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The Local Effects of Monetary Policy

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The Local Effects of Monetary Policy*

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Abstract

Many studies have documented disparities in the regional responses to monetary policy shocks. However, because of computational issues, the literature has often neglected the richest level of disaggregation: the city. In this paper, we estimate the city-level responses to monetary policy shocks in a Bayesian VAR. The Bayesian VAR allows us to model the entire panel of metropolitan areas through the imposition of a shrinkage prior. We then seek the origin of the city-level asymmetric responses. We find strong evidence that population density and the size of the local government sector mitigate the effects of monetary policy on local employment. The roles of the traditional interest rate, equity, and credit channels are marginalized relative to the previous findings based on less-granular definitions of regions. However, the relevance of the interest rate and credit channels appears to be more robust to business cycle uncertainty. [JEL codes: C32, E32, E52]

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"I believe that a successful theory of development (or of anything else) has to involve more than aggregative modeling." - Lucas (1988)

1 Introduction

Intranational U.S. business cycle dynamics are not necessarily harmonious: A growing literature has documented regional asymmetries in business cycles, the incidence of regional shocks, and the differential responses to aggregate shocks.[1] This heterogeneity highlights the importance of understanding the mechanism by which monetary policy propagates throughout various regions of the U.S. economy. In this paper, we establish an empirical benchmark for regional asymmetries in monetary policy transmission and examine why certain regions respond differently to monetary policy interventions.[2]

The empirical literature on geographically disaggregated effects of monetary policy uses structural VARs to identify the regional responses to innovations in the federal funds rate. Carlino and DeFina (1998) show that certain Bureau of Economic Analysis (BEA) regions respond differently from the U.S. aggregate response to a monetary policy shock. Furthermore, while repeating the exercise for state-level data, Carlino and DeFina (1999) find substantial within- and cross-region variability. Other papers [Mihov (2001), Hanson et al. (2006)] have shown that these regional asymmetries exist at varying levels of disaggregation, for different datasets, and various identifying restrictions governing the propagation of policy shocks.

In addition to documenting the presence of asymmetries, these studies consider their implications. In particular, they consider whether the notion of regional variation in response to monetary shocks provides insight into the channels through which monetary policy affects the economy. In other words, differences in industry mix, banking concentration, firm size, or demographics can

[1]For example, Carlino and Sill (2001), Carlino and DeFina (2004), and Owyang et al. (2005) study regional business cycles at different levels of disaggregation. Carlino and DeFina (1998) and others document differences in the regional response to monetary policy shocks. Canova and Pappa (2007) consider price dispersion across U.S. states due to fiscal policy effects, while Beck et al. (2009) document the importance of aggregate and local shocks to the inflation differentials across U.S. cities.

[2]There is a vast amount of literature debating the importance of monetary policy shocks for the business cycle fluctuations of the aggregate U.S. economy. Sims and Zha (2006) and Del Negro et al. (2007), among others, argue that monetary policy shock plays a relatively little role and is not the most important factor driving the aggregate U.S. business cycles. Carlino et al. (2001) reach the same conclusion for the disaggregate economy when analyzing the importance of monetary policy shocks in the forecast error variance of employment growth for the five metropolitan areas they consider. In our work, we do not investigate the relative importance of aggregate monetary policy on our disaggregated units. We, therefore, take the relative importance of aggregate monetary policy shocks as given and investigate the monetary policy channels given the city-level data.

affect a region's sensitivity to monetary policy innovations. Carlino and DeFina (1998), for example, attribute most of the differences in responses to the interest rate channel of monetary policy. They also find some evidence of a broad credit channel. Owyang and Wall (2009) show that the industry mix – thus, the interest rate channel – is relevant for the depth of monetary recessions, while the narrow credit channel prevails in determining the total cost of recessions. Fratantoni and Schuh (2003) use a heterogeneous agent VAR to model the propagation from the aggregate sector to the regional sector and highlight the importance of the housing markets.

While the stylized facts supporting the interest rate channel have been preserved, for the most part, the literature has suggested there is considerable within-region variation when less-granular definitions of regions are embraced (i.e., BEA regions). In this light, we focus on the finest unit of geographic disaggregation: cities. Cities define population areas with a high degree of economic and social integration. In this regard counties, states, and countries are more arbitrary economic units.

The economic growth literature has paid considerable attention to cities, as discussed in Glaeser et al. (1995), among others. This choice has been motivated by a high degree of factor mobility and specialization, externalities embodied in the spillover effects of physical and human capital, and rich data capturing the heterogeneity in the political and social structure across cities, all of which are important for growth.

The literature on urban economics also promotes cities as preferred economic units. For example, by drawing concentric circles around U.S. cities, Rosenthal and Strange (2003) find that agglomeration economies attenuate with geographic distance. This points to heterogeneity in units less aggregated than BEA regions and states. Also, Simon and Nardinelli (1996) find evidence of human capital concentration in cities and little evidence of knowledge spillovers across cities. This indicates that a particular city can have a different human capital makeup than neighboring cities, which implies that the flow of knowledge across geographic space is costly.

With an intention to gain from all the advantages of disaggregation, we focus on the city-level properties of monetary policy induced recessions. Disaggregating to the city level provides the benefit of a larger panel across which we may measure regional asymmetries. In the first stage of this paper, we estimate a panel VAR to establish some facts about the regional transmission mechanism of monetary policy, allowing for spillover effects across metropolitan areas. In the second stage, we use a set of metro-area covariates to explain the differences in the city-level economic responses to monetary policy shocks.

While increasing the panel size can sharpen our inference about the cause of variation across cities, it also leads to potential parameter proliferation. The current literature's solution to this problem is to impose restrictions on the propagation of shocks across cities (i.e., restrictions on the lagged coefficients of the VAR), the incidence of shocks (i.e., restrictions on the variance-covariance matrix), or both. Our solution is to estimate a Bayesian VAR, which has been shown to forecast out-of-sample fairly well [Doan et al. (1984), Litterman (1986)], even when the economic model is large [Banbura et al. (2010)].

We find considerable heterogeneity in how cities respond to monetary policy interventions. The differences are noticeable in the levels and persistence of the impulse responses, while cities appear to be more alike with respect to the timing of recovery after economic downturns. Unlike the previous literature, we find marginal evidence that the interest rate, credit, and equity channels help explain the differences in city-level responses to monetary policy shocks. However, there is strong evidence that population density and the size of the local government sector play prominent roles. When considering the uncertainty surrounding the impulse responses, the strong role of the local government sector disappears, while population density, interest rate, and equity channels are marginally (and approximately equally) important.

The paper proceeds as follows: Section 2 describes the structural VAR used to estimate the effects of monetary policy shocks. Section 3 introduces the data used in the estimation and the reference prior and outlines the Gibbs sampler used to obtain the posterior distributions. Section 4 presents the empirical results; specifically, we present some representative city-level impulse responses that highlight the cross-sectional diversity in our sample. Section 5 attempts to explain these differences using city-level characteristics, such as industrial shares, banking concentrations, and demographics among many others. Section 6 concludes.

2 Empirical Model

We consider a structural VAR of the following form:

$$Gz_t = C + \sum_{l=1}^{p} G_l z_{t-l} + \epsilon_t, \quad \forall t = 1, ..., T, \tag{1}$$

where z_t and ϵ_t are $(m \times 1)$ vectors of time-t dependent variables and their time-t structural shocks, respectively. The structural shocks are iid innovations, normally distributed with mean zero and unit variance, $\epsilon_t \sim N(\mathbf{0}_m, I_m)$. The matrix G represents the contemporaneous effect of the structural innovations on the vector of dependent variables.

Typically, the structural system (1) is not directly estimated. Instead, one estimates the reduced-form VAR

$$z_t = c + \sum_{l=1}^{p} B_l z_{t-l} + e_t, \tag{2}$$

where $e_t \sim N(\mathbf{0}_m, \Omega)$ and the variance-covariance matrix $\Omega = (G'G)^{-1}$. The standard methods identify G from (2) by specifying a Wold causal chain structure, often by imposing an effect ordering on the variables in the vector z_t (e.g., interest rates respond to output and prices but not vice versa). This system is, in general, estimated by a two-step procedure, where the reduced-form variance-covariance matrix is estimated in the first step, then the restricted contemporaneous matrix is mapped from the variance-covariance matrix by a maximum likelihood procedure.

In contrast, the methodology we consider estimates the structural system (1) directly. This allows us to accommodate partially identified, just identified, overidentified, as well as near-VAR cases via linear restrictions on the contemporaneous and lagged coefficients in a relatively simple manner with a few advantages. As discussed in Sims and Zha (1999), the indirect estimation of the contemporaneous effects in the VAR is valid when the restricted and unrestricted posterior distributions for the reduced-form parameters have the same shape. This assumption, though asymptotically satisfied, can be violated, for example, in overidentified cases in small samples.

Since this paper focuses on the local propagation of aggregate disturbances and, specifically, on monetary policy shocks, there is a need to model local-level variables in conjunction with the aggregate variables. Therefore, we impose the following general structure to the dynamic process described by (1):

$$G = \begin{bmatrix} D_n & 0_{m-n} \\ G_{21} & G_{22} \end{bmatrix}, \quad z_t = \begin{bmatrix} loc_t \\ agg_t \end{bmatrix},$$

where loc_t is the vector of n local- or regional-level variables and agg_t is the vector of $m-n$ aggregate variables. D is a diagonal matrix and G_{21} and G_{22} are unrestricted partitions of G.

The identification of the system is achieved by restrictions in the spirit of Christiano et al. (1999)

for the aggregate VAR and Carlino and DeFina (1998) for the regional system. Local shocks are assumed to contemporaneously affect the region of origin only. Aggregate shocks affect regional variables no sooner than with a one-period lag. Although the ordering of the aggregate variables can vary depending on the case at hand, it is, in general, true that monetary policy responds to unexpected movements in both regional and aggregate variables.[3]

3 Estimation

We take a Bayesian approach to the estimation of the model specified above, implementing the Gibbs sampler for structural VARs as outlined in Waggoner and Zha (2003). In addition to improving the small-sample properties of parameter estimates that are accommodated by the imposition of a prior, the Gibbs sampler naturally provides an appropriate characterization of parameter distributions. Furthermore, a distribution for impulse responses is easily obtained.[4]

3.1 The Data

The benchmark model considers the dynamic behavior of

$$z_t = [y_{1,t},\, ...,\, y_{i,t},\, ...,\, y_{n,t},\, Y_t,\, p_t,\, lead_t,\, r_t,\, nbr_t,\, tr_t,\, m2_t]', \tag{3}$$

where $y_{i,t}$ is the total non-farm employment for region i; Y_t is (aggregate) GDP; p_t is the core CPI price level; and $lead_t$ is the Conference Board's composite index of 10 leading indicators. Leading indicators capture macro-economic expectations in the empirical specifications as in Sims (1992) and Hanson (2004). The effective federal funds rate, r_t, is the monetary instrument. We capture the behavior of aggregate monetary variables by the dynamic paths of total non-borrowed reserves, nbr_t, total reserves, tr_t, and money supply, $m2_t$. The series are observed at the quarterly frequency. Except for the interest rate, all variables are seasonally adjusted and in logarithms (multiplied by 100). The latter standardizes the unit of measurement across the variables to percentage points.[5]

[3] For robustness we also consider the case where local shocks are correlated contemporaneously. This specification results in a partially identified system. The results are fairly robust to the results of the benchmark scenario presented further in the paper.

[4] Sims and Zha (1998) show that the 16th and 84th percentiles of the acquired distribution are well suited for characterizing the shape of the posterior distribution of impulse responses compared with the alternative methods that generate error bands. In addition, Monte Carlo studies considered in Kilian and Chang (2000) suggest that the confidence bands calculated this way are likely to be more accurate in high-dimensional VAR models.

[5] Total non-farm employment for metropolitan areas is taken from the Current Employment Statistics Survey released by the Bureau of Labor Statistics and covers the period of 1972:I-2004:IV. Core CPI is defined for all urban

To achieve identification, we allow aggregate variables to respond contemporaneously to regional innovations. For our purposes, a region is defined as a city (equivalently a metropolitan area) meeting certain criteria detailed below. We impose the standard recursive VAR restrictions on the aggregate block. As a result, even though the aggregate output, prices, and leading indicators are in the contemporaneous feedback rule of the central banker, monetary policy has no contemporaneous effect on any of these aggregate variables. These restrictions, together with the general restrictions outlined previously, yield an overidentified system.

INSERT TABLE 1

The cities/metropolitan area units are selected to have at least 200,000 in total employment by the end of 2004 and comparative data coverage for the sample period considered.[6] The resulting final sample includes 105 cities/metropolitan areas listed in Table 1. It captures 63 percent of aggregate total non-farm employment as of 2004:Q4. Some previous studies have used the BEA regions to measure asymmetries within the U.S. economy. Our sample of cities/metropolitan areas is representative of the cross-section of BEA regions: 6 percent of the metropolitan areas are from the New England region, while 16 percent are from the Mideast, 18 percent are from the Great Lakes, 6 percent are from the Plains, 27 percent are from the Southeast, 9 percent are from the Southwest, 3 percent are from the Rocky Mountains, and 15 percent are from the Far West. These numbers are broadly consistent with the populations of each region.

3.2 The Prior

The prior we use is proposed by Sims and Zha (1998) and discussed extensively in Robertson and Tallman (1999). Let $x_t' = [z_{t-1}' \ ... \ z_{t-p}' \ 1]$, $A = G'$, and $F_{k\times m} = [G_1 \ ... \ G_p \ C]'$, where $k = mp + 1$. The system in (1) can be rewritten as

$$z_t' A = x_t' F + \epsilon_t', \tag{4}$$

consumers as the price level for all items less food and energy. Except for the index of leading indicators, the data are obtained from the FRED database of the St. Louis Fed. The index of leading indicators comes from the Conference Board.

[6] Metropolitan areas include Metropolitan Statistical Areas (MSAs) and Primary Metropolitan Statistical Areas (PMSAs) and are intended to define population areas that have a high degree of economic and social integration. The definitions of MSAs and PMSAs that we employ are based on the 1995 Federal Information Processing Standards Publication 8-6. The metropolitan areas of Westchester County, NY, Camden, NJ, Philadelphia, PA, and Northern Virginia, VA, are eliminated since they were counted as part of the New York, Philadelphia, Pennsylvania-New Jersey, and Washington metropolitan areas, respectively. In 2004, the MSA and PMSA definitions have changed and the old definitions have no longer been maintained, which explains the choice of our end-of-sample period.

where a_i and f_i are the respective ith columns of A and F. It should be noted that our sample size allows only for one lag in the VAR specification in equation (1).

INSERT TABLE 2

The prior on A imposes independence across the structural equations, where the elements of a_i are assumed to be jointly normal with mean zero. The prior mean of $f_i|a_i$ is parameterized such that it sets the conditional mean of the first lag equal to a_i and the rest to zero. The prior postulates the following prior distributions:

$$\begin{aligned} a_i &\sim N(0, \bar{S}_i), \\ f_i|a_i &\sim N(\bar{P}_i a_i, \bar{H}_i), \end{aligned} \tag{5}$$

for $i = 1, ..., m$. Given the setup of (4), the corresponding columns of A and F represent a structural equation in the VAR. We impose priors on the order of integration and the possibility of cointegration between the m variables by adding observations to the dataset as in Doan et al. (1984) and Sims (1993). Values for the six hyperparameters are set as in Sims and Zha (1998) and are shown in Table 2. The specifics of the prior are discussed in the Appendix.

3.3 The Sampler

The Gibbs sampler is operationalized by defining b_i and g_i such that $a_i = U_i b_i$ and $f_i = V_i g_i$, where U_i and V_i are orthonormal rotation matrices that reduce the parameter space of the VAR, taking into account the linear restrictions on the contemporaneous and lagged dynamics of the system. The prior (5), together with the likelihood function, yield marginal posterior probability density functions for b_i and g_i defined by

$$p(b_1, ..., b_m|X, Y) \propto |det[U_1 b_1|...|U_m b_m]|^T exp\left(-\frac{T}{2}\sum_{i=1}^{n} b_i' S_i^{-1} b_i\right) \tag{6}$$

$$p(g_i|b_i, X, Y) = \varphi(P_i b_i, H_i), \tag{7}$$

where H_i, P_i, and S_i are the appropriate transformations of the prior mean and variance matrices $\bar{H}_i$, $\bar{P}_i$, and $\bar{S}_i$.

The implied conditional posterior distribution of A is non-standard and independent of F. The strategy implemented by Waggoner and Zha (2003) is to sample a set of normally distributed coefficients which, projected over a proper basis, generates the conditional distribution $p(b_i|b_1 \ldots b_{i-1}\ b_{i+1} \ldots b_m,\ X,\ Y)$. The Gibbs sampler – outlined in Gelfand and Smith (1990), Casella and George (1992), and Carter and Kohn (1994) – sequentially draws from the conditional posteriors of each of the b_i-s, starting with some arbitrary initial values of $\{b_1^* \ldots b_{i-1}^*\ b_i^*\ b_{i+1}^* \ldots b_m^*\}$. The first 5,000 draws are discarded to eliminate the effect of the initial values. The results presented are based on the remaining 10,000 accumulated draws. Once the appropriate distribution of A is at hand, obtaining a distribution for F via equation (7) is a straightforward task.[7]

4 Impulse Responses

We present the first-stage empirical results in two parts. First, we elaborate on the behavior of the aggregate block in our large Bayesian VAR. Next, we summarize the city-level impulse responses to a monetary shock.

Figure 1 shows the responses of aggregate output, prices, index of leading indicators, non-borrowed reserves, total reserves, and money supply to an approximate 33 basis point increase in the effective federal funds rate. The results for the aggregate block are consistent with those reported by Christiano et al. (1999). After the initial increase the effective federal funds rate declines in a persistent manner, such that it is essentially zero around period 7. The contractionary shock to the federal funds rate drives down output while there is evidence of a price puzzle with a short-run increase in prices. Leading indicators decline and their recovery leads the recovery of output. The liquidity effect drives non-borrowed reserves downward. The effect on total reserves is overall insulated: Total reserves increase marginally upon impact and do not decline much in later periods. The money supply declines and recovers at around period 7 when the federal funds rate reaches zero.

INSERT FIGURE 1

Next, we present the city-level employment responses. Figure 2 shows the distributions of modal impulse responses across the cities at various forecast horizons. In Period 4 the distribution is fairly dispersed and mildly skewed to the left. There is a small proportion of cities for which a contractionary monetary policy has a positive effect on employment. The skewness increases

[7]In order to assess the convergence of the algorithm, we have compared the reported benchmark results with those obtained based on 20,000 accumulated draws; the results are similar.

as the monetary policy induced business cycle reaches period 8, which roughly coincides with the average trough period across the cities. Four years into the monetary policy induced recession (period 16), the modal impulse response distribution becomes somewhat tighter, and the mode of the distribution indicates that for most cities the effects of monetary policy are close to zero. Figure 3 (panel a) shows that cities differ in both the magnitude of their employment responses at the trough and in the timing of the trough. As for the latter, the trough for most cities occurs between 7 and 9 quarters after the initial shock.

INSERT FIGURES 2 AND 3

In order to facilitate comparison of the impulse responses, we group the cities into clusters based on similarities of their impulse responses over the 16-period business cycle horizon. While grouping cities exogenously – say, by BEA region – might seem appropriate, we note that even cities in close geographic proximity can exhibit very different responses to monetary policy, thus motivating the necessity of an alternative grouping. More specifically, we use the k-means algorithm to collect the 105 city-level responses into 4 mutually exclusive groups.[8]

The composition of the clusters is presented in Table 3, while Table 4 highlights the average behavior of the modal employment response for each of the clusters. The largest cluster, with about a 44 percent membership rate, is Cluster 3. The behavior of the second-largest cluster, Cluster 4, is qualitatively similar to the latter. The main difference is in the overall magnitude of the city-level employment response, which is on average twice as high for Cluster 4. The two small clusters, Cluster 1 and Cluster 2, represent the extremes. The first one is the cluster with cities that are overall not very responsive to monetary policy, and when they respond, there is an "employment puzzle" in that employment first goes up and then contracts. Due to the puzzle, the contraction occurs much later in the business cycle dynamics compared to the other clusters. Cluster 2, on the other hand, has cities that are much more sensitive to the interest rate fluctuations compared to the rest.

Another feature obvious from Table 3 is that metropolitan areas from various BEA regions belong to the same cluster, which implies that geographic distance is not as important factor as gravity models would suggest. For example, Cluster 1, the smallest of all the clusters, includes

[8]The algorithm minimizes the total squared Euclidean distance of the metro areas in each cluster from the cluster mean. At each iteration, the algorithm chooses the center for the clusters, reallocates the metropolitan areas, and recalculates the center points until the algorithm converges. The exogenous number of clusters is chosen such that it provides meaningful and qualitatively different groupings across the cities.

cities from five out of the eight BEA regions. Figure 3 (panel b) plots the cluster membership for the modal response at the trough. It appears that our k-means clustering captures the magnitude differences in employment response at the trough fairly well.

INSERT TABLES 3 AND 4

Next, we take a closer look at the results reported in Table 4. The second column reports the maximum depth of the recession measured as the maximum employment contraction attained during the recession; the level of contraction is averaged across the cities in respective clusters. Cities in Cluster 1, for example, are not very sensitive to changes in the federal funds rate. On average, cities in Cluster 2 appear to be the most sensitive to monetary shocks – the recession trough results on average in a 0.16-percentage-point decline in employment. According to the third column, the trough across the cities occurs on average between 8 and 12 quarters. The total cost of the recession – measured by the total absolute deviation of employment from the steady-state equilibrium and reported in column four – is on average higher for clusters with higher average troughs.

The last three columns of Table 4 show the average behavior of the impulse responses across the clusters at 4, 8, and 16 quarters after impact. Cities in Cluster 1 are expanding during the initial quarters after the shock – these cities have the lowest trough response. Cluster 2 appears to be the most sensitive to monetary policy shocks: At all horizons considered, the average decline in employment for the cities in this cluster is considerably greater than that of other cities in other clusters. The responses of employment in Clusters 3 and 4 are similar in shape but different in magnitude. At any given period considered, the responses of Cluster 4 are about twice the magnitude of the responses in Cluster 3. Consequently, Cluster 4 has roughly twice the total cost of the Cluster 3 recession. However, there is no considerable difference in the persistence of the response: The timing for the trough roughly coincides for these two clusters. Thus, we could conclude that most of the cities react to monetary policy contraction in a similar shape. The main difference is in the magnitudes of the responses. Cities do not differ much from each other in the timing of a recession: When cities in one cluster start the recovery, the remaining clusters recover within a year.

INSERT FIGURES 4 AND 5

Figure 4 shows the geographic location of the cities in various clusters. The figure highlights that geographic proximity is not the only factor that determines how cities are clustered. For example, the state of California includes cities from three out of four clusters we have identified. Finally, we plot the employment response of a "representative" city from each cluster. We do so by plotting the most frequent impulse responses (calculated based on the mode of the parameter distributions) alongside the 68 percent coverage areas for the city closest to the cluster median over the forecast horizons 1 to 16, jointly. The "representative city" in each cluster (Baton Rouge, LA; Boise City, ID; Albany-Schenectady-Troy, NY; Albuquerque, NM) is depicted in Figure 5.[9] Monetary policy shocks are shown to have transitory effects on employment for the representative cities. Baton Rouge initially responds positively to the monetary policy contraction, slipping into a recession between 6 and 12 quarters. Boise City represents the cluster most sensitive to monetary policy. Albany-Schenectady-Troy and Albuquerque respond similarly with the response of the latter being stronger.

5 Why Do Asymmetries Exist?

In the previous section, we documented the asymmetries across the metropolitan areas, in both the depth and the duration of monetary policy induced recessions. In this section, we present results of second-stage regressions, investigating whether certain city-level covariates may help explain the variation in the cross-sectional impulse responses.

5.1 The Channels of Monetary Policy and the Economic Structure

Economic theory suggests a few potential causes for the asymmetric responses of real activity to a monetary policy innovation: The distinctive economic and financial structures of the local economies, as well as the local-level policy, should factor into how regions respond. The discussion relies on the hypothesis that certain features of the economy are, to a great extent, responsible for the short-run or impact responses. We think of these features as indicators of a monetary policy channel. Mishkin (1996), among others, has emphasized several channels for monetary transmission: the interest rate, equity price, exchange rate, credit, and cost channels. Other aspects of the economy predominantly affect the propagation mechanism, thus determining the properties of the employment response in the longer run.

[9] The full sample of impulse responses is available upon request.

In the interest rate channel hypothesis, an increase in the cost of borrowing triggers a decline in investment spending, including business and residential fixed investment and inventories. The interest rate elasticity of each of these can vary at a local level because cities differ in their industry mix, contractual agreements governing the housing market, and institutional details that affect interest rate sensitivity. For example, industries such as construction and manufacturing are presumed to be more sensitive to interest rate fluctuations because they rely more heavily on borrowing and inventories. Thus, in cities where these industries are dominant, one would expect greater reactions to changes in real interest rates. Although the traditional interest rate channel appears to be less important on the aggregate level [see Chirinko (1993) and Mishkin (1996)], several studies have shown that industry composition is significant in explaining the asymmetric responses of real activity to monetary policy shocks across regions [Carlino and DeFina (1998); Carlino and DeFina (1999); and Owyang and Wall (2009)].

The equity channel of monetary policy works through a wealth effect spurred by a decrease in interest rates. The types of equities that have the potential to create heterogeneous effects locally via this channel are housing and land, since housing and land markets are substantially affected by local supply and demand conditions [Lamont and Stein (1999), Abraham and Hendershott (1992)], while other equity markets are fairly centralized and homogeneous. Differences in neighborhood amenities, such as the quality of schools and the kinds of local businesses, are some of the myriad of factors that determine local valuations of housing and land. For example, residents in a high-priced neighborhood may be willing to absorb the brunt of unfavorable economic shocks in order to keep their housing values high, whereas residents in lower-priced areas may have different motives.

The local transmission of monetary policy may also be affected by international trade and the exchange rate. Regional asymmetries can arise if there are differences in the proportion of traded and non-traded sectors at the city level. Because manufacturing and mining are largely traded industries, while construction and services are largely non-traded, a city having a greater proportion of manufacturing firms would be more sensitive to innovations to monetary policy via this channel.

Differences in the financial structure of cities are important for the credit channel of monetary policy. Under the narrow credit channel (or bank lending channel) hypothesis, a contractionary monetary policy decreases bank reserves and deposits and, therefore, also the amount of funds available for lending [Kashyap and Stein (1994)], which curtails investment and real economic activity. If banks rely heavily on deposit liabilities and borrowers are unable to tap alternative sources of funding, having more small banks and small firms translates into greater regional sensitivity to monetary policy.[10]

On the other hand, the broad credit channel hypothesis emphasizes general credit market imperfections and is not limited to bank lending [Bernanke et al. (1999)]. The broad credit channel assumes that a wedge between external and internal financing is induced by agency costs. During monetary contractions, firms' cash flows, net worth, and collateral values decline, increasing the agency costs associated with distinguishing "high-quality" firms. As external financing becomes more expensive, investments and real activity decline. Therefore, cities with less-established firms and industries and/or less-capitalized entities – features associated with high agency costs – will be greatly affected by monetary policy via this channel.

Under the cost channel of monetary policy, interest rate movements result in supply-side effects – output contracts and prices increase with an increase in the real interest rate. Whenever a rigidity causes marginal cost to depend on interest rates [Barth, III and Ramey (2002) and Christiano et al. (1997)]. For example, when factors of production are paid before sales revenues are received and firms have to borrow to finance working capital, increases in interest rates may have severe consequences for these firms. Thus, monetary policy may have larger effects in manufacturing-dominated cities.

The monetary policy transmission channels discussed up to this point are the main sources of monetary business cycles identified by the literature. Nevertheless, the general socio-economic structure of cities has the potential to create asymmetric propagation effects. For example, if a city is more industrially diverse, it should be able to absorb the effects of economic shocks more easily. A similar argument also applies to a diverse labor force: A more educated labor force can more easily shift across different sectors, thus reducing the effects of monetary shocks on city-level employment. The overall flexibility of the labor markets matters as well. If a greater proportion of the labor force is unionized, then the adjustment process for employment is less accentuated because firms find it harder to fire workers. Access to financial markets invariably depends on an individual's net worth. One source of net worth is an individual's income. Therefore, cities having residents with relatively high incomes should be more sensitive to monetary policy. On the other

[10] The empirical evidence in support of the narrow credit channel has been mixed. Studies conducted at the firm level [Gertler and Gilchrist (1994) and Oliner and Rudebusch (1995, 1996a,b)] find no substantive evidence supporting the bank lending channel for small versus large firms because the ratio of bank credit to nonbank credit does not change substantially over the business cycle depending on a firm type. However, small firms do appear to exhibit more interest rate sensitivity compared to the large ones.

end of the spectrum, the poverty level not only provides a way to measure the proportion of the population that tends not to participate in financial markets, but also signals the degree to which resources are allocated to welfare programs. Such welfare programs typically divert resources from productive uses. Finally, high crime rates tend to discourage entrepreneurship. Residents in high-crime neighborhoods may refuse to take advantage of favorable interest rates even if profitable investment opportunities are available. Also, higher crime rates usually exist in an environment in which more resources are allocated away from production and into law enforcement. These additional factors, though demographic in nature, can cause monetary policy to have differential effects on cities.

Local-level fiscal policy could also have propagation effects on monetary policy. The higher the share of government employment, the more acyclical the local business cycle can be. This argument indeed can be reconciled with the thinking that the government sector is slow to adjust or that it might not have the incentive to adjust quickly in order to absorb some of the adverse effects of the business cycle. On the expenditure side, the type and magnitude of local government spending could potentially crowd out federal-level policies. Cities having sizable expenditure outlays may find their local residents saving more to meet expected future tax burdens. Thus, expansionary (wealth-increasing) monetary policy may prove futile if local residents exhibit such Ricardian-type behavior. Additionally, the degree of the local tax burden determines the number of businesses that operate in a certain locale, which influences the extent to which policy is propagated locally.

5.2 Testing the Transmission Hypothesis

To identify which channels are important for determining the local effects of monetary policy shocks, we assess how well certain city-level characteristics explain the variation in the impulse responses. We should note that at times, an exact identification between monetary policy channels and various propagation mechanisms is impossible since some of the covariates can be relevant under many different channels. Specifically, we consider a cross-sectional regression of the following form:

$$ir = \alpha + X\beta + v, \tag{8}$$

where ir is an $n \times 1$ vector that describes a certain property of the impulse response for the local variables. The $n \times k$ vector X represents k covariates for each city n; v is the residual and is assumed to be $N(0_n, h^{-1}I_n)$.

As the discussion of the asymmetric responses suggests, a large number of covariates can be correlated with the increased sensitivity of local employment to monetary policy innovations. In addition, it is difficult to assess a priori which of the covariates are more important. Therefore, we consider k (in our case $k = 24$) covariates and allow any subset of k covariates to constitute a model. By doing so we have 2^k ($2^{24} = 16,777,216$) alternative models to choose from. To evaluate which model (set of covariates) best explains the asymmetric monetary policy effects, we rely on the Bayesian Model Averaging technique. In particular, we implement the Bayesian Model Averaging via the Markov Chain Monte Carlo Model Composition (MC^3) algorithm initially developed in Madigan et al. (1995) and discussed in detail in Koop (2003).

We consider a sequence of models $M_r,\ r = 1, 2,\ \dots\ R$ ($R = 2^k$). To estimate a linear regression model r, we use a standard set of priors. The parameters common to all of the models take noninformative priors, i.e., $p(h) \propto \frac{1}{h}$ and $p(\alpha) \propto 1$.[11] We assume a standard, conjugate Normal-Gamma prior for the β's centered around zero, which emphasizes our prior hypothesis that the covariates are not related to monetary policy effects. More specifically,

$$\beta_r | h \propto N(0_r,\ h^{-1}[g_r X_r' X_r]^{-1}), \tag{9}$$

where g_r is a hyperparameter set to $1/max\{n, k^2\}$.[12]

The prior, together with the likelihood function, implies a multivariate-t distribution for the coefficient vector ($[\alpha \quad \beta_r]'$) and a Gamma distribution for h. The marginal likelihood for model r (M_r) is

$$p(ir|M_r) \propto \left(\frac{g_r}{g_r + 1}\right)^{\frac{k_r}{2}} \left[\frac{1}{g_r + 1} ir' P_{X_r} ir' + \frac{g_r}{g_r + 1}(ir - \bar{ir})'(ir - \bar{ir})\right]^{-\frac{n-1}{2}}, \tag{10}$$

where $\bar{ir} = \frac{\sum_{j=1}^{n} ir_j}{n}$ and $P_{X_r} = I_n - X_r(X_r' X_r)^{-1} X_r'$. Since ultimately we are interested in model choice/averaging, the quantity in concern is the probability of various models given the data, $p(M_r|ir) \propto p(ir|M_r)p(M_r)$, where $p(M_r)$ is the prior probability assigned to the model r.

The essence of the MC^3 algorithm is to simulate from the model space by taking more model draws from the regions where the model probabilities are high and fewer model draws from the

[11] Given the prior, to ensure that the intercept has identical interpretation for every model, we demean the regressors.

[12] The prior and its convenient properties are thoroughly discussed in Fernández et al. (2001). In essence, this prior allows for analytic marginal likelihood calculations while leading to satisfactory results from the predictive point of view.

regions where the model probabilities are low. In particular, starting from a model M^0, the MC^3 draws a sequence of models M^s, $s = 1, ..., S$, where M^s is a particular realization of M_r, $r = 1, ..., R$. More specifically, the MC^3 algorithm is implemented as follows:

1. Start with a model M^0 (to initialize we run an ordinary least squares regression of the dependent variable on the set of all covariates and include the covariates with t-statistics > 0.5).

2. Generate a candidate model draw (M^*) and choose with an equal probability from the current model M^{s-1}, all models that delete one covariate, and all models that add one explanatory variable (the constant is always included).

3. Accept the candidate with a probability

$$\alpha(M^{s-1}, M^*) = min\left[\frac{p(y|M^*)p(M^*)}{p(y|M^{s-1})p(M^{s-1})}, 1\right], \tag{11}$$

which simplifies when we assume equal prior probabilities for each model, $p(M^*) = p(M^{s-1})$.

Given the $S = S_0 + S_1$ draws, we truncate the first $S_0 = 10,000$ draws and calculate the posterior inclusion probabilities and coefficient estimates based on remaining $S_1 = 100,000$ accumulated draws. The coefficient estimates are conditional on covariates being included in the model specification; the marginal posterior distribution of slope parameters becomes a mixture of t-distributions implied by each model that includes the specific set of regressors. Hence, the mean and the variance of the slope coefficients are approximated by equations (12) and (13), respectively:

$$\overline{\beta} = \frac{1}{S_1} \sum_{s=S_0+1}^{S} E[\beta_r|ir, M^s] \tag{12}$$

$$\overline{var(\beta)} = \frac{1}{S_1} \sum_{s=S_0+1}^{S} var[\beta_r|ir, M^s]. \tag{13}$$

5.3 Covariate Data

The covariate set that we use to account for the variability in the employment response across the cities is broadly divided into six categories: demographic and general socio-economic, industry mix, housing, banking, industrial organization, and fiscal variables. The original series and their sources are provided in Table 5.

INSERT TABLE 5

The covariates in the demographic and socio-economic category capture the general city-size effects, human capital endowment, and various measures of income distribution across cities. We use the total number of people and households to get proportional measures for poverty, households with no wage or salary income, and households with no interest, dividend, or net rental income. Per capita crime numbers are calculated as a ratio of total crimes to the population.[13] Industry mix is calculated as a share of total employment in a specific industry and by construction sums to 1. For certain metropolitan areas, construction and mining indicators are constructed as the sum of construction and mining series available separately. In the estimation, we leave out the construction and mining to avoid singularity. The data in the housing category control for the overall level of housing prices, as well as the proportion of owner-occupied housing. Banking indicators include covariates to proxy for the number of small firms and large banks that, as discussed previously, are thought to be important under the credit channel of monetary policy. The covariates under the industrial organization category (i.e., average establishment size, industrial diversity index, and union membership) measure the overall flexibility of the economy. The fiscal variables measure the effect of local government activity on heterogeneity upon the monetary policy response. In order to get per capita measures for the fiscal variables, we adjust the nominal revenue and expenditure figures by the midpoint of recorded population in the respective metropolitan areas between 1980 and 1986 and between 1990 and 2000. The list of all of the covariates, their relevance under various channels of monetary policy, and their potential to create asymmetric propagation effects are provided in Table 6. Table 7 provides the descriptive statistics on the covariates.

INSERT TABLES 6 AND 7

It should be noted that although our choice of covariates is motivated by economic theory, it is constrained by availability of data. Since for most of the series comparable data coverage is not available, we target the year 1990 for our covariate series: It is about the middle of our sample period and the 1990 Census data make the covariate set richer. For series that do not have 1990 data readily available, we construct an approximation by taking averages for the years for which data are available (see Table 5).

[13]Given the availability of comparable data that came from the same source, we calculate the per capita crime measures using 1985 (1999) values of total serious crimes known to police and 1986 (2000) population figures.

5.4 Empirical Results for Modal Impulse Responses

Tables 8 and 9 present our second-stage regression results when we consider the modal impulse responses across the cities as a dependent variable. We test the transmission mechanisms of monetary policy using certain features of the modal impulse responses: the maximum (negative) response, the total cost of a recession expressed as the area under the impulse response, or the values of the impulse responses at select horizons. For each covariate we highlight its inclusion probability. The constant has an inclusion probability of 1 by construction. In addition, we present the posterior mean [see (12)] and the posterior standard deviation [calculated as the square root of (13)] of the slope coefficients. The latter can be used to approximate the 68 percent (or 95 percent) coverage areas of the posterior distributions and whether or not either area supports the hypothesis of the slope coefficient being statistically different from zero.

INSERT TABLES 8 AND 9

Table 8 presents the results using the maximum employment contraction and the total cost of monetary policy induced business cycles as left-hand-side variables. Two of the covariates considered perform particularly well in this exercise in that they are included in at least 90 percent of the models that attempt to explain the differences in monetary policy responses across cities. Under the specification with the maximum contraction, population density has almost 100 percent inclusion probability, while government employment is included in 90 percent of the models. Additionally, the posterior distribution of the slope coefficients indicates that the 95 percent coverage areas exclude zero in both cases. Similar results hold when we use the total cost of the business cycle as a regressand, except, in this case, the inclusion probability for government employment drops from 90 percent to 76 percent.

In Table 9, we present the results for values of the impulse responses at select horizons. We use the levels of output contraction at 4, 8, and 16 periods after the initial shock as left-hand-side variables for regression (8). Consistent with the previous results, population density is included in almost all of the models for each of the response periods. The results also indicate that the fraction of population with no wage/salary income and the fraction of owner-occupied housing are relatively important a year or so after the initial shock. Government sector employment is important in the short to medium run (at least up to 2 years after the shock). Establishment size and housing price index (HPI) are important in the long run (up to 4 years after the shock).

Manufacturing, an interest rate sensitive industry, is important in the short to medium run with inclusion probabilities of 29 and 25 percent, respectively. The standard errors of the covariates with high inclusion probabilities are relatively small, which implies concentrated posterior distributions with 95 percent coverage areas that exclude zero.

In general, all covariates that have high inclusion probabilities behave according to expectation. Manufacturing and home-ownership amplify the effects of the interest rate increase. The latter could be due to wealth effects. Housing prices, government employment, establishment size, and population density, on the other hand, mitigate the effects of the contractionary monetary policy.

5.5 Empirical Results for the Distribution of Impulse Responses

In order to account for the uncertainty around the impulse responses, we conduct our model selection exercise based on a distribution (as opposed to the mode) of our parameter estimates. More specifically, we take every 100th draw from the simulated posterior distribution of the VAR parameters, generate an impulse response corresponding to the selected draw, then conduct the model selection exercise for that particular response. The results are in Tables 10 and 11.

INSERT TABLES 10 AND 11

The inclusion probabilities for the covariates tend to decline. This is expected given that we now account for the uncertainties associated with the VAR coefficients and these uncertainties are not small. Overall, population density is still an important covariate. Interestingly, the role of government employment declines significantly when we consider the trough response, as well as the total cost of the business cycles. However, this covariate still appears to be relatively important for the short- to medium-term responses (periods 4 and 8). The roles of manufacturing and home-ownership are greater for the trough response and the total cost of the recession when compared to the results obtained based on modal impulse responses. In addition, the relative importance of the unionization rate for the overall recession costs also increases.

In summary, when we look at the inclusion probabilities of the covariates when explaining the cross-sectional variability of a distribution of impulse responses, we find that population density still continues to be the relatively more important covariate. We find that manufacturing and home-ownership rates are also as important in this case as they were when explaining the cross-sectional variation in the modal impulse response. Furthermore, their role has become increasingly important, which is reflected in the increased inclusion probabilities, most notably for period 16. Towards the end of the monetary policy induced recession, the inclusion probabilities for manufacturing increases from 0.05 to 0.15; for home-ownership rates it increases from 0.05 to 0.17.

5.6 Relation to the Existing Literature

Carlino and DeFina (1998), Owyang and Wall (2009), and Fratantoni and Schuh (2003) found significant roles for the interest rate, credit, and equity channels. In our case, the inclusion probabilities for the variables proxying the interest rate and equity channels (namely, share of manufacturing, home-ownership rates, house prices) are smaller compared to the inclusion probabilities of variables that proxy the overall propagation effects (such as population density and share of government employment). Population density appears to be the most important covariate in explaining the cross-sectional variation. However, the results about the importance of manufacturing and home-ownership rates appear to be the most robust: They hold for both the modal responses, as well as for a distribution of impulse responses.

The framework we chose to analyze monetary policy channels with the city-level data is more general than that considered in the literature and comes with certain intricacies. First, accounting for model uncertainty using Bayesian Model Averaging may make the importance of the major channels responsible for the variations in the local effects of monetary policy diminish compared to results obtained with only a subset of potentially important covariates. Second, the regional covariation modeled in studies that examine larger geographic regions than cities may be too coarse. Third, the employment across the metropolitan area sample examined here does not sum to the national employment. Because we included only the larger cities, any propagation that occurs in smaller cities or rural areas is essentially excluded. If, for example, factories are located away from more densely populated areas, some standard monetary channels (e.g., the interest rate channel) may be de-emphasized in this analysis. Finally, it may be that no single channel is effective for all of the cities within the sample.

6 Conclusion

The previous literature testing variations in the regional responses to monetary policy shocks has revealed that industry share, among other factors, plays an important role. To avoid parameter proliferation in the VAR, these studies have considered the differences between the effects in large regions (e.g., BEA regions) or have placed substantial restrictions on cross-regional (especially cross-state) comovements. The economic growth and urban literature, on the other hand, has long recognized that cities may be a better unit of analysis than BEA regions or even states. Cross-city variation in industrial mix exists, even within states, potentially confounding the researcher's ability to truly identify regional variation. Moreover, agglomeration and other effects (e.g., local housing markets) can be observed only at the city level.

Using a large Bayesian VAR with city-level data, we find significant and important cross-metro-area variation in the response of employment to a monetary policy shock. This variation extends to cities even in close geographic proximity or even within the same state. In testing the channels through which monetary policy affects employment, we find – at the city level – propagation effects to be more important in explaining the cross-sectional variation of the "most common" recessions across the cities. The more traditional channels of monetary policy, such as the interest rate channel (measured with the manufacturing share) or the equity channel (measured with the house prices and home-ownership rates), appear to be less important in explaining the business cycle variations across the cities. However, the results in regard to these covariates appear to be robust to the uncertainty around the impulse responses.

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Appendix: The Reference Prior

The standard deviation for all elements in the jth row of $\bar{S}_i$ is defined by $\frac{\lambda_0}{\sigma_j}$. In each equation i, the standard deviation of a coefficient on lag p for variable j is determined by $\bar{H}_i = \frac{\lambda_0 \lambda_1}{\sigma_j p^{\lambda_3}}$. The prior standard deviation for the constant is $\lambda_0 \lambda_4$. For example, let's consider the case of $p = 1$ as it is in our empirical specification. For simplicity, suppose $m = 2$. It follows from the discussion above that for $i = 1, 2$,

$$\bar{S}_i = diag\left(\begin{bmatrix} \lambda_0/\sigma_1 & \lambda_0/\sigma_2 \end{bmatrix}\right),$$

$$\bar{P}_i = \begin{bmatrix} I_2 & 0_{2,1} \end{bmatrix}',$$

and

$$\bar{H}_i = diag\left(\begin{bmatrix} \frac{\lambda_0 \lambda_1}{\sigma_1} & \frac{\lambda_0 \lambda_1}{\sigma_2} & \lambda_0 \lambda_4 \end{bmatrix}\right),$$

where $diag(v)$ represents a matrix with elements of v on the main diagonal and zeros everywhere else. The role of the hyperparameters is presented in Table 2. A scaling factor, σ_j, is included to mitigate the unit of measure effect across the variables. In practice, σ_j is approximated by the sample standard deviation of the residuals that result from a univariate autoregression of order p for each series j.

The initial observations are added as follows. In order to impose beliefs on the order of integration, we add m observations to the dataset indexed by $t = 1, ..., m$, such that for $j = 1, ..., m,\ s = 1, ..., k,$

$$z_{tj} = \begin{cases} \mu_5 \bar{z}_{0j} & j = t \\ 0 & \text{otherwise} \end{cases}, \quad x_{st} = \begin{cases} \mu_5 \bar{z}_{0j} & j = t, s \leq k-1 \\ 0 & \text{otherwise} \end{cases},$$

where $\bar{z}_{0j}$ is the average of the first p observations for each series j.

In order to adjust the prior to allow for cointegration, the data matrix is augmented with a single new observation. This initial observation is constructed such that for $j = 1, ..., m$ and $s = 1, ..., k$, $z_j = \mu_6 \bar{z}_{0j}$ and

$$x_s = \begin{cases} \mu_6 \bar{z}_{0j} & s \leq k-1 \\ \mu_6 & s = k \end{cases}.$$

Table 1: **Description of Metropolitan Areas (MAs)**

Label	Metropolitan Area	Label	Metropolitan Area
ABQ	Albuquerque, NM	LEX	Lexington, KY
AKR	Akron, OH	LOI	Louisville, KY-IN
ALB	Albany-Schenectady-Troy, NY	LRS	Little Rock-North Little Rock, AR
ALL	Allentown-Bethlehem-Easton, PA	LSV	Las Vegas, NV-AZ
ANA	Ann Arbor, MI	MDS	Madison, WI
ANH	Orange County, CA	MIA	Miami, FL
APP	Appleton-Oshkosh-Neenah, WI	MOB	Mobile, AL
ATL	Atlanta, GA	MPH	Memphis, TN-AR-MS
AUG	Augusta-Aiken, GA-SC	MSP	Minneapolis-St. Paul, MN-WI
AUS	Austin-San Marcos, TX	MWK	Milwaukee-Waukesha, WI
BAK	Bakersfield, CA	NFK	Norfolk-Virginia Beach-Newport News, VA-NC
BIR	Birmingham, AL	NHV	New Haven-Meriden, CT
BOI	Boise City, ID	NOR	New Orleans, LA
BOS	Boston, MA-NH	NSS	Nassau-Suffolk, NY
BTM	Baltimore, MD	NVL	Nashville, TN
BTR	Baton Rouge, LA	NWK	Newark, NJ
BUF	Buffalo-Niagara Falls, NY	NYP	New York, NY
CBA	Columbia, SC	OAK	Oakland, CA
CGR	Charlotte-Gastonia-Rock Hill, NC-SC	OKC	Oklahoma City, OK
CHI	Chicago, IL	OMA	Omaha, NE-IA
CHT	Chattanooga, TN-GA	ORL	Orlando, FL
COL	Columbus, OH	PHP	Philadelphia, PA-NJ
CRL	Charleston-North Charleston, SC	PHX	Phoenix-Mesa, AZ
CTI	Cincinnati, OH-KY-IN	PIT	Pittsburgh, PA
CVL	Cleveland-Lorain-Elyria, OH	POR	Portland-Vancouver, OR-WA
DAL	Dallas, TX	PRI	Providence-Fall River-Warwick, RI-MA
DEM	Des Moines, IA	RAD	Raleigh-Durham-Chapel Hill, NC
DEN	Denver, CO	RCP	Richmond-Petersburg, VA
DET	Detroit, MI	REN	Reno, NV
DYS	Dayton-Springfield, OH	ROH	Rochester, NY
ELP	El Paso, TX	RSB	Riverside-San Bernardino, CA
FRE	Fresno, CA	SAC	Sacramento, CA
FTL	Ft. Lauderdale, FL	SAT	San Antonio, TX
FWA	Fort Wayne, IN	SDI	San Diego, CA
GNS	Greensboro-Winston-Salem-High Point, NC	SFR	San Francisco, CA
GNV	Greenville-Spartanburg-Anderson, SC	SJO	San Jose, CA
GRR	Grand Rapids-Muskegon-Holland, MI	SLC	Salt Lake City-Ogden, UT
GRY	Gary, IN	SPD	Springfield, MA
HAR	Harrisburg-Lebanon-Carlisle, PA	STL	St Louis, MO-IL
HON	Honolulu, HI	STO	Stockton-Lodi, CA
HST	Houston, TX	SYR	Syracuse, NY
HTF	Hartford, CT	TMA	Tampa-St. Petersburg-Clearwater, FL
IND	Indianapolis, IN	TOL	Toledo, OH
JAS	Jackson, MS	TRT	Trenton, NJ
JAX	Jacksonville, FL	TUC	Tucson, AZ
JYC	Jersey City, NJ	TUL	Tulsa, OK
KAL	Kalamazoo-Battle Creek, MI	VEN	Ventura, CA
KNC	Kansas City, MO-KS	WIC	Wichita, KS
KNX	Knoxville, TN	WIL	Wilmington-Newark, DE-MD
LAC	Lancaster, PA	WOR	Worcester, MA-CT
LAN	Lansing-East Lansing, MI	WPB	West Palm Beach-Boca Raton, FL
LAX	LA-Long Beach, CA	WSH	Washington, DC-MD-VA-WV
		YNG	Youngstown-Warren, OH

Table 2: **Sims-Zha Reference Prior**

Hyperparameter	Value	Interpretation
λ_0	1	Controls the overall tightness of the beliefs
λ_1	0.2	Tightens the prior around a random walk
λ_3	1	Directs the rate at which the prior contracts with an increase in lag length
λ_4	1	Controls the tightness of the constant
μ_5	1	Governs the prior on the order of integration
μ_6	1	Sets the prior belief on the presence of cointegration

Table 3: **Clustering the Metropolitan Areas**

MA	**BEA Region**	**MA**	**BEA Region**	**MA**	**BEA region**
Cluster 1		*Cluster 3*		*Cluster 4*	
BTR	SE	ALB	ME	ABQ	SW
DAL	SW	ALL	ME	AKR	GL
HST	SW	AUS	SW	ANA	GL
LAN	GL	BAK	FW	ANH	FW
NFK	SE	BOS	NE	APP	GL
NYP	ME	BTM	ME	ATL	SE
OKC	SW	BUF	ME	AUG	SE
RCP	SE	CBA	SE	BIR	SE
SFR	FW	CHI	GL	CGR	SE
TUL	SW	CRL	SE	CHT	SE
		DEM	PL	COL	GL
		DET	GL	CTI	GL
Cluster 2		DYS	GL	CVL	GL
BOI	RM	ELP	SW	DEN	RM
FTL	SE	HON	FW	FRE	FW
GRR	GL	JAX	SE	FWA	GL
KAL	GL	JYC	ME	GNS	SE
LSV	SW	KNC	PL	GNV	SE
POR	FW	LAC	ME	GRY	GL
PRI	NE	LAX	FW	HAR	ME
TUC	SW	LEX	SE	HTF	NE
		LRS	SE	IND	GL
		MDS	GL	JAS	PL
		MIA	SE	KNX	SE
		MPH	SE	LOI	SE
		NHV	NE	MOB	SE
		NSS	ME	MSP	PL
		NVL	SE	MWK	GL
		NWK	ME	NOR	SE
		OAK	FW	ORL	SE
		OMA	PL	PHX	SW
		PHP	ME	PIT	ME
		ROH	ME	RAD	SE
		SAC	FW	REN	FW
		SAT	SW	RSB	FW
		SLC	RK	SDI	FW
		SPD	NE	SJO	FW
		STL	PL	TMA	SE
		STO	FW	TOL	GL
		SYR	ME	VEN	FW
		TRT	ME	YNG	GL
		WIC	PL		
		WIL	ME		
		WOR	NE		
		WPB	SE		
		WSH	ME		

Notes: NE, ME, GL, PL, SE, SW, RM, and FW stand for New England, Mideast, Great Lakes, Plains, Southeast, Southwest, Rocky Mountain, and Far West regions, respectively. Details are at www.bea.gov/regional/docs/regions.cfm. Metropolitan areas are abbreviated as in Table 1.

Table 4: **Properties of the Metropolitan Area Clusters**

	Depth		Employment Response			
	Max	Period	Total	Period 4	Period 8	Period 16
Cluster 1	-0.03	11.60	0.41	0.03	-0.01	-0.02
Cluster 2	-0.16	9.13	1.79	-0.09	-0.16	-0.09
Cluster 3	-0.04	8.26	0.37	-0.02	-0.04	0.00
Cluster 4	-0.08	8.12	0.83	-0.05	-0.08	-0.02

Notes: The values in the table are averages across the cities in a respective cluster. "Max" refers to the depth of the recession measured by the maximum employment contraction attained during the recession. "Period" documents the period when the maximum contraction is attained. "Total" refers to the total cost of the recession measured as a total absolute deviation of employment from the steady-state equilibrium. "Period 4," "Period 8," and "Period 16" measure the employment response at the specified horizon.

Table 5: **Metropolitan Area Covariate Data Sources**

Description	**Freq**	**Period**	**S**
Demographic & General Socio-Economic			
Total Resident Population (Thous.)	A	1990	H2
Persons Per Square Mile	A	1990	O
Persons 18 years and over: with at least an Associate degree	A	1990	S
Households: Median household income	A	1989	S
Persons for whom poverty status is determined	A	1989	S
Households: No wage or salary income	A	1989	S
Households: No interest, dividend, or net rental income	A	1989	S
Serious Crimes Known To Police, Total	A	1985, 1999	D
Industry Mix - Total Employment by Industry Sector (Thous.)			
Construction	M	1990	H1
Mining	M	1990	H1
Construction and Mining	M	1990	H1
Trade	M	1990	H1
Finance, Insurance, and Real Estate	M	1990	H1
Government	M	1990	H1
Manufacturing	M	1990	H1
Services	M	1990	H1
Transportation, Communications, Electric, Gas, & Sanitary Services	M	1990	H1
Housing			
Housing Price Index (HPI)	Q	1990	F
Housing: Percent Owner-Occupied	A	1980, 2000	D
Banking			
Herfindahl-Hirschman Index (HHI)	A	1990	B
Banking Market Deposits	A	1990	B
Loans to Businesses with Gross Annual Revenues $\leq$1 Million (Thous.)	A	1996	C
Industrial Organization			
Average Establishment Size	A	1990	O
"Dixit-Stiglitz" Index of Industrial Diversity	A	1990	O
Total Labor Union Membership (%)	A	1990	U
Fiscal Variables			
City Government General Revenue: Total	A	1984-85,1996-97	D
City Government General Expenditures: Total	A	1984-85,1996-97	D

Notes: Sources are abbreviated as follows: B - Federal Reserve Board of Governors; C - CRA (Community Reinvestment Act) MSA Aggregate Report; D - County and City Data Book, 1988 Edition and 2000 Edition; F - Federal Housing Finance Agency; H1 - Haver's LABORR database (vintage 02/21/2003; the Bureau of Labor Statistics was the original source); H2 - Haver's USPOP database (vintage 2/18/2005; the Census Bureau was the original source); O - Owyang et al. (2008); S - Census 1990 Summary File 3; U - Union Membership and Coverage Database (www.unionstats.com). "A", "M", and "Q" indicate annual, monthly, and quarterly frequencies, respectively.

Table 6: **Covariates and Channels of Monetary Policy**

Covariate	Interest Rate	Equity	Exchange Rate	Narrow Credit	Broad Credit	Propagation
Demographic & General Socio-Economic						
Population						√
Population Density						√
Fract. of Pop. with College Degree						√
Median Household Income		√				√
Fract. of Pop. Below Poverty		√				√
Fract. of HH: No Wage/Salary		√				√
Fract. of HH: No Interest/Dividend		√				√
Serious Crimes Known to Police						√
Industry Mix						
Finance, Insurance, & Real Estate					√	
Government						√
Manufacturing	√		√			
Services	√					√
Transport, Communications, etc.	√					√
Trade			√			
Housing						
HPI		√				
Fract. of Owner-Occupied Housing		√				
Banking						
HHI				√	√	
Banking Market Deposits				√	√	
Small Business Loans				√		
Industrial Organization						
Establishment Size				√	√	
Industrial Diversity Index						√
Union Membership						√
Fiscal Variables						
Government Revenue						√
Government Expenditures	√					

Notes: The table lists the covariates, their relevance under various channels of monetary policy, and their potential to create asymmetric propagation effects. HH, HHI, and HPI stand for Households, Herfindahl-Hirschman Index, and Housing Price Index, respectively.

Table 7: **Descriptive Statistics for the Covariates**

Covariate	Average	Standard Deviation	Minimum	Maximum
Demographic & General Socio-Economic				
Population	6.92	0.76	5.55	9.09
Population Density	6.61	1.04	3.69	10.19
Fract. of Pop. with College Degree	0.27	0.06	0.11	0.47
Median Household Income	10.33	0.17	9.87	10.85
Fract. of Pop. Below Poverty	0.13	0.05	0.04	0.29
Fract. of HH: No Wage/Salary	0.21	0.04	0.13	0.34
Fract. of HH: No Interest/Dividend	0.59	0.08	0.36	0.83
Serious Crimes Known to Police	0.08	0.02	0.02	0.14
Industry Mix				
Finance, Insurance, & Real Estate	0.06	0.02	0.03	0.14
Government	0.17	0.05	0.09	0.32
Manufacturing	0.16	0.07	0.03	0.33
Services	0.26	0.04	0.18	0.46
Transport, Communications, etc.	0.05	0.02	0.03	0.13
Trade	0.24	0.02	0.16	0.29
Housing				
HPI	0.92	0.12	0.66	1.25
Fract. of Owner-Occupied Housing	0.54	0.12	0.22	1.13
Banking				
HHI	7.26	0.46	6.05	8.06
Banking Market Deposits	14.90	1.36	12.84	19.22
Small Business Loans	12.43	0.71	10.24	14.23
Industrial Organization				
Establishment Size	1.35	0.12	1.03	1.57
Industrial Diversity Index	5.52	0.19	5.06	5.92
Union Membership	0.16	0.08	0.01	0.39
Fiscal Variables				
Government Revenue	6.97	0.54	5.29	8.78
Government Expenditures	6.97	0.50	6.03	8.71

Notes: The table lists the descriptive statistics for the covariates after the respective transformations. HH, HHI, and HPI stand for Households, Herfindahl-Hirschman Index, and Housing Price Index, respectively.

Table 8: **Testing the Transmission Hypothesis Based on Modal Response**

Covariate	Maximum Response			Total Cost of Business Cycle		
	$P(\beta \neq 0 \| y)$	$\hat{\beta}$	$std(\beta)$	$P(\beta \neq 0 \| y)$	$\bar{\beta}$	$\hat{std}(\beta)$
Constant	1.0000	-0.0648	0.0033	1.0000	0.6607	0.0365
Population	0.0546	0.0000	0.0003	0.0491	0.0017	0.0034
Population Density	0.9964	0.0169	0.0035	0.9936	-0.1782	0.0382
Fract. of Pop. with College Degree	0.0420	-0.0008	0.0026	0.0447	-0.0093	0.0303
Median Household Income	0.0566	0.0010	0.0013	0.0606	-0.0143	0.0154
Fract. of Pop. Below Poverty	0.0388	-0.0009	0.0032	0.0549	0.0176	0.0492
Fract. of HH: No Wage/Salary	0.0635	-0.0042	0.0052	0.0666	0.0680	0.0599
Fract. of HH: No Interest/Dividend	0.0370	-0.0004	0.0017	0.0409	0.0071	0.0207
Serious Crimes Known to Police	0.0661	-0.0101	0.0095	0.0468	0.0379	0.0743
Finance, Insurance, & Real Estate	0.1478	0.0441	0.0271	0.1014	-0.3266	0.2059
Government	0.8961	0.2476	0.0614	0.7557	-1.7863	0.5679
Manufacturing	0.2097	-0.0330	0.0125	0.1655	0.2453	0.1074
Services	0.0992	-0.0134	0.0091	0.0890	0.1521	0.0887
Transport, Communications, etc.	0.0913	0.0232	0.0189	0.0849	-0.2495	0.1944
Trade	0.0628	0.0017	0.0107	0.0484	0.0177	0.0908
HPI	0.1330	0.0064	0.0038	0.1775	-0.1080	0.0569
Fract. of Owner-Occupied Housing	0.0821	-0.0029	0.0024	0.0579	0.0183	0.0187
HHI	0.0630	-0.0005	0.0005	0.0628	0.0044	0.0052
Banking Market Deposits	0.0546	0.0001	0.0001	0.0413	-0.0003	0.0012
Small Business Loans	0.1617	-0.0016	0.0009	0.1300	0.0134	0.0080
Establishment Size	0.0764	0.0028	0.0024	0.0829	-0.0393	0.0281
Industrial Diversity Index	0.0447	-0.0004	0.0010	0.0483	0.0013	0.0120
Union Membership	0.0503	0.0010	0.0022	0.0476	-0.0122	0.0231
Government Revenue	0.0424	-0.0001	0.0003	0.0428	-0.0010	0.0034
Government Expenditures	0.0509	-0.0003	0.0004	0.0414	0.0019	0.0037

Notes: The table represents the Bayesian Model Averaging results for the regression in (8). The first column represents the covariate set considered, i.e., the set of potential x variables. The columns under "Maximum Response" and "Total Cost of Business Cycle" depict the inclusion probabilities [$P(\beta \neq 0|ir)$], the posterior means [calculated by (12)], and the posterior standard deviation [calculated as a square root of (13)] when the regressand is the respectively titled property of the modal impulse response. HH, HHI, and HPI stand for Households, Herfindahl-Hirschman Index, and Housing Price Index, respectively.

Table 9: **Testing the Transmission Hypothesis Over Different Periods Based on Modal Response**

Covariate	Period 4			Period 8			Period 16		
	$P(\beta \neq 0\|y)$	$\bar{\beta}$	$\hat{std}(\beta)$	$P(\beta \neq 0\|y)$	$\hat{\beta}$	$std(\beta)$	$P(\beta \neq 0\|y)$	$\hat{\beta}$	$std(\beta)$
Constant	1.0000	-0.0334	0.0030	1.0000	-0.0596	0.0034	1.0000	-0.0164	0.0029
Population	0.0543	0.0003	0.0003	0.0559	-0.0001	0.0004	0.1199	-0.0009	0.0006
Population Density	0.9818	0.0137	0.0032	0.9994	0.0184	0.0036	0.8600	0.0092	0.0026
Fract. of Pop. with College Degree	0.0584	-0.0008	0.0035	0.0609	-0.0021	0.0039	0.0400	0.0000	0.0021
Median Household Income	0.0540	0.0001	0.0012	0.0556	0.0009	0.0013	0.0487	0.0007	0.0010
Fract. of Pop. Below Poverty	0.0418	-0.0002	0.0031	0.0438	-0.0021	0.0037	0.0483	-0.0018	0.0033
Fract. of HH: No Wage/Salary	0.3457	-0.0628	0.0258	0.1126	-0.0153	0.0094	0.0485	-0.0020	0.0035
Fract. of HH: No Interest/Dividend	0.0386	0.0003	0.0017	0.0444	0.0004	0.0021	0.0425	0.0002	0.0017
Serious Crimes Known to Police	0.0577	-0.0046	0.0077	0.0651	-0.0109	0.0096	0.0419	0.0011	0.0053
Finance, Insurance, & Real Estate	0.0484	0.0012	0.0084	0.0617	0.0098	0.0118	0.0956	0.0216	0.0152
Government	0.5041	0.0906	0.0319	0.8538	0.2416	0.0606	0.1051	0.0099	0.0066
Manufacturing	0.2848	-0.0352	0.0143	0.2521	-0.0472	0.0155	0.0537	0.0011	0.0027
Services	0.0702	-0.0043	0.0058	0.1388	-0.0301	0.0133	0.1530	-0.0202	0.0110
Transport, Communications, etc.	0.0483	-0.0011	0.0093	0.1297	0.0457	0.0276	0.0478	0.0027	0.0087
Trade	0.0732	-0.0133	0.0113	0.0650	-0.0071	0.0113	0.0556	0.0068	0.0084
HPI	0.0636	0.0019	0.0017	0.1233	0.0060	0.0037	0.3024	0.0179	0.0078
Fract. of Owner-Occupied Housing	0.2529	-0.0145	0.0067	0.0438	-0.0006	0.0013	0.0458	0.0002	0.0012
HHI	0.0996	-0.0010	0.0007	0.0655	-0.0005	0.0005	0.0505	0.0000	0.0003
Banking Market Deposits	0.0544	0.0001	0.0001	0.0480	0.0001	0.0001	0.0624	-0.0001	0.0001
Small Business Loans	0.1794	-0.0018	0.0010	0.1427	-0.0014	0.0008	0.0630	-0.0003	0.0003
Establishment Size	0.0873	-0.0036	0.0024	0.0532	0.0015	0.0017	0.3448	0.0213	0.0087
Industrial Diversity Index	0.0871	-0.0020	0.0017	0.0489	-0.0005	0.0011	0.0561	0.0008	0.0010
Union Membership	0.0741	-0.0032	0.0030	0.0440	-0.0009	0.0020	0.1347	0.0087	0.0052
Government Revenue	0.0488	0.0002	0.0004	0.0478	0.0001	0.0004	0.0504	0.0002	0.0003
Government Expenditures	0.0539	-0.0003	0.0004	0.0499	-0.0002	0.0004	0.0409	0.0000	0.0003

Notes: The table represents the Bayesian Model Averaging results for the regression in (8). The first column represents the covariate set considered, i.e., the set of potential x variables. The columns under "Period 4," "Period 8," and "Period 16" depict the inclusion probabilities [$P(\beta \neq 0|ir)$], the posterior means [calculated by (12)], and the posterior standard deviation [calculated as a square root of (13)] when the regressand is the respectively titled property of the modal impulse response. HH, HHI, and HPI stand for Households, Herfindahl-Hirschman Index, and Housing Price Index, respectively.

Table 10: **Testing the Transmission Hypothesis Based on a Distribution of Responses**

Covariate	Maximum Response			Total Cost of Business Cycle		
	$P(\beta \neq 0\|y)$	$\hat{\beta}$	$std(\beta)$	$P(\beta \neq 0\|y)$	$\bar{\beta}$	$\hat{std}(\beta)$
Constant	1.0000	-0.1553	0.0154	1.0000	1.4090	0.1076
Population	0.0719	0.0012	0.0016	0.0845	-0.0192	0.0143
Population Density	0.2142	0.0071	0.0030	0.2297	-0.0544	0.0232
Fract. of Pop. with College Degree	0.0607	-0.0034	0.0168	0.0583	0.0277	0.1142
Median Household Income	0.0678	0.0029	0.0069	0.0588	-0.0225	0.0456
Fract. of Pop. Below Poverty	0.0673	0.0102	0.0240	0.0718	-0.1709	0.1807
Fract. of HH: No Wage/Salary	0.0646	0.0063	0.0250	0.0665	-0.0799	0.1728
Fract. of HH: No Interest/Dividend	0.0542	-0.0028	0.0114	0.0579	0.0442	0.0868
Serious Crimes Known to Police	0.1185	-0.1508	0.0813	0.1441	1.5127	0.7229
Finance, Insurance, & Real Estate	0.1020	0.0384	0.0752	0.0825	-0.1305	0.4410
Government	0.1021	0.0513	0.0340	0.1119	-0.4007	0.2570
Manufacturing	0.2261	-0.1363	0.0556	0.3489	1.6315	0.5936
Services	0.0759	0.0069	0.0298	0.0899	-0.2308	0.2333
Transport, Communications, etc.	0.0921	0.1380	0.0912	0.1156	-1.4323	0.8077
Trade	0.0636	0.0064	0.0485	0.0645	-0.1655	0.3429
HPI	0.0996	-0.0002	0.0142	0.0736	-0.0168	0.0736
Fract. of Owner-Occupied Housing	0.1953	-0.0518	0.0220	0.1850	0.3681	0.1566
HHI	0.0626	-0.0010	0.0021	0.0603	0.0095	0.0145
Banking Market Deposits	0.1268	0.0034	0.0019	0.1188	-0.0173	0.0101
Small Business Loans	0.0686	-0.0007	0.0016	0.0709	0.0066	0.0125
Establishment Size	0.0693	0.0030	0.0092	0.0915	-0.0728	0.0832
Industrial Diversity Index	0.0709	0.0026	0.0060	0.0713	-0.0349	0.0449
Union Membership	0.1297	0.0460	0.0258	0.1939	-0.5635	0.2526
Government Revenue	0.0711	-0.0016	0.0024	0.0738	0.0117	0.0170
Government Expenditures	0.0819	-0.0019	0.0029	0.0875	0.0207	0.0210

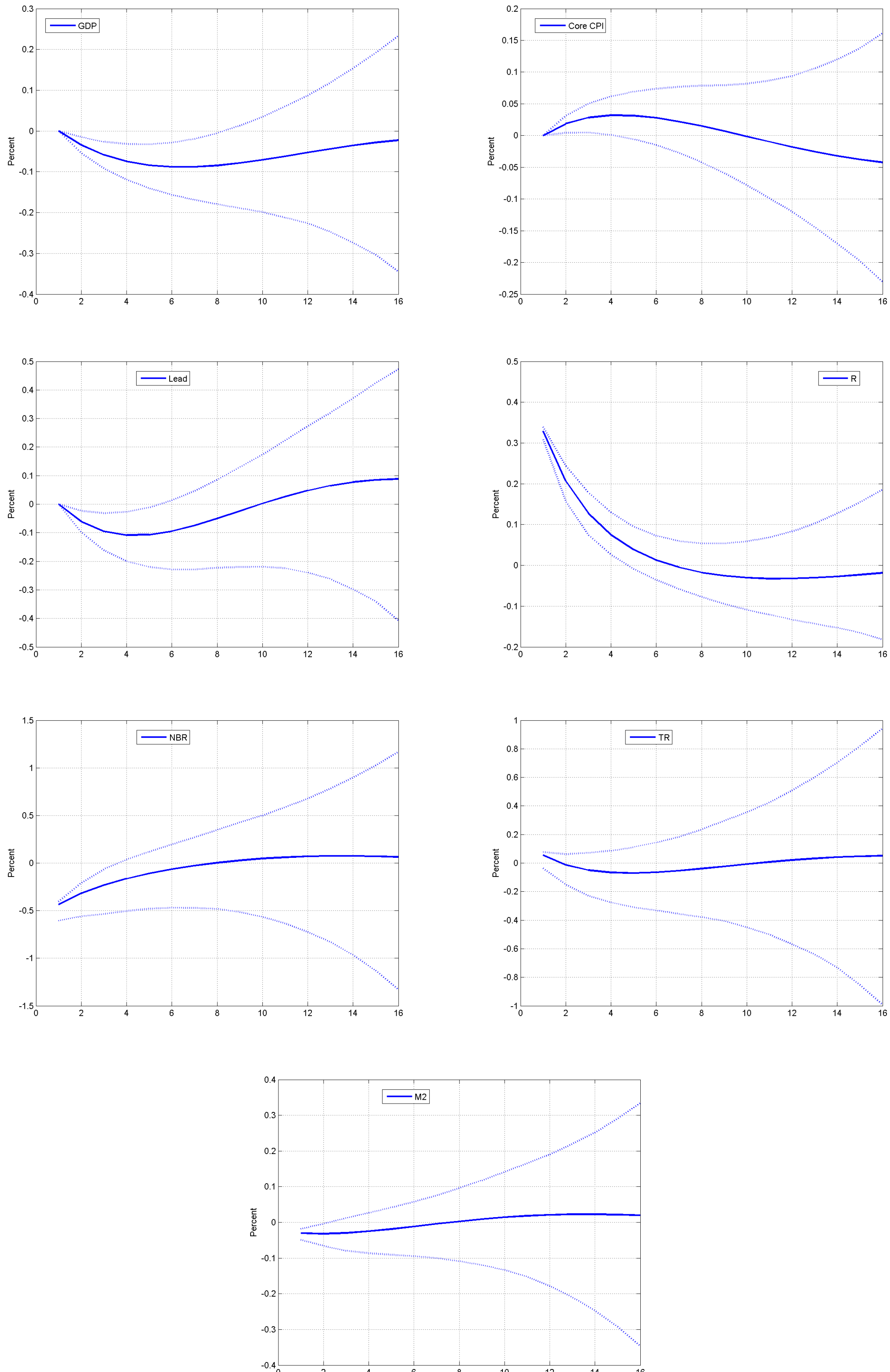
Notes: The table represents the Bayesian Model Averaging results for the regression in (8). The first column represents the covariate set considered, i.e., the set of potential x variables. The columns under "Maximum Response" and "Total Cost of Business Cycle" depict the inclusion probabilities [$P(\beta \neq 0|ir)$], the posterior means [calculated by (12)], and the posterior standard deviation [calculated as a square root of (13)] when the regressand is a particular property of the impulse response based on every 100th draw of parameter distribution. The presented results are the averages over these draws. HH, HHI, and HPI stand for Households, Herfindahl-Hirschman Index, and Housing Price Index, respectively.

Table 11: **Testing the Transmission Hypothesis Based on a Distribution of Responses**

Covariate	Period 4			Period 8			Period 16		
	$P(\beta \neq 0\|y)$	$\bar{\beta}$	$\hat{std}(\beta)$	$P(\beta \neq 0\|y)$	$\hat{\beta}$	$std(\beta)$	$P(\beta \neq 0\|y)$	$\hat{\beta}$	$std(\beta)$
Constant	1.0000	-0.0350	0.0046	1.0000	-0.0647	0.0075	1.0000	-0.0515	0.0236
Population	0.0865	0.0009	0.0007	0.0690	0.0004	0.0008	0.0675	-0.0006	0.0024
Population Density	0.4939	0.0068	0.0023	0.3426	0.0074	0.0026	0.1098	0.0024	0.0027
Fract. of Pop. with College Degree	0.0551	0.0001	0.0046	0.0712	-0.0035	0.0094	0.0705	0.0068	0.0292
Median Household Income	0.0672	0.0024	0.0022	0.0660	0.0024	0.0033	0.0681	0.0035	0.0108
Fract. of Pop. Below Poverty	0.0614	0.0042	0.0070	0.0580	0.0014	0.0104	0.0630	-0.0073	0.0356
Fract. of HH: No Wage/Salary	0.1430	-0.0299	0.0155	0.0842	-0.0188	0.0151	0.0635	-0.0058	0.0377
Fract. of HH: No Interest/Dividend	0.0491	0.0000	0.0031	0.0515	0.0006	0.0053	0.0574	-0.0008	0.0185
Serious Crimes Known to Police	0.0872	-0.0218	0.0177	0.1228	-0.0752	0.0418	0.1144	-0.1119	0.1105
Finance, Insurance, & Real Estate	0.0774	0.0149	0.0188	0.1041	0.0424	0.0378	0.1028	0.0059	0.1194
Government	0.2056	0.0428	0.0187	0.2253	0.0864	0.0349	0.1025	0.0143	0.0500
Manufacturing	0.2304	-0.0401	0.0171	0.2148	-0.0642	0.0268	0.1478	-0.0330	0.0550
Services	0.0628	-0.0031	0.0074	0.0836	-0.0206	0.0161	0.0871	-0.0340	0.0549
Transport, Communications, etc.	0.0619	0.0109	0.0177	0.1112	0.0787	0.0504	0.0818	0.0599	0.1139
Trade	0.0837	-0.0243	0.0186	0.0820	-0.0275	0.0280	0.0843	-0.0137	0.0864
HPI	0.0790	0.0037	0.0033	0.1181	0.0107	0.0075	0.1157	0.0032	0.0248
Fract. of Owner-Occupied Housing	0.2799	-0.0283	0.0104	0.1467	-0.0138	0.0090	0.1671	-0.0303	0.0317
HHI	0.0921	-0.0013	0.0009	0.0713	-0.0007	0.0012	0.0642	-0.0005	0.0034
Banking Market Deposits	0.1405	0.0011	0.0005	0.1488	0.0021	0.0010	0.1401	0.0040	0.0031
Small Business Loans	0.0872	-0.0009	0.0007	0.0977	-0.0015	0.0011	0.0825	-0.0006	0.0028
Establishment Size	0.0773	-0.0031	0.0031	0.0759	0.0008	0.0048	0.0814	0.0103	0.0157
Industrial Diversity Index	0.0667	-0.0010	0.0019	0.0685	-0.0003	0.0030	0.0771	0.0034	0.0095
Union Membership	0.0562	-0.0010	0.0034	0.0600	0.0027	0.0058	0.0738	0.0165	0.0225
Government Revenue	0.0555	0.0002	0.0006	0.0631	0.0005	0.0010	0.0741	-0.0002	0.0037
Government Expenditures	0.0589	-0.0004	0.0007	0.0652	-0.0002	0.0011	0.0792	0.0006	0.0044

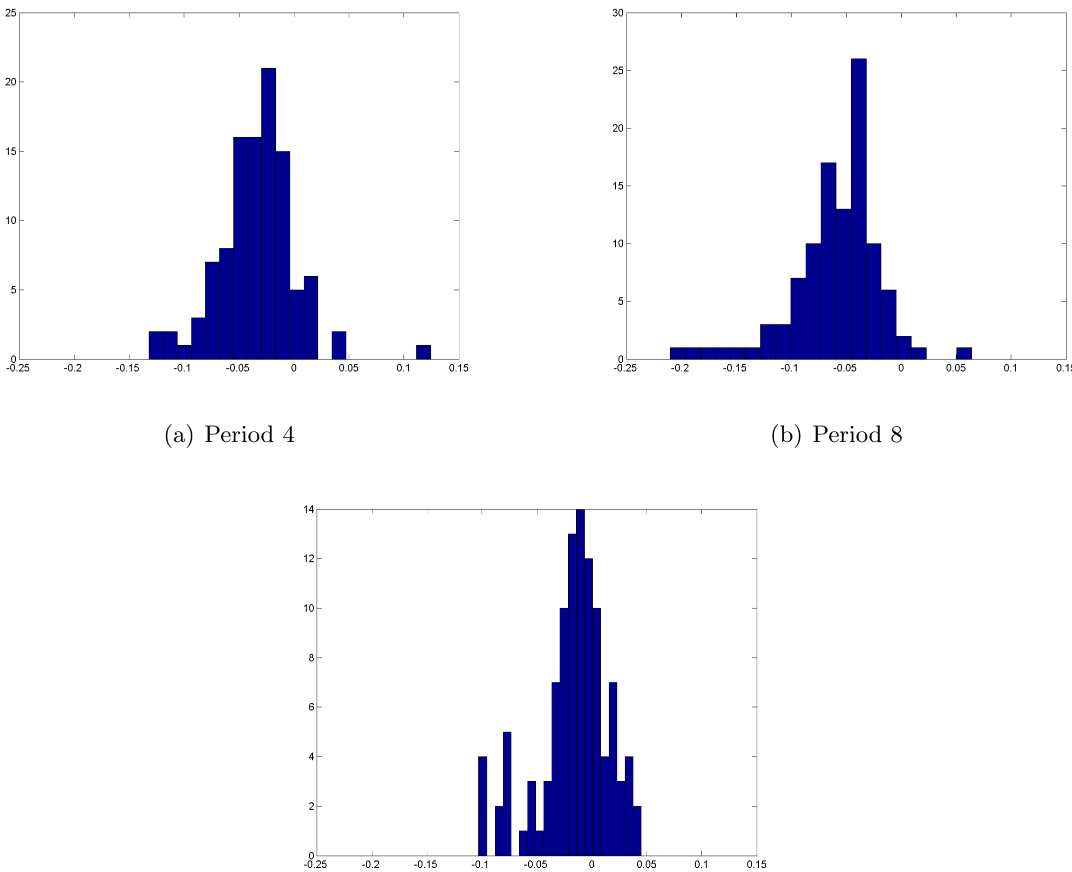
Notes: The table represents the Bayesian Model Averaging results for the regression in (8). The first column represents the covariate set considered, i.e., the set of potential x variables. The columns under "Period 4," "Period 8," and "Period 16" depict the inclusion probabilities [$P(\beta \neq 0|y)$], the posterior means [calculated by (12)], and the posterior standard deviation [calculated as a square root of (13)] when the regressand is a particular property of the impulse response based on every 100th draw of parameter distribution. The presented results are the averages over this draws. HH, HHI, and HPI stand for Households, Herfindahl-Hirschman Index, and Housing Price Index, respectively.

Figure 1: **The Response of the Aggregate Economy to a Contractionary Monetary Shock**



Notes: The solid line indicates the modal impulse response, while the dotted lines are the 16th and 84th percentiles of the impulse response function distributions.

Figure 2: **(Modal) Employment Response to a Contractionary Monetary Shock - All Cities**

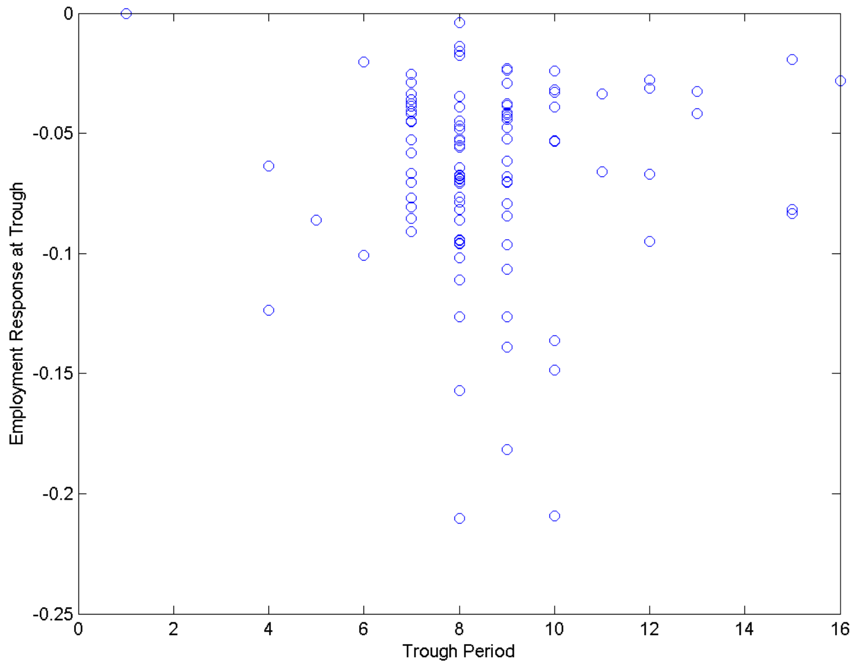


(a) Period 4

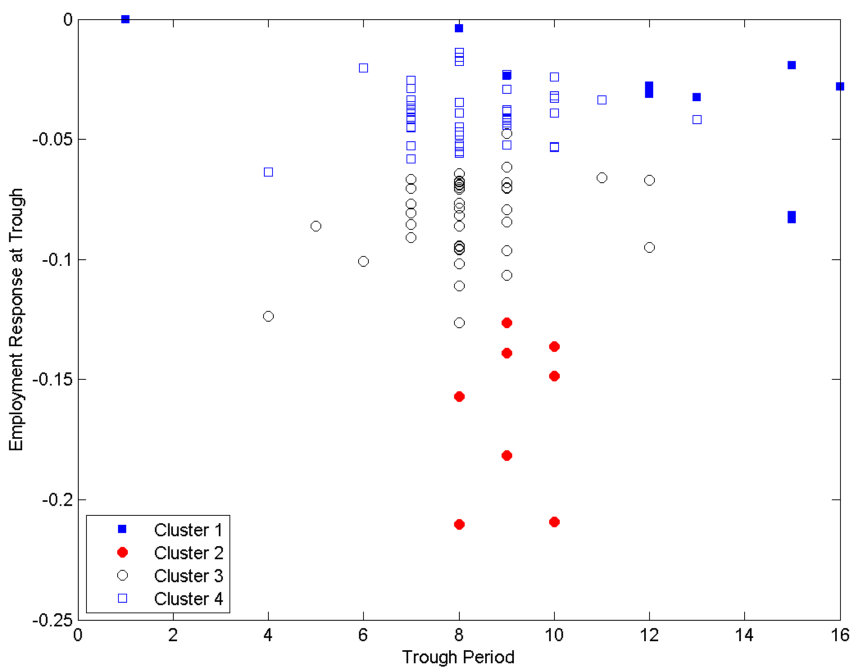
(b) Period 8

(c) Period 16

Figure 3: **(Modal) Employment Response at the Trough - All Cities**



(a) All Cities



(b) All Cities and Clusters

Figure 4: **Location of the Cities in Various Clusters Across the U.S**

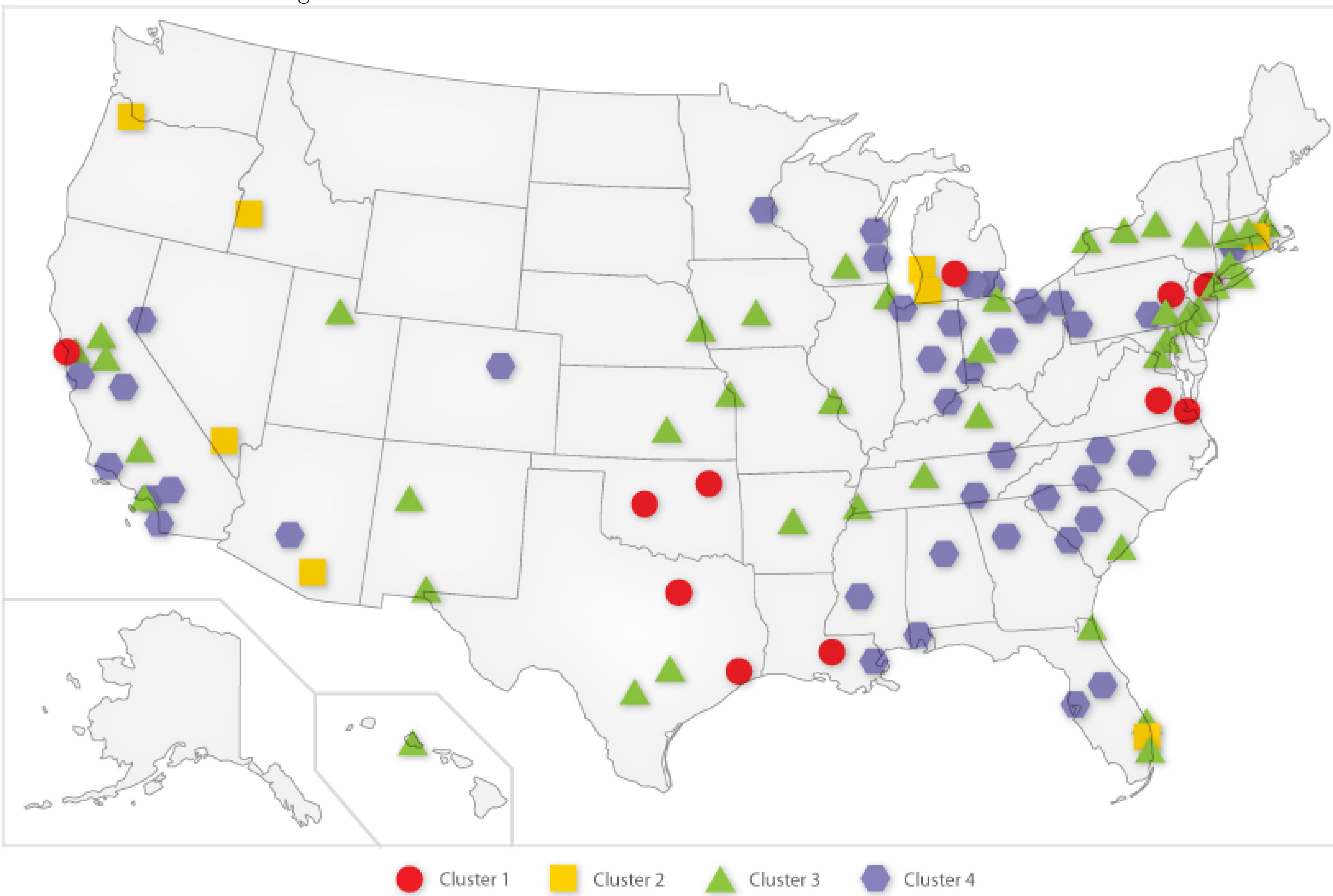
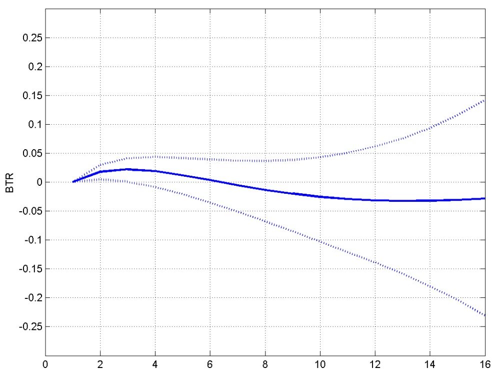
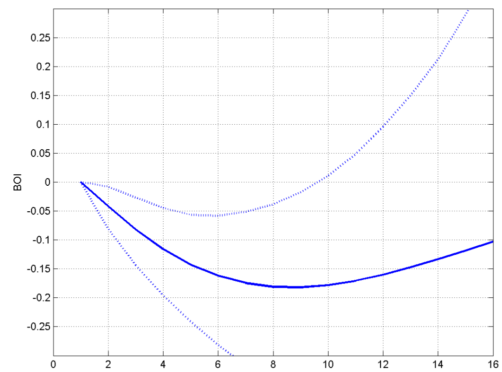


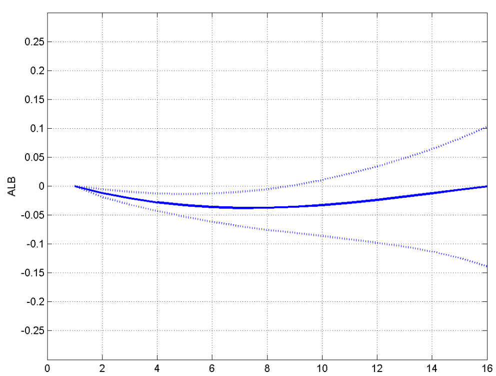
Figure 5: **Employment Response to Monetary Shock - Representative Cities**



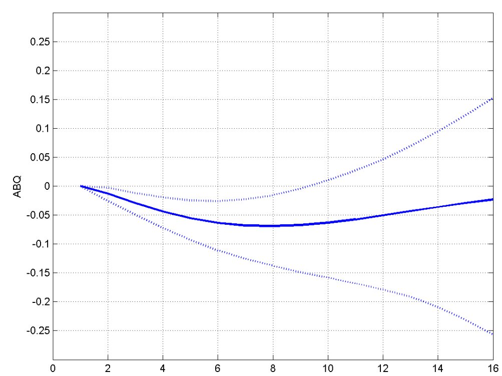
(a) Baton Rouge, LA



(b) Boise City, ID



(c) Albany-Schenectady-Troy, NY



(d) Albuquerque, NM

Notes: The solid line indicates the modal impulse response, while the dotted lines are the 16th and 84th percentiles of the impulse response function distributions.