for October, November, and December of the previous year; and so on. Table C1 gives the release dates, the months for which we provide preliminary estimates, and the data vintages used to compute the indices over a typical calendar year.

As new data become available, we reestimate the dynamic factor model via the EM algorithm and use the Kalman smoother to compute the updated indices. In addition to providing initial estimates for three additional months at the end of the sample, this process generates revised estimates for all previous months in the sample. The estimates throughout much of the sample will presumably change relatively little, although the October release employs revised GMP data, which could affect the historical estimates more substantially due to the calibration method (depending on the magnitudes of the GMP revisions). Because the complete history of each index potentially changes with a new release, as revised estimates are posted on FRED, the previous vintage of estimates will be moved to ArchivaL Federal Reserve Economic Data (ALFRED).[23]

[23]Available at http://alfred.stlouisfed.org.

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Table 1
50 largest U.S. metropolitan statistical areas

(1) Metropolitan statistical area	(2) 2014 pop. (mil.)	(3) Metropolitan statistical area	(4) 2014 pop. (mil.)
1. New York-Newark-Jersey City, NY-NJ-PA	20.09	26. Orlando-Kissimmee-Sanford, FL	2.32
2. Los Angeles-Long Beach-Santa Ana, CA	13.26	27. Sacramento-Roseville-Arden-Arcade, CA	2.24
3. Chicago-Naperville-Joliet, IL-IN-WI	9.55	28. Cincinnati-Middletown, OH-KY-IN	2.15
4. Dallas-Fort Worth-Arlington, TX	6.95	29. Kansas City, MO-KS	2.07
5. Houston-The Woodlands-Sugar Land, TX	6.49	30. Las Vegas-Henderson-Paradise, NV	2.07
6. Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	6.05	31. Cleveland-Elyria, OH	2.06
7. Washington-Arlington-Alexandria, DC-VA-MD-WV	6.03	32. Columbus, OH	1.99
8. Miami-Fort Lauderdale-West Palm Beach, FL	5.93	33. Indianapolis-Carmel-Anderson, IN	1.97
9. Atlanta-Sandy Springs-Marietta, GA	5.61	34. San Jose-Sunnyvale-Santa Clara, CA	1.95
10. Boston-Cambridge-Quincy, MA-NH	4.73	35. Austin-Round Rock, TX	1.94
11. San Francisco-Oakland-Hayward, CA	4.59	36. Nashville-Davidson-Murfreesboro-Franklin, TN	1.79
12. Phoenix-Mesa-Scottsdale, AZ	4.49	37. Virginia Beach-Norfolk-Newport News, VA-NC	1.72
13. Riverside-San Bernardino-Ontario, CA	4.44	38. Providence-Warwick, RI-MA	1.61
14. Detroit-Warren-Dearborn, MI	4.30	39. Milwaukee-Waukesha-West Allis, WI	1.57
15. Seattle-Tacoma-Bellevue, WA	3.67	40. Jacksonville, FL	1.42
16. Minneapolis-St. Paul-Bloomington, MN-WI	3.50	41. Memphis, TN-MS-AR	1.34
17. San Diego-Carlsbad, CA	3.26	42. Oklahoma City, OK	1.34
18. Tampa-St. Petersburg-Clearwater, FL	2.92	43. Louisville/Jefferson County, KY-IN	1.27
19. St. Louis, MO-IL	2.81	44. Richmond, VA	1.26
20. Baltimore-Towson, MD	2.79	45. New Orleans-Metairie, LA	1.25
21. Denver-Aurora-Lakewood, CO	2.75	46. Raleigh-Cary, NC	1.24
22. Charlotte-Concord-Gastonia, NC-SC	2.38	47. Hartford-West Hartford-East Hartford, CT	1.21
23. Pittsburgh, PA	2.36	48. Salt Lake City, UT	1.15
24. Portland-Vancouver-Hillsboro	2.35	49. Birmingham-Hoover, AL	1.14
25. San Antonio-New Braunfels, TX	2.33	50. Buffalo-Cheektowaga-Niagara Falls, NY	1.14

Notes: The table lists the largest 50 U.S. MSAs by population in 2014. The areas are delineated by the U.S. Office of Management and Budget. The 2014 population estimates in the second and fourth columns are from the U.S. Census Bureau.

Table 2
Data series for construction of metro economic activity indices

(1) Data series	(2) Source	(3) Frequency	(4) Transformation	(5) Last obs.
1. Average weekly hours worked by private sector employees	BLS (CES)	Monthly	Δ	2015:06
2. Unemployment rate	BLS (CES)	Monthly	Δ	2015:06
3. Private sector goods-producing employment	BLS (CES)	Monthly	$\Delta \log$	2015:06
4. Private sector service-producing employment	BLS (CES)	Monthly	$\Delta \log$	2015:06
5. Government sector employment	BLS (CES)	Monthly	$\Delta \log$	2015:06
6. Real average hourly earnings	BLS (CES)	Monthly	$\Delta \log$	2015:06
7. Construction permits for new private residential buildings	CENSUS	Monthly	Δ	2015:06
8. Real average quarterly wages per employee	BLS (QCEW)	Quarterly	$\Delta \log$	2015:1
9. Total real personal income per capita	BEA, BLS, CENSUS	Quarterly	$\Delta \log$	2013:4
10. Return on average assets	FFIEC	Quarterly	Δ	2015:2
11. Net interest margin	FFIEC	Quarterly	Δ	2015:2
12. Loan loss reserve ratio	FFIEC	Quarterly	Δ	2015:2
13. Gross metropolitan product	BEA	Annual	$\Delta \log$	2014

Notes: The first column reports the individual series used to compute monthly economic activity indices for the 50 largest U.S. MSAs. Abbreviations for the data sources in the second column are as follows: BLS = Bureau of Labor Statistics, CES = Current Employment Statistics, CENSUS = U.S. Census Bureau, QCEW = Quarterly Census of Employment and Wages, BEA = Bureau of Economic Analysis, and FFIEC = Federal Financial Institutions Examination Council. Data transformations in the fourth column are as follows: Δ = first difference, $\Delta \log$ = first difference of log level. The fifth column gives the last observation for each variable used to compute the 50 metro economic activity indices for 1990:02 to 2015:06 reported in this paper.

Table 3
Business-cycle peaks and troughs for the 50 largest U.S. metropolitan statistical areas, 1990:02–2015:06

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	First recession		Second recession		Third recession		Fourth recession	
MSA	Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough
1. New York	Feb 1990	Jun 1992	May 2001	Jun 2002	Apr 2008	Sep 2009	–	–
2. Los Angeles	Mar 1990	Apr 1993	Mar 2001	Jan 2002	Dec 2007	Nov 2009	–	–
3. Chicago	Aug 1990	Jul 1991	Mar 2001	Mar 2002	Mar 2008	Jan 2010	–	–
4. Dallas	Apr 2001	Feb 2002	Jul 2008	Sep 2009	–	–	–	–
5. Houston	Jun 1991	Jan 1992	May 2001	May 2003	Jul 2008	Nov 2009	–	–
6. Philadelphia	Aug 1990	Jul 1991	Jul 2008	Aug 2009	–	–	–	–
7. Washington	Feb 1990	Dec 1991	Apr 2008	Jan 2010	–	–	–	–
8. Miami	Mar 1990	Dec 1991	Jun 2007	Jan 2010	–	–	–	–
9. Atlanta	Aug 1990	Mar 1991	Jun 2001	Jan 2002	Jan 2008	Nov 2009	–	–
10. Boston	Feb 1990	Jul 1991	Feb 2001	Apr 2003	Jul 2008	Aug 2009	–	–
11. San Francisco	Feb 2001	Mar 2002	Mar 2008	Sep 2009	–	–	–	–
12. Phoenix	Apr 2001	Jan 2002	Aug 2007	Dec 2009	–	–	–	–
13. Riverside	Feb 1990	Mar 1991	Aug 2006	Jan 2010	–	–	–	–
14. Detroit	Jul 1990	Feb 1992	Jun 2000	Aug 2003	Oct 2005	Jun 2009	–	–
15. Seattle	Feb 2001	Feb 2002	May 2008	Oct 2009	–	–	–	–
16. Minneapolis	Feb 2001	Mar 2002	Mar 2008	Sep 2009	–	–	–	–
17. San Diego	Mar 2008	Dec 2009	–	–	–	–	–	–
18. Tampa	Aug 1990	Jun 1991	Nov 2000	Dec 2001	Feb 2007	Dec 2009	–	–
19. St. Louis	Jun 1990	Mar 1991	Feb 2008	Nov 2009	–	–	–	–
20. Baltimore	Sep 1990	Apr 1991	Aug 2008	Apr 2009	–	–	–	–
21. Denver	Mar 2001	Jan 2002	Aug 2008	Sep 2009	–	–	–	–
22. Charlotte	Jun 1990	Mar 1991	Feb 2008	Oct 2009	–	–	–	–
23. Pittsburgh	Aug 1990	Mar 1991	Feb 2001	Oct 2001	Sep 2008	Feb 2010	–	–
24. Portland	Feb 2001	Dec 2001	May 2008	Jul 2009	–	–	–	–
25. San Antonio	Aug 2008	Aug 2009	–	–	–	–	–	–

Notes: The table reports business-cycle peaks and troughs for individual MSAs for 1990:02 to 2015:06. The months of peaks and troughs are identified using the metro economic activity indices and nonparametric algorithm described in the text.

Table 3 (continued)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	First recession		Second recession		Third recession		Fourth recession	
MSA	Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough
26. Orlando	Mar 1990	Jun 1991	Mar 2001	Dec 2001	May 2007	Dec 2009	–	–
27. Sacramento	Sep 1991	Apr 1992	May 2007	Mar 2010	–	–	–	–
28. Cincinnati	Feb 2001	Mar 2002	Feb 2008	Jan 2010	–	–	–	–
29. Kansas City	Jul 2008	Dec 2009	–	–	–	–	–	–
30. Las Vegas	May 2007	Oct 2010	–	–	–	–	–	–
31. Cleveland	Jun 1990	Feb 1992	Dec 2000	Dec 2002	Jan 2008	Oct 2009	–	–
32. Columbus	Mar 2001	Nov 2001	Feb 2008	Dec 2009	–	–	–	–
33. Indianapolis	Mar 2008	Oct 2009	–	–	–	–	–	–
34. San Jose	Jan 2001	Mar 2003	Aug 2008	Aug 2009	–	–	–	–
35. Austin	Feb 2001	Jan 2002	Aug 2008	Jun 2009	–	–	–	–
36. Nashville	Apr 2008	Jul 2009	–	–	–	–	–	–
37. Virginia Beach	May 2008	Nov 2009	–	–	–	–	–	–
38. Providence	Feb 1990	Jul 1991	May 2007	Sep 2009	–	–	–	–
39. Milwaukee	Jan 2001	Feb 2002	May 2008	Nov 2009	–	–	–	–
40. Jacksonville	Jun 1990	Oct 1991	Nov 2000	Feb 2002	May 2007	Feb 2010	–	–
41. Memphis	Apr 1990	Apr 1991	Apr 2000	Mar 2002	Jun 2007	Feb 2010	–	–
42. Oklahoma City	–	–	–	–	–	–	–	–
43. Louisville	Feb 2001	Dec 2001	Feb 2008	Feb 2010	–	–	–	–
44. Richmond	Mar 1990	Sep 1991	Jan 2001	Dec 2001	Aug 2007	Jan 2010	–	–
45. New Orleans	Apr 1990	Nov 1993	Feb 1998	Aug 2010	May 2011	Mar 2013	Feb 2014	Jun 2015
46. Raleigh	May 2001	Dec 2001	May 2008	Jul 2009	–	–	–	–
47. Hartford	Feb 1990	Dec 1992	Nov 2000	Jul 2003	Mar 2008	Feb 2010	–	–
48. Salt Lake City	Feb 2001	Jul 2002	Apr 2008	Sep 2009	–	–	–	–
49. Birmingham	Jan 2001	May 2002	Feb 2008	Oct 2009	–	–	–	–
50. Buffalo	Sep 1990	May 1991	Oct 2008	Jun 2009	–	–	–	–

Table 4

National and metropolitan statistical area business-cycle phase correspondences, 1990:02–2015:06

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MSA	E/E	R/R	E/R	R/E	Match (%)	MSA	E/E	R/R	E/R	R/E	Match (%)
1. New York	246	28	25	6	89.84	26. Orlando	250	34	21	0	93.11
2. Los Angeles	235	34	36	0	88.20	27. Sacramento	248	18	23	16	87.21
3. Chicago	256	30	15	4	93.77	28. Cincinnati	259	24	12	10	92.79
4. Dallas	265	18	6	16	92.79	29. Kansas City	265	11	6	23	90.49
5. Houston	241	17	30	17	84.59	30. Las Vegas	248	18	23	16	87.21
6. Philadelphia	265	18	6	16	92.79	31. Cleveland	239	33	32	1	89.18
7. Washington	250	22	21	12	89.18	32. Columbus	265	24	6	10	94.75
8. Miami	245	26	26	8	88.85	33. Indianapolis	267	15	4	19	92.46
9. Atlanta	264	29	7	5	96.07	34. San Jose	251	18	20	16	88.20
10. Boston	242	27	29	7	88.20	35. Austin	268	18	3	16	93.77
11. San Francisco	263	23	8	11	93.77	36. Nashville	270	14	1	20	93.11
12. Phoenix	259	25	12	9	93.11	37. Virginia Beach	266	13	5	21	91.48
13. Riverside	243	26	28	8	88.20	38. Providence	252	26	19	8	91.15
14. Detroit	204	34	67	0	78.03	39. Milwaukee	261	21	10	13	92.46
15. Seattle	263	21	8	13	93.11	40. Jacksonville	241	34	30	0	90.16
16. Minneapolis	263	23	8	11	93.77	41. Memphis	238	34	33	0	89.18
17. San Diego	265	15	6	19	91.80	42. Oklahoma City	271	0	0	34	88.85
18. Tampa	247	33	24	1	91.80	43. Louisville	261	24	10	10	93.44
19. St. Louis	265	24	6	10	94.75	44. Richmond	247	34	24	0	92.13
20. Baltimore	270	14	1	20	93.11	45. New Orleans	74	34	197	0	35.41
21. Denver	266	18	5	16	93.11	46. Raleigh	269	19	2	15	94.43
22. Charlotte	266	24	5	10	95.08	47. Hartford	213	31	58	3	80.00
23. Pittsburgh	262	23	9	11	93.44	48. Salt Lake City	259	22	12	12	92.13
24. Portland	268	21	3	13	94.75	49. Birmingham	259	24	12	10	92.79
25. San Antonio	269	10	2	24	91.48	50. Buffalo	269	14	2	20	92.79
						Average	251.84	22.80	19.16	11.20	90.05

Notes: The table reports correspondences between national and MSA business-cycle phases. The national business-cycle phases are defined by the NBER-dated peaks and troughs. The MSA business-cycle phases are defined by the peaks and troughs reported in Table 3. E/E (R/R) is the number of months when both the national and MSA economies are in expansion (recession); E/R (R/E) is the number of months when the national economy is in expansion (recession) and an MSA economy is in recession (expansion). The sixth (twelfth) column is the sum of the second and third (eighth and ninth) columns divided by the sum of the second through fifth (eighth through eleventh) columns.

Table 5
Cross-sectional and mixed regressive, spatial autoregressive model estimation results

(1)	(2)	(3)	(4)	(5)
MSA characteristic	Cross-sectional regression	MRSAR, $l = 2$	MRSAR, $l = 4$	MRSAR, $l = 6$
Intercept	2.56 [1.02]	2.13 [0.79]	3.15 [1.22]	1.97 [0.73]
Northeast	0.51 [0.87]	0.35 [0.63]	0.45 [0.82]	0.35] [0.63]
Midwest	0.11 [0.31]	0.07 [0.20]	0.20 [0.56]	0.09 [0.27]
South	0.08 [0.32]	0.17 [0.68]	0.24 [0.93]	0.16 [0.64]
Population	−0.001 [−0.03]	0.02 [0.56]	0.02 [0.53]	0.02 [0.50]
Private sector service-producing employment share	2.31 [0.66]	−0.12 [−0.03]	−1.12 [−0.31]	0.25 [0.07]
Government sector employment share	−2.10 [−0.56]	−2.03 [−0.60]	−2.35 [−0.67]	−1.75 [−0.50]
Share of population 25 and over with high school diploma	−8.75 [−2.34]**	−7.20 [−2.11]**	−7.21 [−2.05]**	−6.85 [−1.91]*
Share of population 25 and over with Bachelor's degree or higher	−5.90 [−2.61]***	−5.17 [−2.31]**	−5.34 [−2.37]**	−5.22 [−2.28]**
Housing supply elasticity	−0.28 [−2.26]**	−0.21 [−1.82]*	−0.24 [−2.05]**	−0.23 [−1.98]**
Average establishment size	0.09 [1.43]	0.13 [2.00]**	0.13 [1.85]*	0.13 [1.95]*
Spatial effect		0.40 [2.31]**	0.39 [1.84]*	0.38 [1.63]
R^2	28.70%	34.86%	35.17%	34.01%

Notes: The table reports cross-sectional regression model (second column) and mixed regressive, spatial autoregressive model (third through fifth columns) estimation results, where the dependent variable is the MSA total depth of recession measure reported in Fig. 2 and the explanatory variables are given in the first column. The MRSAR models use a spatial weighting matrix based on the inverse of squared distance and the l nearest neighbors. The sample size is 50. Brackets report t-statistics; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

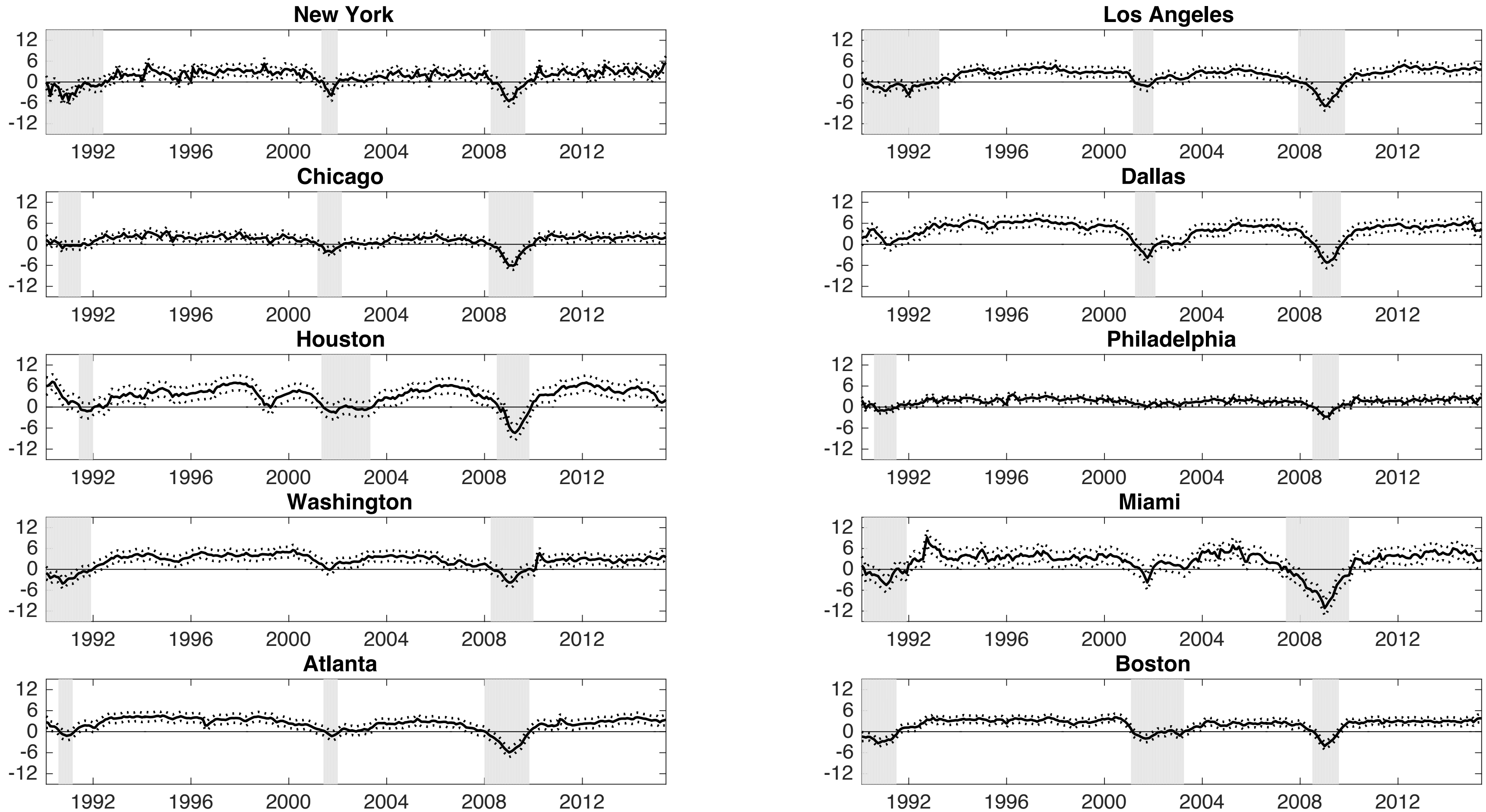

Fig. 1. Economic activity indices for the 50 largest U.S. metropolitan statistical areas, 1990:02–2015:06. The solid line in each panel shows the economic activity index for the MSA in the panel heading. The dotted lines delineate 95% confidence bands for the index. The indices are scaled to annualized real gross metropolitan product log growth rates. Vertical bars delineate business-cycle recessions computed using the nonparametric algorithm described in the text.

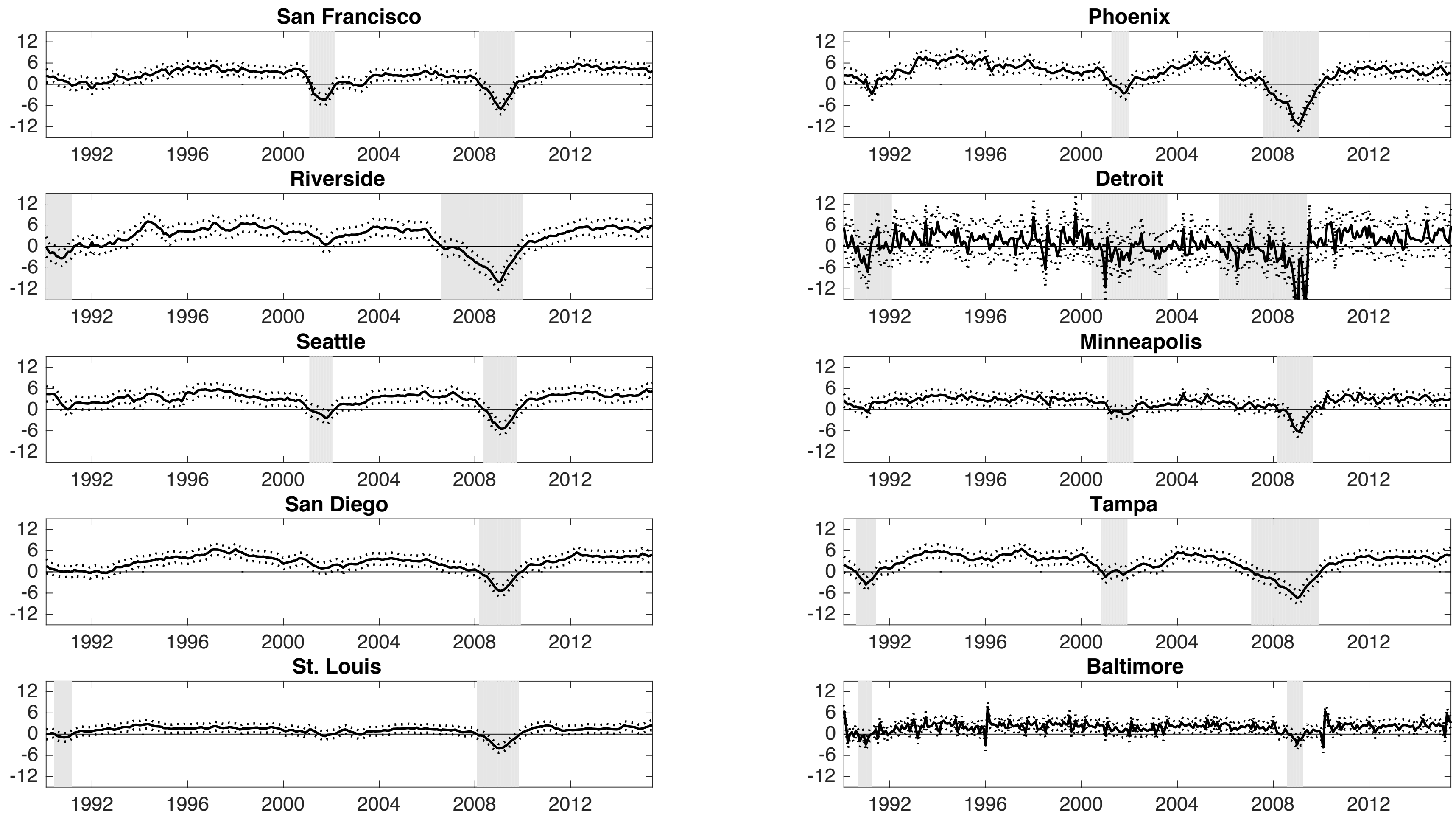

Fig. 1 (continued)

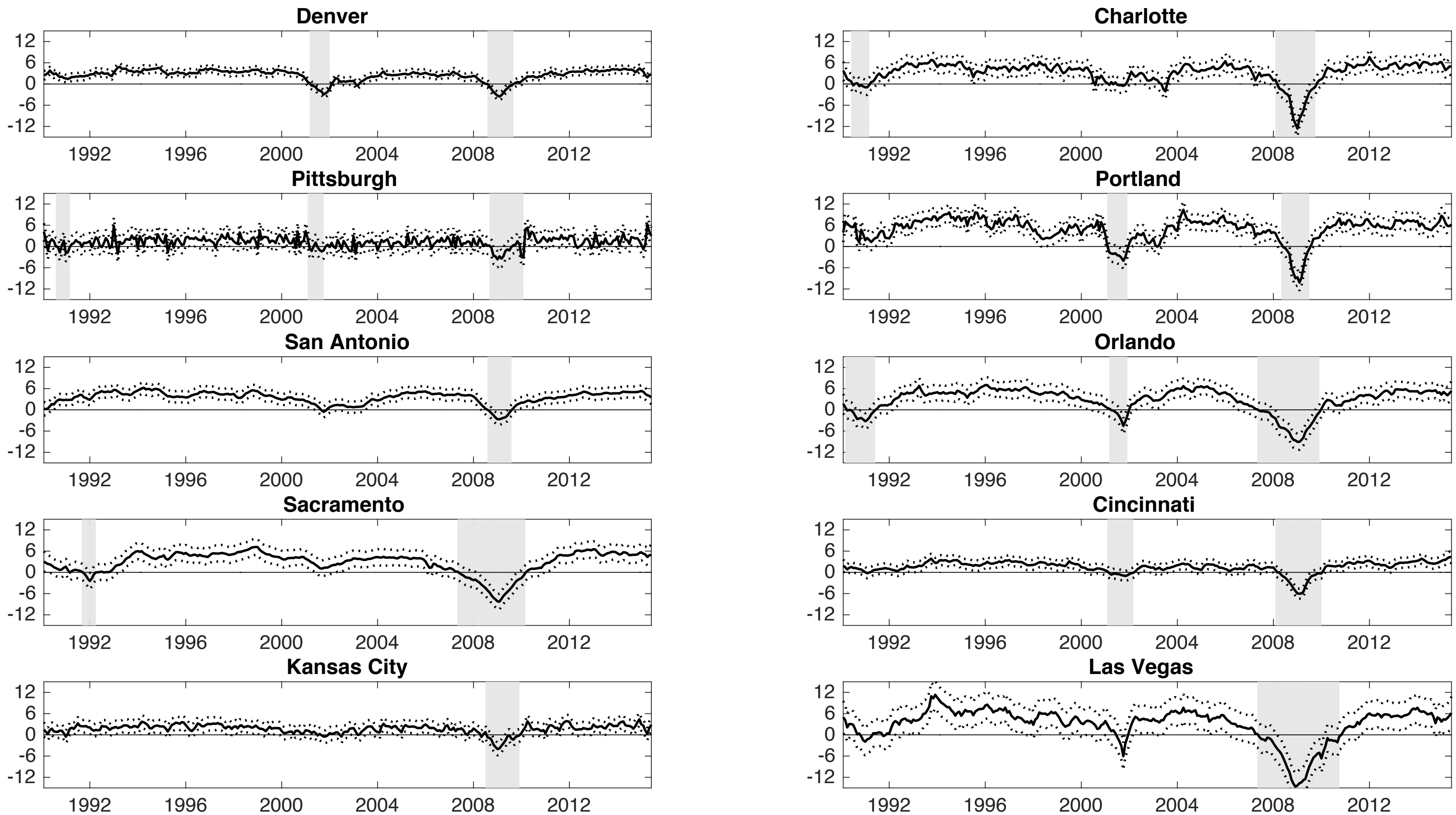

Fig. 1 (continued)

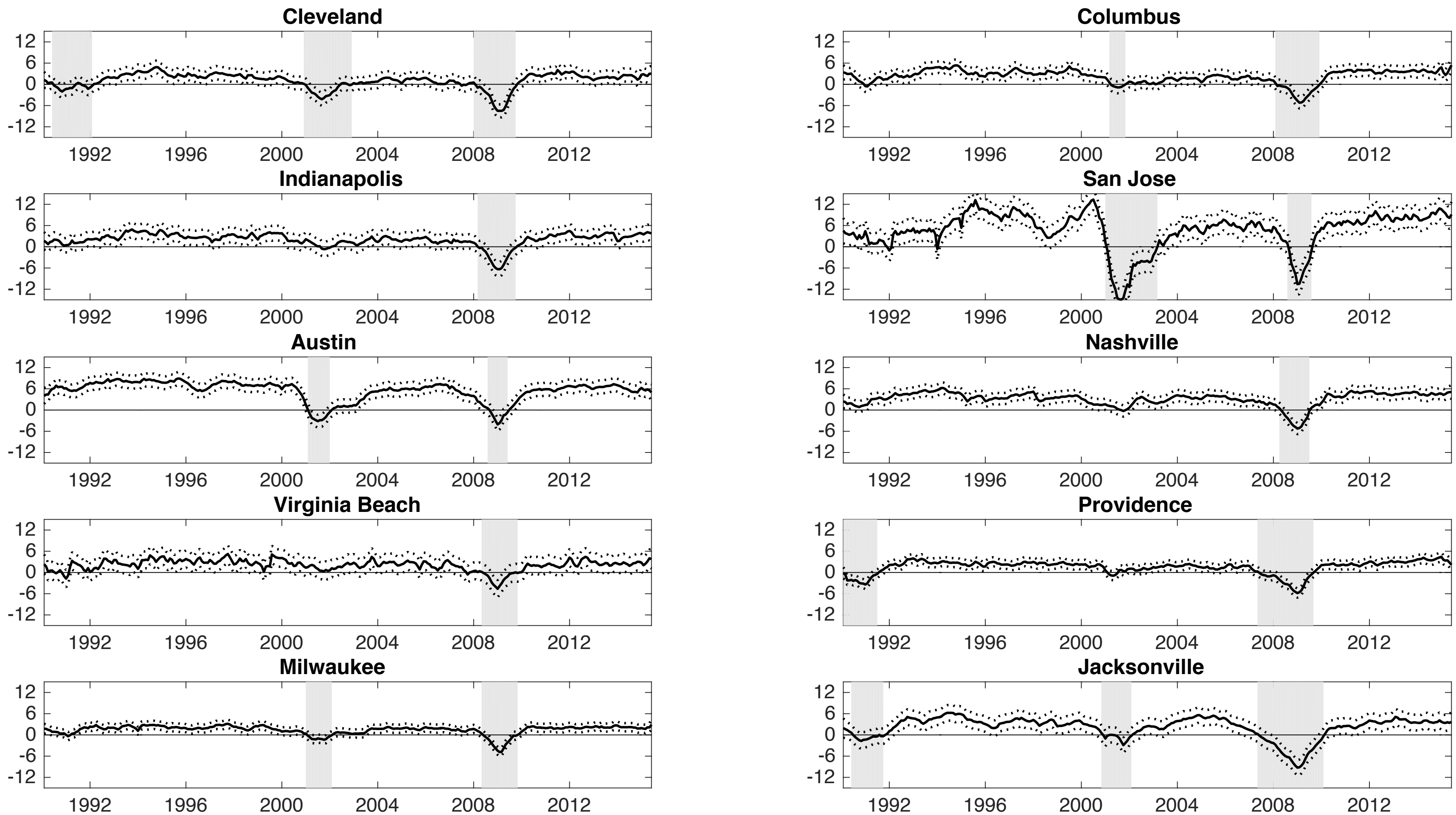

Fig. 1 (continued)

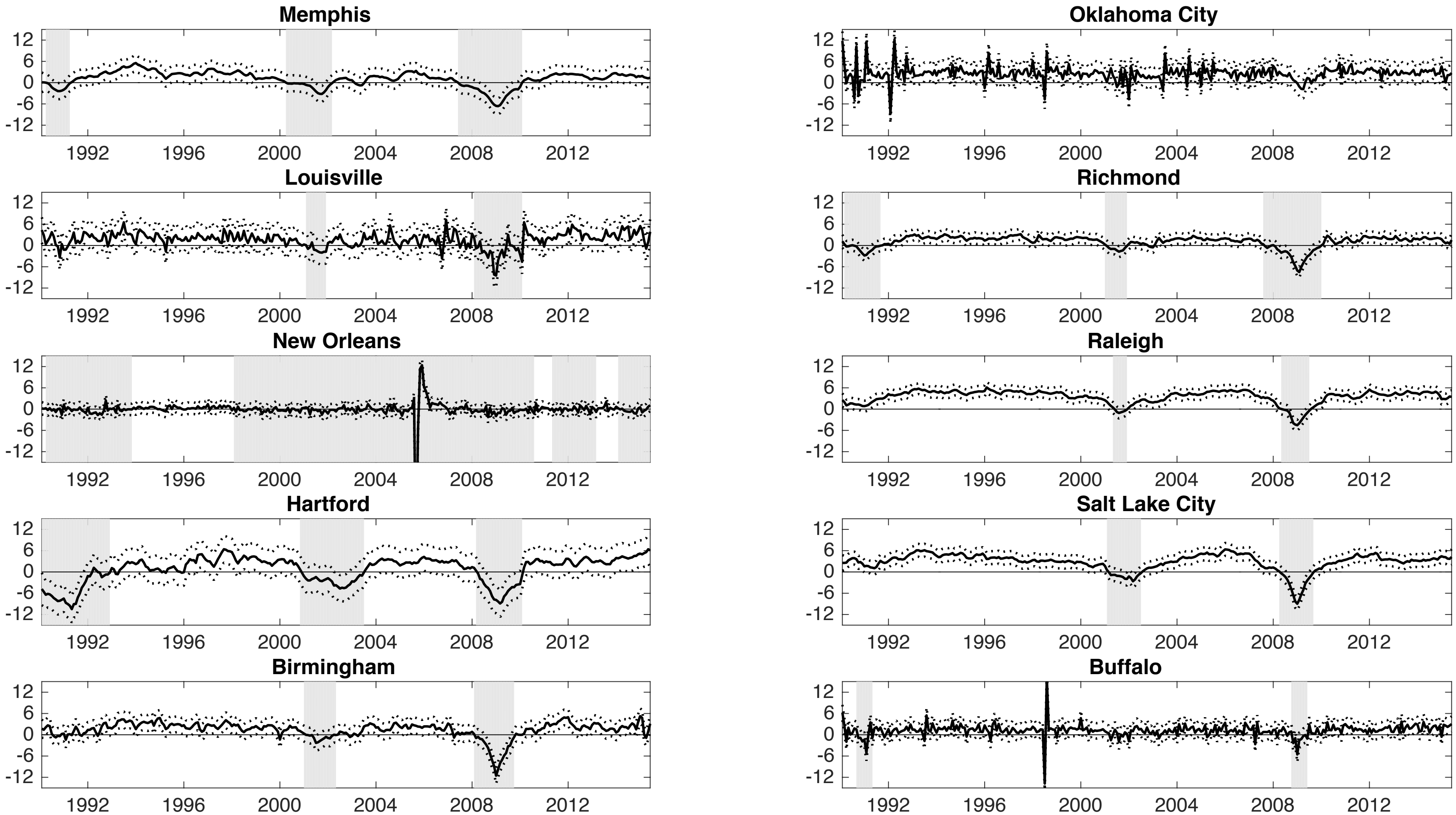

Fig. 1 (continued)

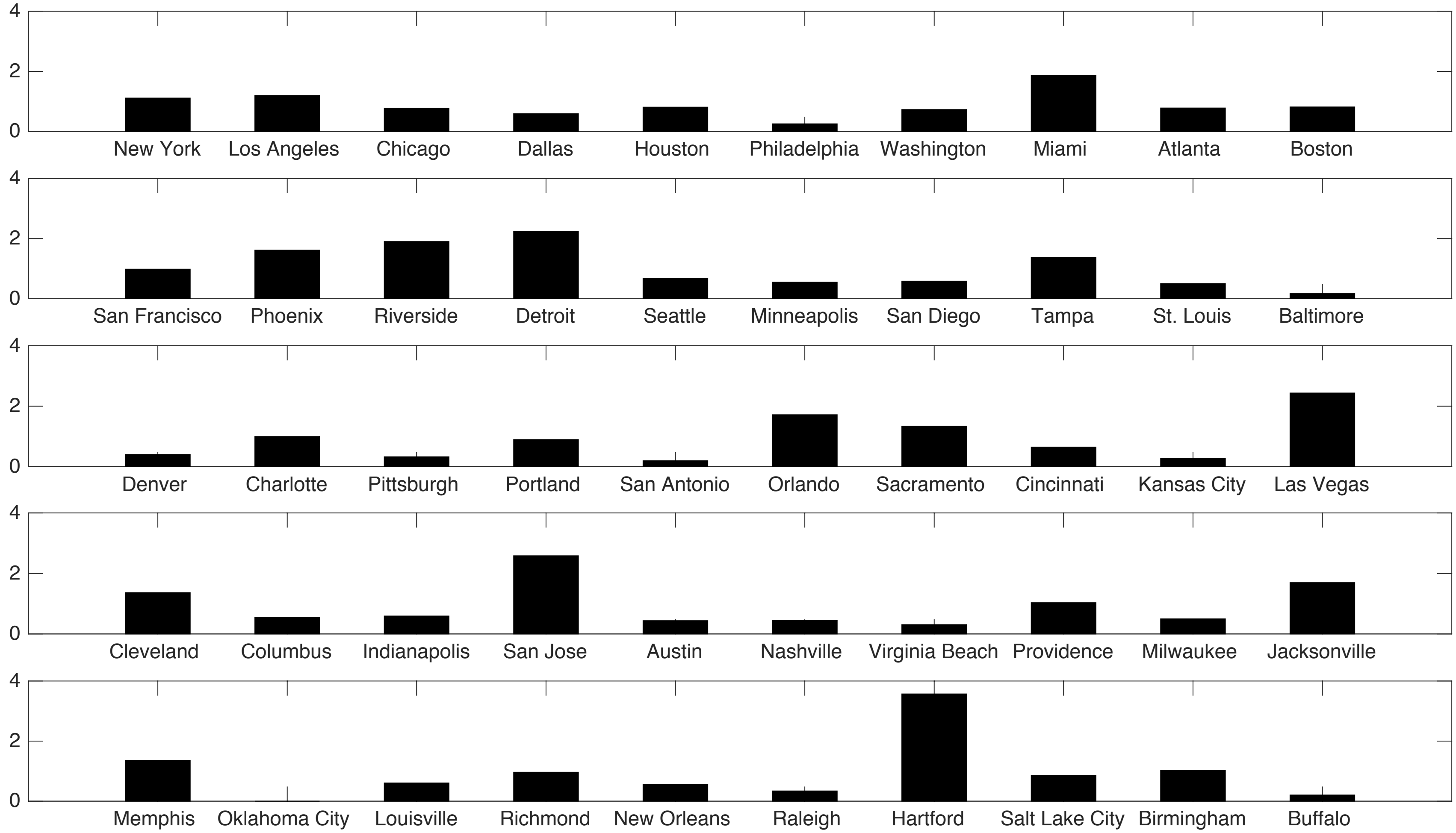

Fig. 2. Total depth of recession measures for the 50 largest U.S. metropolitan statistical areas. Each bar plots the total depth of recession measure described in the text for each MSA over the 1990:02 to 2015:06 period.

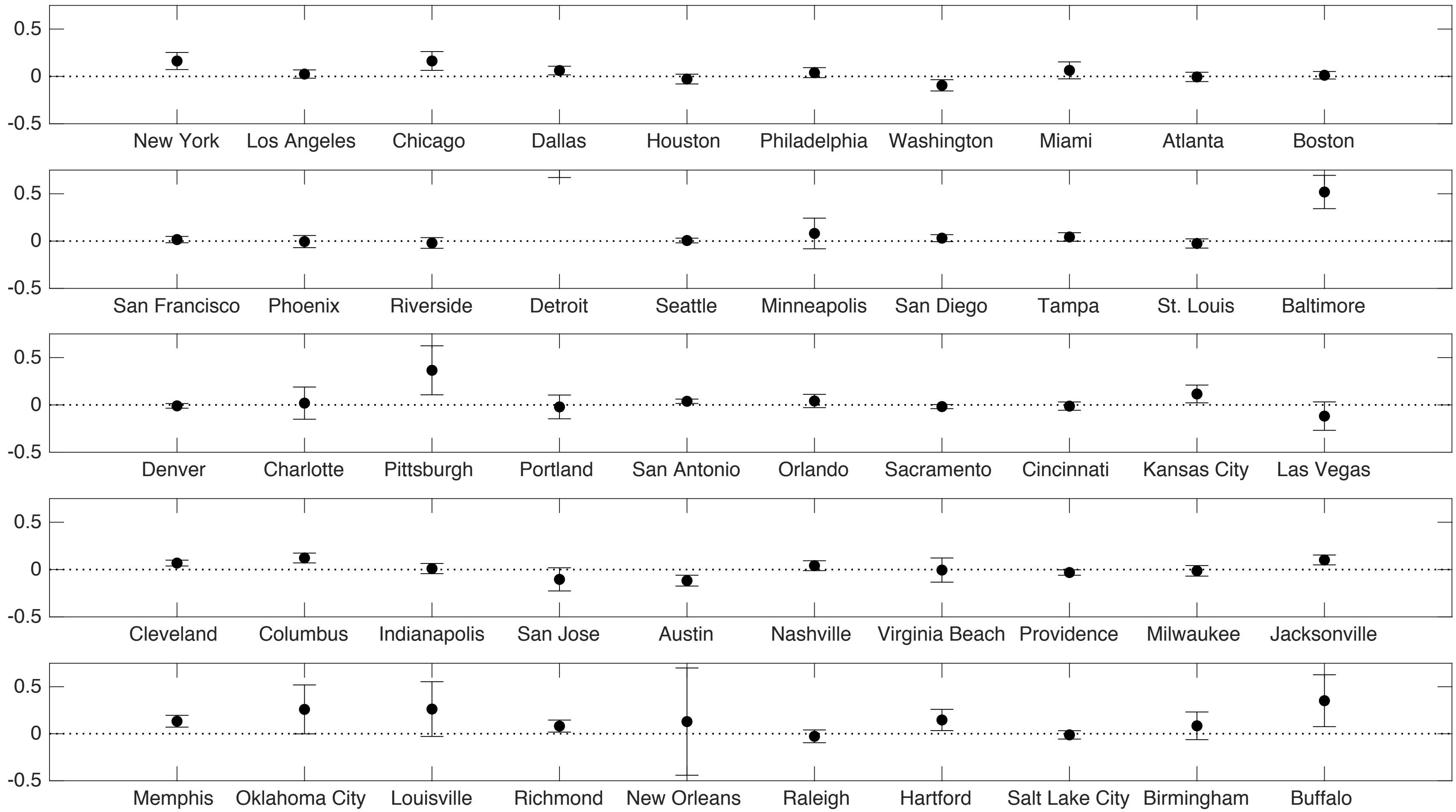

Fig. 3. Estimated dynamic spatial effects for the 50 largest U.S. metropolitan statistical areas. For each MSA, the figure plots the estimated dynamic spatial effect coefficient and corresponding 95% confidence band based on the 1990:02 to 2015:06 sample period.

A. Two quarters before national peak (June 2007)

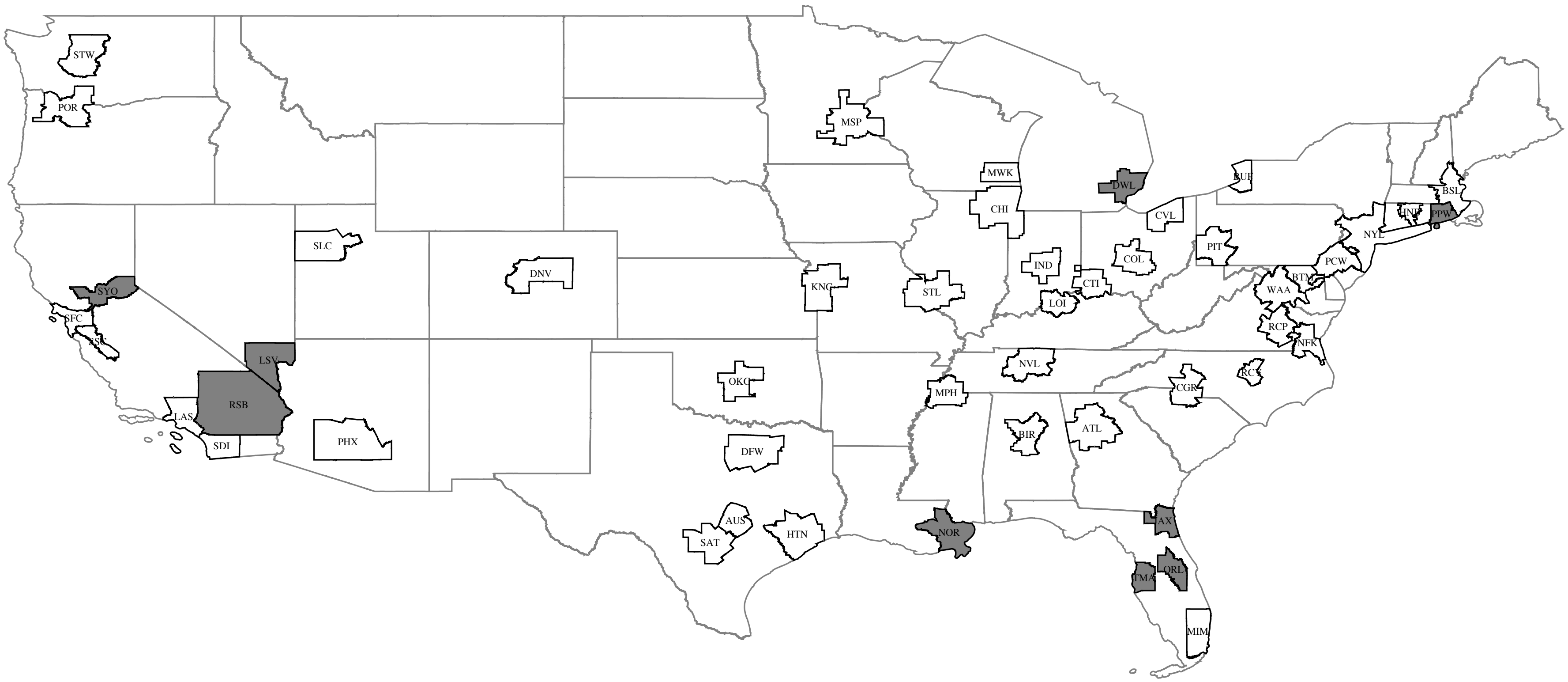

Fig. 4. Diffusion of Great Recession across U.S. metropolitan statistical areas. Shaded MSAs are in recession according to Table 3 for the month in the panel heading.

B. One quarter before national peak (September 2007)

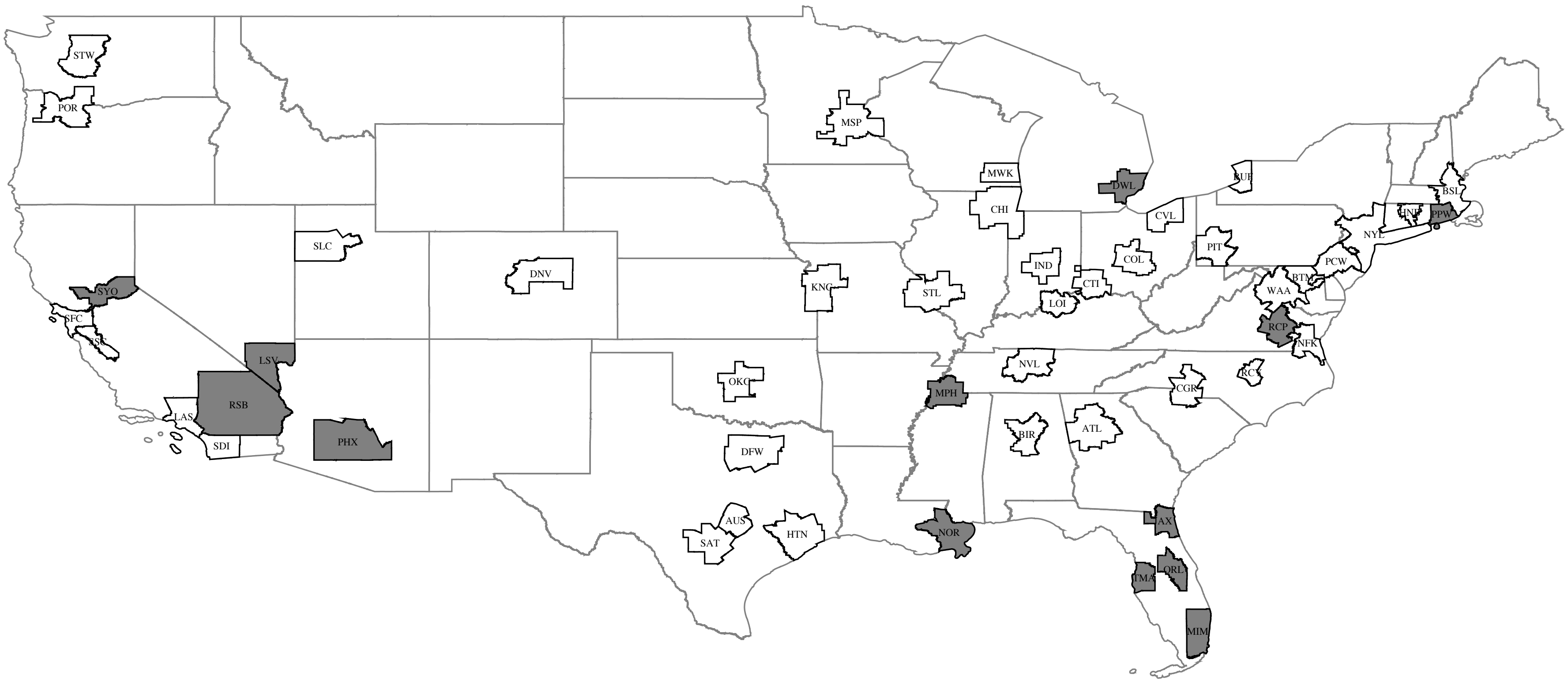

Fig. 4 (continued)

C. National peak (December 2007)

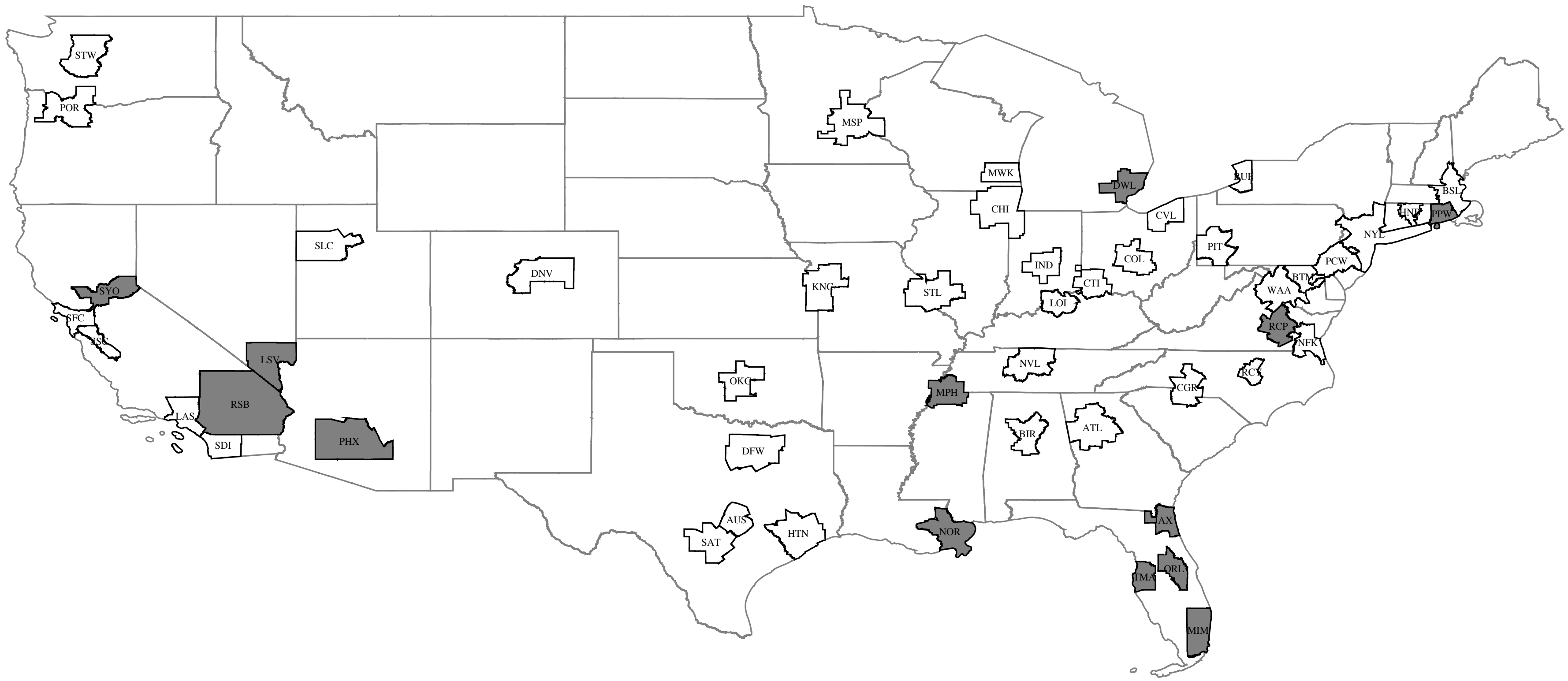

Fig. 4 (continued)

D. Middle of national recession (September 2008)

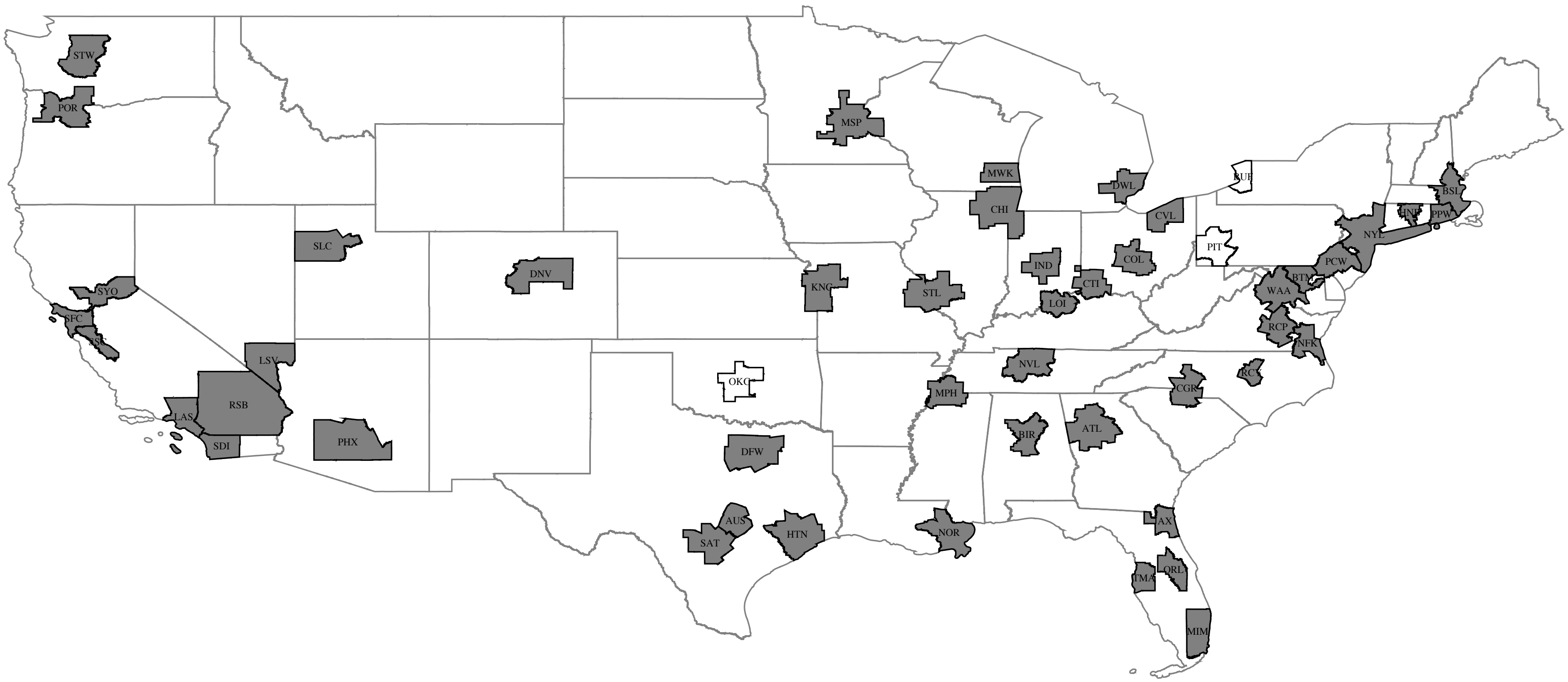

Fig. 4 (continued)

E. National trough (June 2009)

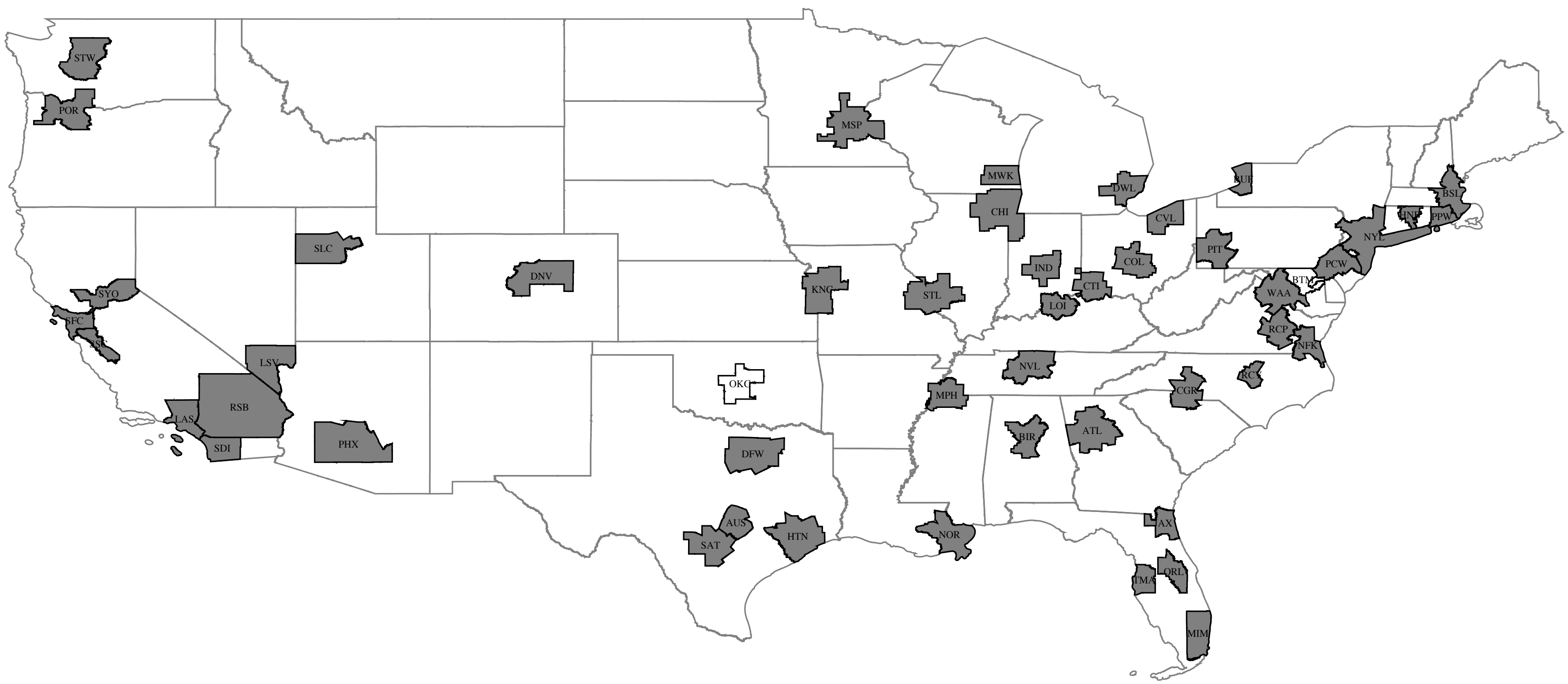

Fig. 4 (continued)

F. One quarter after national trough (September 2009)

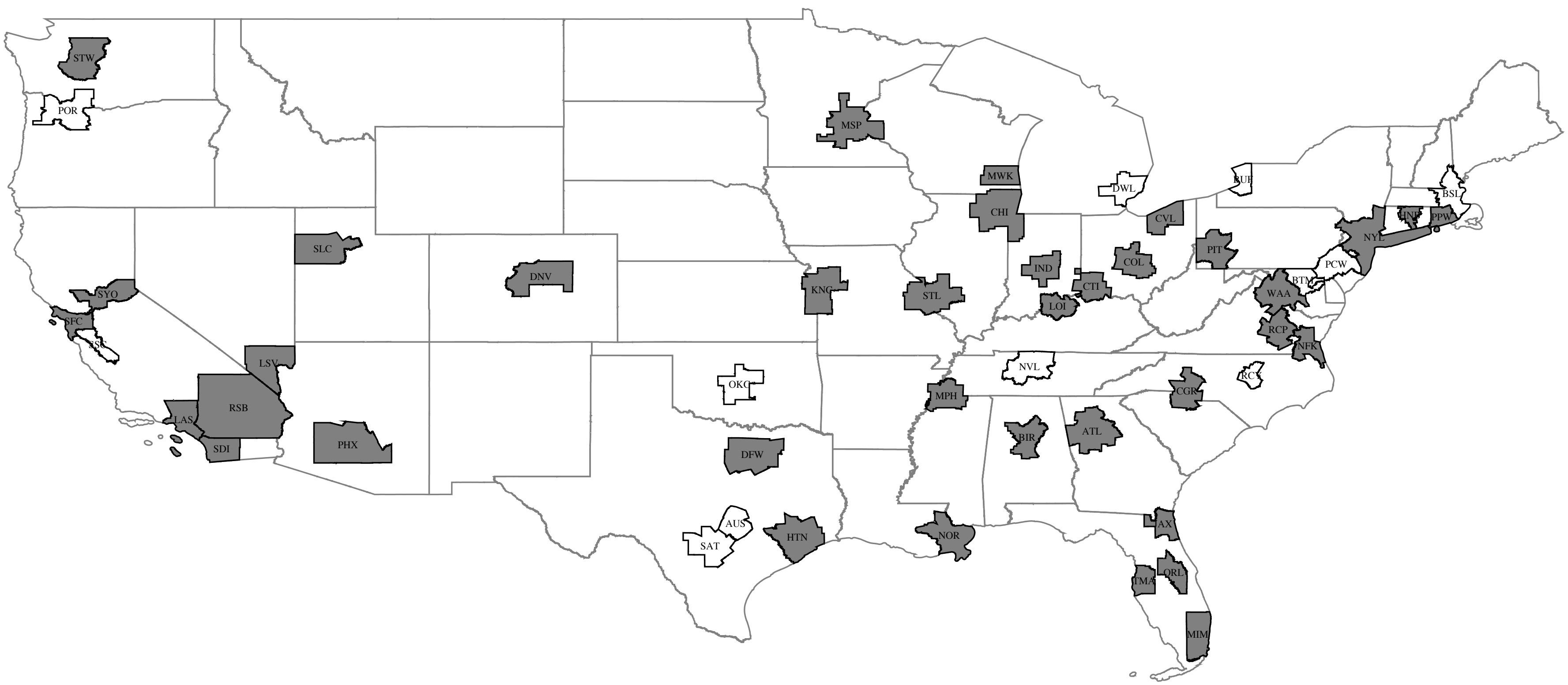

Fig. 4 (continued)

G. Two quarters after national trough (December 2009)

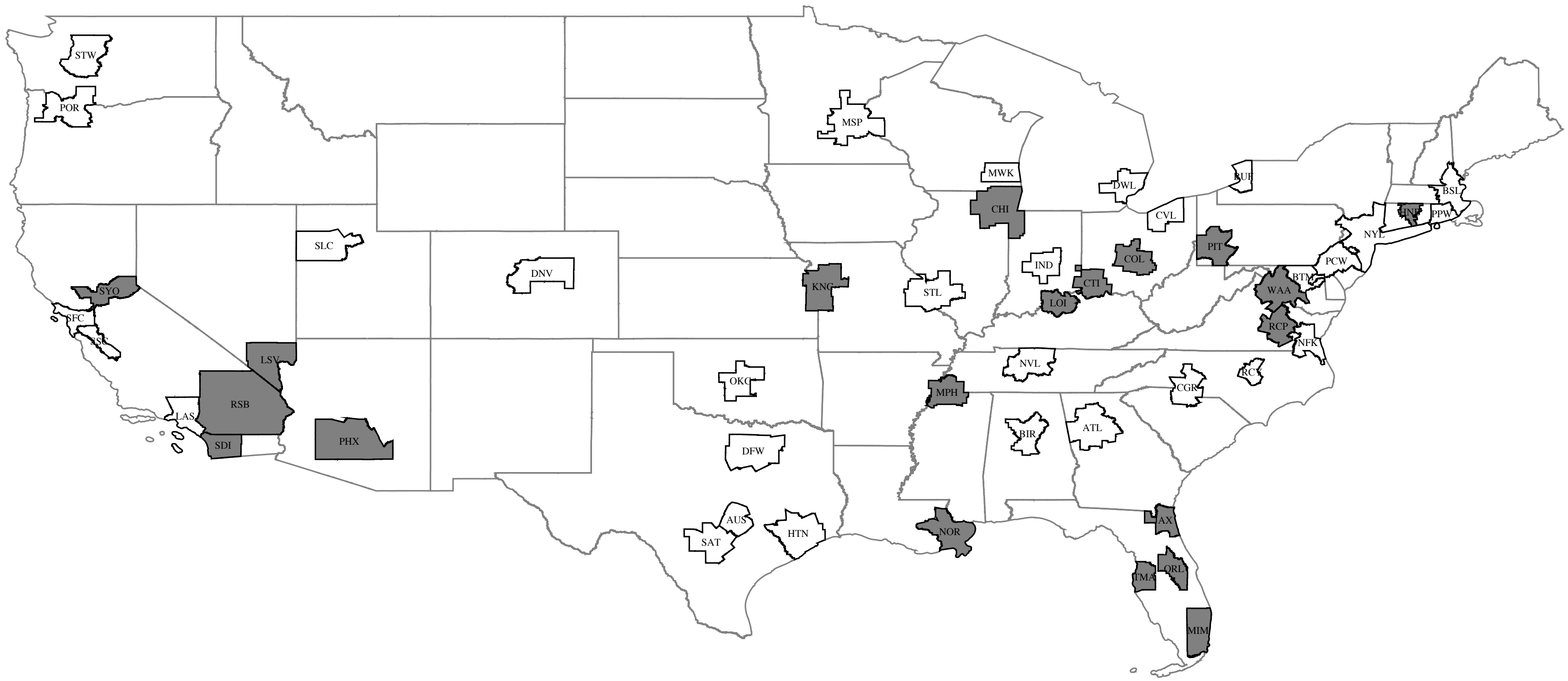

Fig. 4 (continued)

Table C1
Last available metro variable observations for regular FRED updates in a calendar year

(1) Data series	(2) Jan release (Jul/Aug/Sep $t-1$)	(3) April release (Oct/Nov/Dec $t-1$)	(4) Jul release (Jan/Feb/Mar)	(5) Oct release (Apr/May/Jun)
1. Average weekly hours worked by private sector employees	Nov $t-1$	Feb	May	Aug
2. Unemployment rate	Nov $t-1$	Feb	May	Aug
3. Private sector goods-producing employment	Nov $t-1$	Feb	May	Aug
4. Private sector service-producing employment	Nov $t-1$	Feb	May	Aug
5. Government sector employment	Nov $t-1$	Feb	May	Aug
6. Real average hourly earnings	Nov $t-1$	Feb	May	Aug
7. Construction permits for new private residential buildings	Nov $t-1$	Feb	May	Aug
8. Real average quarterly wages per employee	Q2 $t-1$	Q3 $t-1$	Q4 $t-1$	Q1
9. Total real personal income per capita	Q4 $t-2$	Q4 $t-2$	Q4 $t-2$	Q4 $t-2$
10. Return on average assets	Q3 $t-1$	Q4 $t-1$	Q1	Q2
11. Net interest margin	Q3 $t-1$	Q4 $t-1$	Q1	Q2
12. Loan loss reserve ratio	Q3 $t-1$	Q4 $t-1$	Q1	Q2
13. Gross metropolitan product	Year $t-2$	Year $t-2$	Year $t-2$	Year $t-1$

Notes: The table reports the last observation available for each individual metro variable used for regular updates of the metro indices in a typical calendar year. The updates will be posted on the Federal Reserve Economic Database website. For the second through fifth columns, the column heading gives the scheduled release month for the updated metro indices; the months in parentheses give the new months for which metro index observations are available. The release will occur on the second Tuesday in the scheduled release month. $t-1$ ($t-2$) indicates the previous year (two years previous).