The Local Effects of Monetary Policy*

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Abstract

Previous 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, the size of the local government sector, and unionization rate play prominent roles in mitigating 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. [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.

The empirical literature on the 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 implication. In particular, they consider whether the notion of regional variation in response to monetary shocks provides insight into the channels with which monetary policy affects the economy. In other words, differences in industry mix, banking concentration, firm size, or demographics can 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

[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.

(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 to be 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 make-up 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–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 either 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 in out-of-sample fairly well [Doan et al. (1984), Litterman (1986)], even when the economic model is large [Banbura et al. (2008)].

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, the size of the local government sector, and unionization rate play prominent roles.

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. 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). It 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):

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

where loc_t is the vector of n local- or regional-level variables and ag_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.[2]

[2] For robustness we also allow local shocks to be correlated contemporaneously. This specification results in a

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.[3]

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.[4] The effective federal funds rate, r_t, is the monetary instrument. We capture the behavior of the 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 at quarterly frequency. Except 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]

To achieve identification, we allow aggregate variables respond to the regional fluctuations contemporaneously. The restrictions within the aggregate block alone are recursive. As a result, even though the aggregate output, prices, and leading indicator 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

partially identified system. The results are robust. A few cities might change clusters and the title of a representative city might switch between the cities in the group. The changes in inclusion probabilities and average coefficient values are negligible.

[3]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.

[4]Leading indicators measure expectations in the empirical specifications as in Sims (1992) and Hanson (2004).

[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 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.

overidentified system.

INSERT TABLE 1

The 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 metropolitan areas listed in Table 1. It captures 63% 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 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.[7]

3.2 The Prior

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

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

where a_i and f_i are the respective ith columns of A and F.

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 a 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

[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 were no longer maintained, which explains the choice of our end-of-sample period.

[7] These numbers are broadly consistent with the populations of each region. Additional details about the BEA regions are in the notes to Table 3.

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 by adding observations to the data set 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 pdfs 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 $p(b_i|b_1\ ...\ b_{i-1}\ b_{i+1}\ ...\ b_m,\ X,\ Y)$. 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 $\{b_1^*\ ...\ b_{i-1}^*\ b_i^*\ b_{i+1}^*\ ...\ b_m^*\}$. The initial 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.[8] Once the appropriate distribution

[8]The results based on 20,000 accumulated draws are similar.

of A is at hand, obtaining a distribution for F via equation (7) is a straightforward task.

4 City-level 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 output, prices, index of leading indicators, non-borrowed reserves, total reserves, and money supply to an approximate of 34 basis point increase in the effective federal funds rate. The results in the aggregate block are consistent with those reported by Christiano et al. (1999). The effective federal funds rate declines in a persistent manner, such that it is essentially zero around period 6. Contractionary shock to the federal funds rate drives output and prices down, though there is evidence of a price puzzle. Leading indicators decline and their recovery leads the recovery of output. The liquidity effect drives non-borrowed reserves down, though total reserves are insulated from that effect since they increase initially and do not decline as much in general. The money supply declines.

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 horizons. In Period 4 the distribution is fairly dispersed and mildly skewed to the left. The skewness increases as the monetary induced business cycle reaches period 8, which roughly coincides with the average trough period across the cities. Four years into the monetary induced recession (period 16), the modal impulse response distribution becomes tighter, yet the mode of the distribution indicates that for most cities the effects of monetary policy have not died down. Figure 3 (panel a) shows that cities differ in both the magnitude of the output contraction at the trough and in its timing. In timing, the trough of most cities is concentrated between 7 to 11 quarter horizon.

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 responses over the 16-period business cycle horizon.[9] We use the k-means

[9] 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.

algorithm to collect the 105 city-level responses into 6 mutually exclusive groups.[10]

The composition of the clusters is presented in Table 3. The majority (63 percent) of the metropolitan areas belong to either Cluster 4 or Cluster 6. Metropolitan areas from various BEA regions can adhere to the same group. In addition, geographic separation is not an indicator of whether the cities behave similarly and, therefore, belong to the same cluster. Cluster 3, the smallest cluster of all, for example, includes cities from six out of the eight BEA regions. Figure 3 (panel b) shows that while clustering based on the impulse response over all 16 periods, the algorithm still appears to capture the magnitude differences in the employment response at the trough fairly well.

INSERT TABLE 3

Table 4 summarizes the average behavior of the modal employment response for each of the clusters. The first column presents the maximum depth of the recession measured in the maximum employment contraction attained during the recession; the 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 3 appear to be the most sensitive to monetary shocks – the recession trough on average represents a 0.19-percentage-point decline in employment. The trough occurs on average between Q8 and Q13. The total cost of the recession – measured by the total absolute deviation of employment from the steady-state equilibrium – is on average higher for clusters with higher average troughs.

INSERT TABLE 4

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 Clusters 1 and 5 are the least reactive to contractionary monetary policy on impact. Cities in Cluster 1, while expanding on impact, appear to be the least sensitive to monetary policy shocks overall, with the average city recovering fully by the end of year 4. On the other hand, the monetary–induced recessions in cities in Cluster 3 are persistent: on average, the cities have a 0.12-percentage-point employment contraction after

[10]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. Cluster silhouette plots are used to determine the differences between clusters. We chose 6 clusters based on the relative performance of the silhouette plots for various k-means runs with specifications that allow for a maximum of 12 clusters.

16 quarters. For the same monetary shock, the shapes of the responses for cities in Clusters 4 and 6 are similar; however, the responses for cities in Cluster 6 have about twice the magnitude. Cities in Clusters 2 and 6 behave similarly initially; the latter, though, appear to have less persistent responses. The behavior of cities in Cluster 3 are comparable to those in Cluster 2 qualitatively; however, the overall level of the response and the long-run severity of the recession is considerably higher for Cluster 3.

INSERT FIGURE 4

The most frequent impulse responses (calculated based on the mode of the parameter distributions) and 68-percent-coverage areas for a representative city in each cluster (Newark, NJ; Reno, NV; Gary, IN; Miami, FL; El Paso, TX; Louisville, KY-IN) are depicted in Figure 4.[11] The representative cities are selected such that they have the minimum mean-unweighted sum of deviations from the cluster averages for all categories but the trough period. The employment responses show that monetary policy shocks have transitory effects on employment levels for all cities. The shapes of the responses of Miami and Louisville are very similar to each other, with some differences in both the magnitudes and the recovery times, as are the shapes of the responses of Reno and Gary. The employment responses for Newark and El Paso are comparable in magnitude, with the latter exhibiting more persistent level effects.

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–induced recessions. In this section, we present results of second-stage regressions investigating which 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

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

the short-run or impact responses. We will think of these features as indicators of a monetary policy channel. The previous literature has emphasized several channels for monetary transmission: the interest rate channel, equity price channel, exchange rate channel, credit channel, and cost channel.[12] Other aspects of the economy predominantly affect the propagation mechanism, thus determining the properties of the longer-term employment response.

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.[13] 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.[14] 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

[12] For a more elaborate discussion see Mishkin (1996).

[13] 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 long-term real interest rates.

[14] Housing and land markets are substantially affected by local supply and demand conditions [Lamont and Stein (1999), Abraham and Hendershott (1993)], while other equity markets are fairly centralized and homogeneous.

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.[15]

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 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 more easily absorb the effects of economic shocks. 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 will be less accentuated

[15] 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.

because firms will 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. At the other 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 away 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 is, the more acyclical the local business cycle is. 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 sizeable 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.[16] Specifically, we consider a cross-sectional regression of the following form:

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

[16] At times, exact identification between monetary policy channels or various propagation mechanisms is impossible since some of the covariates can be relevant under many different scenarios.

where ir is an $n \times 1$ vector that describes a certain property of the modal impulse response for the local variables. The $n \times k$ vector X represents k covariates for each city n; υ 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 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 a 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 and York (1995) and discussed in detail in Koop (2004).

We consider a sequence of models $M_r,\ r = 1, 2,\ ...\ R$ ($R = 2^k$). 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 $p(\alpha) \propto 1$.[17] 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 $1/max\{n, k^2\}$.[18]

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,

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

[18] 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.

$p(M_r|y) \propto p(y|M_r)p(M_r)$, 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 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 OLS 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, $p(M^*) = p(M^{s-1})$.

From the total $S = 1,100,000$ draws, we burn the first $S_0 = 100,000$. The posterior inclusion probabilities are calculated based on the frequency by which each covariate appears in the $S_1 = S - S_0$ draws that are kept. The marginal posterior distribution of the slope parameters, for example, becomes a mixture of t-distributions of each model that includes those regressors. Hence, the mean and the variance of the slope coefficients are approximated by equations (12) and (13) respectively:

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

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

5.3 Covariate Data

The covariate set that we use to account for the variability in the employment responses 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. A key advantage of the algorithm in the preceding section is that it allows us to include a greater number of covariates, simultaneously testing more potential channels. The algorithm assesses the posterior probability that the covariate is included.

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.[19] Industry mix is calculated as a share of total employment in a specific industry and by construction sums to one. For certain metropolitan areas, construction and mining indicators are constructed as the sum of construction and mining series available separately. The data in the housing category controls 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

[19]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.

period and the 1990 Census data makes 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).

5.4 Empirical Results

Tables 8 and 9 present our second-stage regression results. 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. 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 different from zero.[20]

INSERT TABLE 8 AND 9

Table 8 presents the results using the lowest (minimum) value of the output response upon a contractionary monetary shock and the total cost of monetary–induced business cycles as left-hand-side variables.[21] 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 the regressand; except, in this case, the inclusion probability for government employment drops from 90 percent to 58 percent.

In Table 9, we present the results for select values of the impulse responses. 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 table, population density is included in almost all

[20]It should be noted that the constant has an inclusion probability of one by construction. Thus, the results pertaining to the constant are omitted from the tables.

[21]As mentioned previously, the total cost of the business cycle is measured by the area under the impulse response. For example, the total cost would be exactly zero if a variable did not respond to monetary policy at any horizon.

of the models for each of the selected response periods. Government employment has inclusion probabilities of 54 percent, 90 percent, and 7 percent, respectively. Interestingly, union membership becomes relatively important at the 16-period horizon with an inclusion rate of about 77 percent. While population density is important at all horizons, the results indicate that the government sector and union membership are important at intermediate (about 2 years into the recession) and long (about 4 years into the recession) horizons, respectively. These results are not so surprising if one believes that the presence of bureaucratic red tape would slow the response of the government sector, while higher rates of union membership could delay the extent of the employment response. The standard errors of these covariates with high inclusion rates are relatively small, which implies condensed posterior distributions such that the 95 percent coverage areas exclude zero.

The covariates in support of more traditional channels of monetary policy appear to be marginally important over the business cycle. Fraction of households with no wage and salary income and fraction of owner occupied housing have 20 and 28 percent inclusion probability on impact (period 4). In addition, they amplify the contractionary effects of the monetary policy. Manufacturing and small business loans have a similar effect with lower inclusion probabilities of 20 and 18 percent respectively. In line with general expectations, by period 16 the importance of certain covariates improves: services, housing price index, and establishment size obtain an inclusion probability of 43, 20, and 36 percents respectively. While the higher level of housing prices and larger establishment size make the contractionary effects of the business cycles milder, services amplify those effects. This is in line with the observation that prices in the service industry adjust more slugishly, thus the adjustment on the quantity side takes affect later compared to the other industries.

Our results may appear at odds with previous studies examining the responses to monetary policy across U.S. states and BEA regions. As discussed previously, 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 these channels are marginalized.

The differences between the results here and in previous studies may stem from a number of methodological differences. 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.[22] Second, the regional covariation modeled in studies that examine

[22]The OLS regression with the a subset of covariates still yields proxies for the traditional major channels significant. When all the covariates are included, the statistical significance vanishes, since the degrees of freedom decreases.

regions may be too coarse.[23] Third, the MSA sample examined here does not sum to 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 excluded or 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 – results that appear at odds with the previous literature. In particular, when we take into account model uncertainty, the effect of more traditional channels of monetary policy like the interest rate channel (measured with the manufacturing share) or the credit channel (measured with the small business loans) appear marginalized at the city level. Instead, we find strong support for the role of population density, the share of government employment, and the unionization level in the asymmetric responses to monetary policy. In addition, all these variables minimize the contractionary effects of monetary shocks.

Accounting for the model uncertainty, however, adds an additional piece to the discussion in a form of inclusion probabilities, which can be used for further assessment on the relevance of various models.

[23]For the most part, studies that examine the effect on states place a large number of zero restrictions on both the cross-equation coefficients and the estimated variance-covariance matrix.

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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, suppose $m = 2$ and $p = 2$. It follows from the discussion above that for $i = 1, 2$,

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

$$\bar{P}_i = \left[\begin{array}{ccc} I_2 & 0_2 & 0 \end{array}\right]',$$

and

$$\bar{H}_i = diag\left(\left[\begin{array}{ccccc} \frac{\lambda_0\lambda_1}{\sigma_1} & \frac{\lambda_0\lambda_1}{\sigma_2} & \frac{\lambda_0\lambda_1}{\sigma_1 2^{\lambda_3}} & \frac{\lambda_0\lambda_1}{\sigma_2 2^{\lambda_3}} & \lambda_0\lambda_4 \end{array}\right]\right),$$

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 effect of a unit of measure across the variables. In practice, σ_j is proxied by the sample standard deviation of the residuals that result from a univariate autoregression of order p for 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 data set, i.e., for $s = 1, ..., k,\ j = 1, ..., m$, and $t = 1, ..., m$,

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

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 new observation. For $s = 1, ..., k$ and $j = 1, ..., m$ this initial observation is constructed such that $z_j = \mu_6 \bar{z}_{0j}$ 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-N 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-Va Bch-Nwprt Nws 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-Rk 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 Riv-Warw 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-S 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	Grnsboro-Winston-Salem-Hi Pt NC	SFR	San Francisco CA
GNV	Grnville-Spartanb-Anderson SC	SJO	San Jose CA
GRR	Gr 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 Pete-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	W Palm Bch-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**	**MA**	**BEA Region**
Cluster 1		*Cluster 4*		*Cluster 5*		*Cluster 6*	
ALL	ME	ALB	ME	AUS	SW	ABQ	SW
DAL	SW	BOS	NE	BAK	FW	AKR	GL
JYC	ME	BTM	ME	BTR	SE	ANH	FW
LAN	GL	BUF	ME	ELP	SW	APP	GL
NFK	SE	CBA	SE	HST	SW	ATL	SE
NWK	ME	CHI	GL	LRS	SE	AUG	SE
NYP	ME	CRL	SE	RCP	SE	BIR	SE
OKC	SW	DEM	PL	SAT	SW	CGR	SE
PHP	ME	DET	GL	SJO	FW	CHT	SE
SFR	FW	DYS	GL	SLC	RM	COL	GL
WIL	ME	HON	FW	TUL	SW	CTI	GL
		JAX	SE			CVL	GL
Cluster 2		KNC	PL			FRE	FW
ANA	GL	LAC	ME			FWA	GL
DEN	RM	LAX	FW			GNS	SE
JAS	SE	LEX	SE			GNV	SE
MOB	SE	MDS	GL			GRY	GL
PHX	SW	MIA	SE			HAR	ME
POR	FW	MPH	SE			HTF	NE
RAD	SE	NHV	NE			IND	GL
REN	FW	NSS	ME			KNX	SE
TMA	SE	NVL	SE			LOI	SE
VEN	FW	OAK	FW			MSP	PL
		OMA	PL			MWK	GL
Cluster 3		PIT	ME			NOR	SE
BOI	RM	ROH	ME			ORL	SE
FTL	SE	SAC	FW			RSB	FW
GRR	GL	SPD	NE			SDI	FW
KAL	GL	STL	PL			WPB	SE
LSV	FW	STO	FW			YNG	GL
PRI	NE	SYR	ME				
TUC	SW	TOL	GL				
		TRT	ME				
		WIC	PL				
		WOR	NE				
		WSH	ME				

Notes: The listing and details for the Bureau of Economic Analysis (BEA) regions are provided at http://www.bea.gov/regional/docs/regions.cfm. 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.

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

	Depth		Employment Response			
	Max	Period	Total	Period 4	Period 8	Period 16
Cluster 1	-0.03	9.27	0.29	0.01	-0.01	-0.00
Cluster 2	-0.12	9.50	1.33	-0.06	-0.11	-0.08
Cluster 3	-0.19	9.29	2.15	-0.10	-0.18	-0.12
Cluster 4	-0.05	8.53	0.51	-0.03	-0.05	-0.01
Cluster 5	-0.07	13.00	0.67	-0.00	-0.05	-0.06
Cluster 6	-0.09	8.33	0.94	-0.06	-0.09	-0.04

Notes: The values in the table are averages across the cities in a respective cluster. 'Max' refers to the depth of the recession measured in 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).

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.

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 Ownder-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.

Table 8: **Testing the Transmission Hypothesis**

Covariate	Maximum Response			Total Cost of Business Cycle		
	$P(\beta \neq 0 \vert y)$	$\hat{\beta}$	$std(\beta)$	$P(\beta \neq 0 \vert y)$	$\bar{\beta}$	$\hat{std}(\beta)$
Population	0.0669	-0.0002	0.0005	0.0807	0.0065	0.0062
Population Density	0.9996	0.0211	0.0038	0.9997	-0.2478	0.0440
Fract. of Pop. with College Degree	0.0515	-0.0023	0.0033	0.0459	0.0049	0.0345
Median Household Income	0.0464	0.0005	0.0011	0.0456	-0.0060	0.0128
Fract. of Pop. Below Poverty	0.0419	-0.0000	0.0035	0.0432	-0.0043	0.0422
Fract. of HH: No Wage/Salary	0.0476	0.0001	0.0041	0.0502	0.0294	0.0506
Fract. of HH: No Interest/Dividend	0.0422	-0.0004	0.0020	0.0422	0.0009	0.0235
Serious Crimes Known to Police	0.0580	-0.0075	0.0087	0.0426	0.0348	0.0750
Finance, Insurance, & Real Estate	0.0920	0.0232	0.0177	0.0620	-0.1341	0.1403
Government	0.8969	0.2265	0.0641	0.5813	-1.3261	0.4821
Manufacturing	0.0982	-0.0112	0.0062	0.0857	0.0882	0.0619
Services	0.0686	-0.0084	0.0064	0.1027	0.1764	0.1082
Transport, Communications, etc.	0.0861	0.0237	0.0187	0.0727	-0.2003	0.1842
Trade	0.0459	0.0024	0.0082	0.0477	0.0346	0.0983
HPI	0.1334	0.0067	0.0041	0.1546	-0.0982	0.0552
Fract. of Owner-Occupied Housing	0.0908	-0.0038	0.0028	0.0786	0.0334	0.0278
HHI	0.0512	-0.0003	0.0004	0.0501	0.0030	0.0046
Banking Market Deposits	0.0489	0.0001	0.0001	0.0422	-0.0004	0.0013
Small Business Loans	0.3271	-0.0043	0.0019	0.3694	0.0589	0.0250
Establishment Size	0.0868	0.0036	0.0028	0.0952	-0.0473	0.0346
Industrial Diversity Index	0.0434	-0.0001	0.0010	0.0452	0.0001	0.0124
Union Membership	0.1050	0.0069	0.0048	0.1018	-0.0784	0.0547
Government Revenue	0.0472	-0.0000	0.0004	0.0438	-0.0016	0.0040
Government Expenditures	0.0533	-0.0003	0.0004	0.0477	0.0026	0.0047

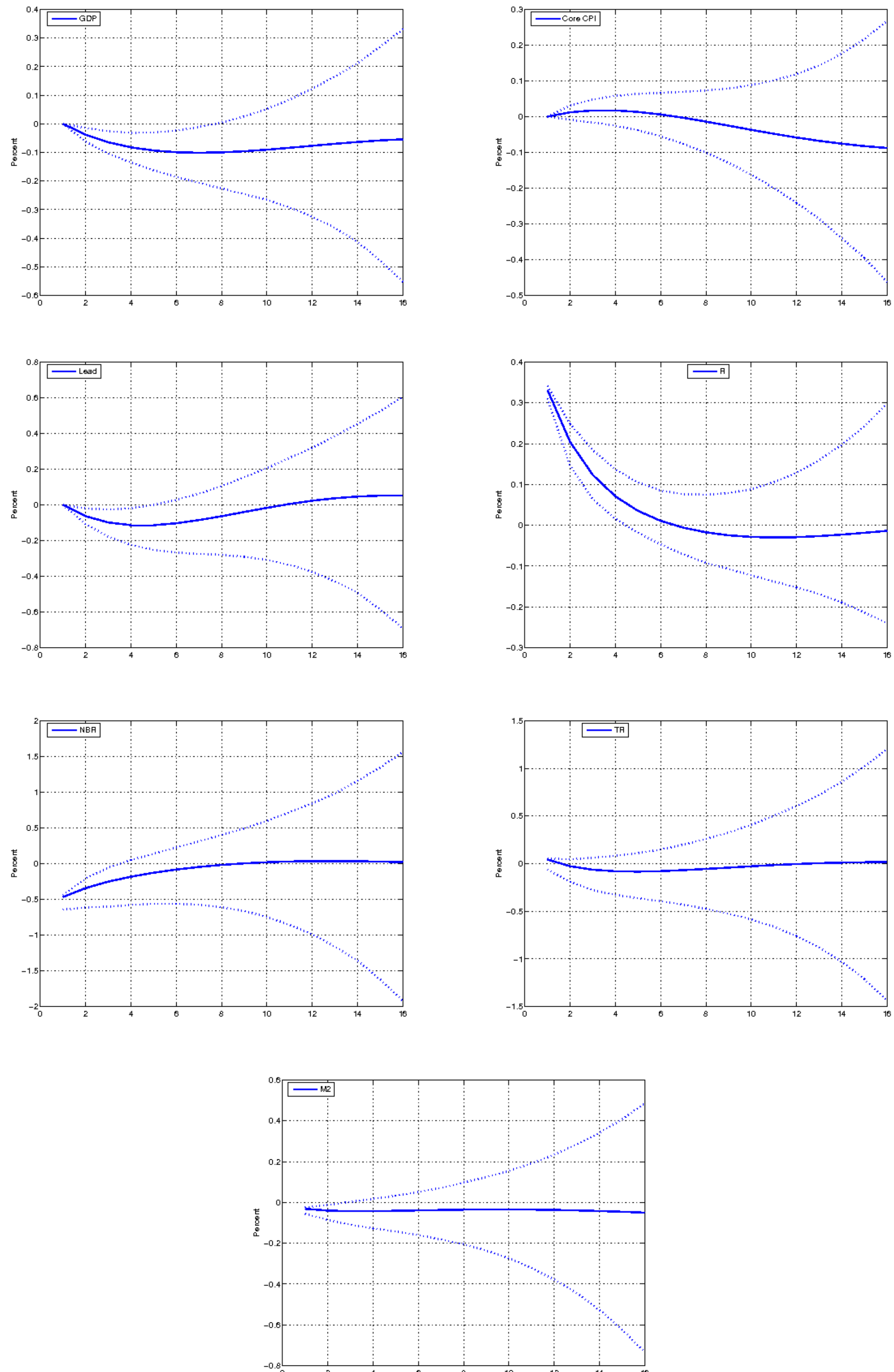
Notes: The table represents the Bayesian Model Averaging (BMA) results for the regression in (8). The first column represents the covariate set considered, i.e., the set of potential x variables. The columns under 'Maximum Response' and 'Total Cost of Business Cycle' depict the inclusion probabilities [$P(\beta \neq 0|y)$], 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.

Table 9: **Testing the Transmission Hypothesis Over Different Periods**

Covariate	Period 4			Period 8			Period 16		
	$P(\beta \neq 0 \mid y)$	$\bar{\beta}$	$\hat{std(\beta)}$	$P(\beta \neq 0 \mid y)$	$\hat{\beta}$	$std(\beta)$	$P(\beta \neq 0 \mid y)$	$\hat{\beta}$	$std(\beta)$
Population	0.0561	0.0002	0.0003	0.0578	-0.0002	0.0004	0.1825	-0.0021	0.0010
Population Density	0.9938	0.0155	0.0033	0.9999	0.0220	0.0038	0.9903	0.0151	0.0033
Fract. of Pop. with College Degree	0.0464	-0.0009	0.0028	0.0639	-0.0040	0.0042	0.0473	-0.0012	0.0026
Median Household Income	0.0466	0.0003	0.0010	0.0455	0.0004	0.0011	0.0450	-0.0000	0.0010
Fract. of Pop. Below Poverty	0.0463	-0.0001	0.0035	0.0434	-0.0011	0.0037	0.0457	-0.0010	0.0032
Fract. of HH: No Wage/Salary	0.2028	-0.0318	0.0155	0.0606	-0.0045	0.0053	0.0539	0.0025	0.0042
Fract. of HH: No Interest/Dividend	0.0438	0.0004	0.0019	0.0422	0.0006	0.0021	0.0425	0.0004	0.0017
Serious Crimes Known to Police	0.0482	-0.0036	0.0066	0.0659	-0.0104	0.0101	0.0574	0.0059	0.0077
Finance, Insurance, & Real Estate	0.0426	0.0007	0.0076	0.0497	0.0061	0.0099	0.0556	0.0080	0.0094
Government	0.5364	0.0968	0.0346	0.9073	0.2511	0.0660	0.0714	0.0053	0.0047
Manufacturing	0.1998	-0.0221	0.0104	0.1306	-0.0200	0.0084	0.0966	0.0063	0.0051
Services	0.0609	-0.0037	0.0051	0.0934	-0.0174	0.0090	0.4452	-0.0827	0.0328
Transport, Communications, etc.	0.0477	0.0012	0.0094	0.1404	0.0511	0.0308	0.0431	0.0021	0.0081
Trade	0.0651	-0.0103	0.0103	0.0515	-0.0023	0.0093	0.0500	0.0020	0.0077
HPI	0.0661	0.0019	0.0018	0.1213	0.0059	0.0038	0.2041	0.0117	0.0056
Fract. of Owner-Occupied Housing	0.2772	-0.0166	0.0075	0.0503	-0.0010	0.0016	0.0464	-0.0005	0.0012
HHI	0.0925	-0.0009	0.0007	0.0578	-0.0004	0.0005	0.0439	-0.0001	0.0003
Banking Market Deposits	0.0576	0.0001	0.0001	0.0543	0.0001	0.0001	0.0622	-0.0001	0.0001
Small Business Loans	0.1837	-0.0020	0.0010	0.2476	-0.0030	0.0015	0.1584	-0.0015	0.0008
Establishment Size	0.0647	-0.0016	0.0018	0.0585	0.0017	0.0019	0.3587	0.0220	0.0092
Industrial Diversity Index	0.0733	-0.0017	0.0015	0.0441	-0.0003	0.0011	0.0737	0.0018	0.0015
Union Membership	0.0521	-0.0014	0.0022	0.0454	0.0010	0.0021	0.7681	0.0953	0.0304
Government Revenue	0.0498	0.0001	0.0004	0.0421	0.0001	0.0003	0.0596	0.0004	0.0004
Government Expenditures	0.0546	-0.0003	0.0004	0.0452	-0.0002	0.0004	0.0443	-0.0001	0.0004

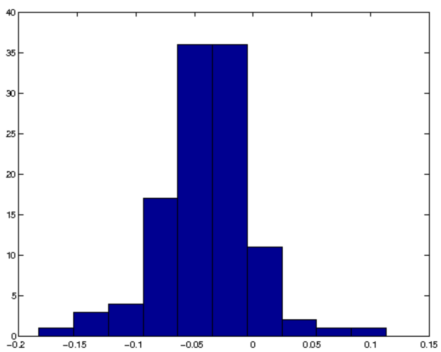
Notes: The table represents the Bayesian Model Averaging (BMA) results for the regression in (8). The first column represents the covariate set considered, i.e., the set of potential x variables. The columns under 'Period 4,' 'Period 8,' and 'Period 16' depict the inclusion probabilities [$P(\beta \neq 0 \mid y)$], 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.

Figure 1: **The response of the aggregate economy to a contractionary monetary shock**

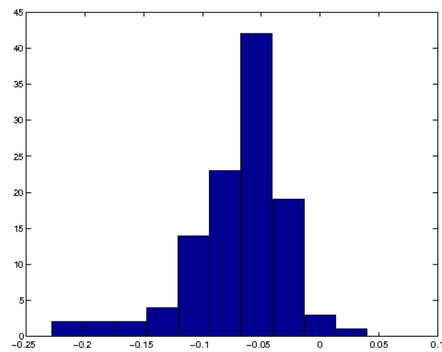


Notes: Modal impulse response and 16th and 84th percentiles of the impulse response function distributions.

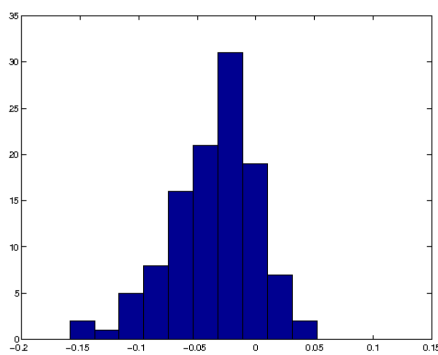
Figure 2: **Employment response to a contractionary monetary shock - all cities**



(a) Period 4



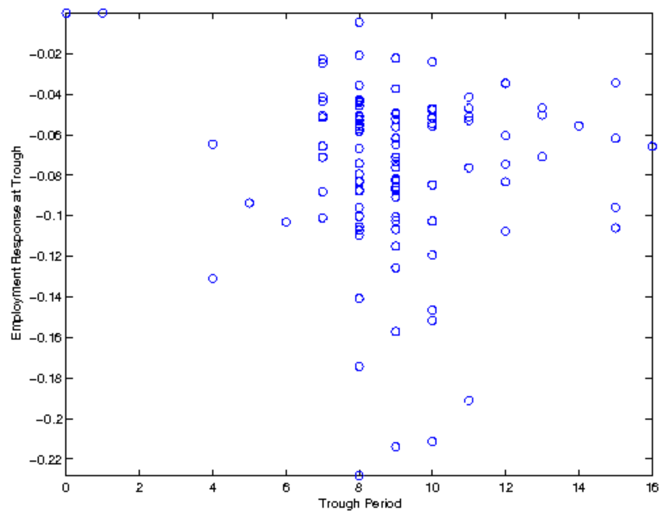
(b) Period 8



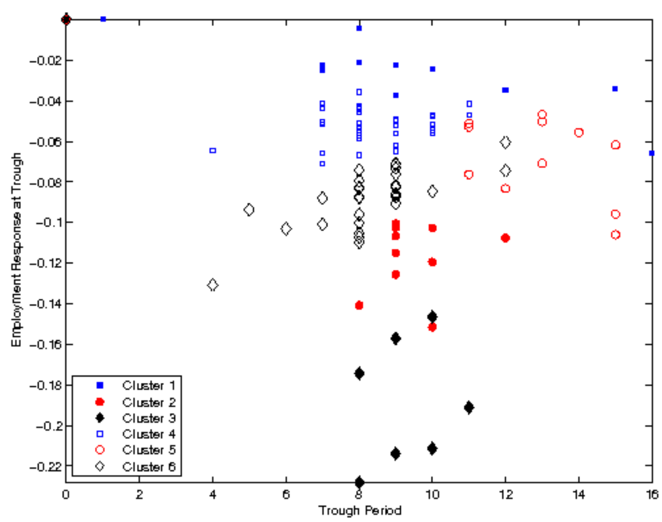
(c) Period 16

Notes: Modal impulse responses at various horizons.

Figure 3: **Employment response at the trough - all cities**



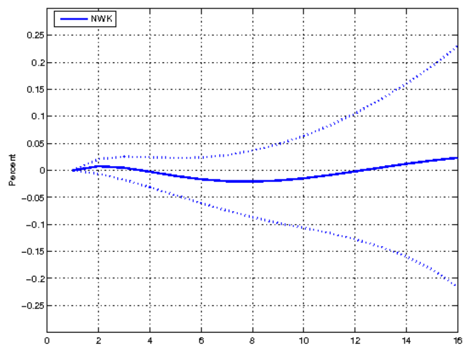
(a) All Cities



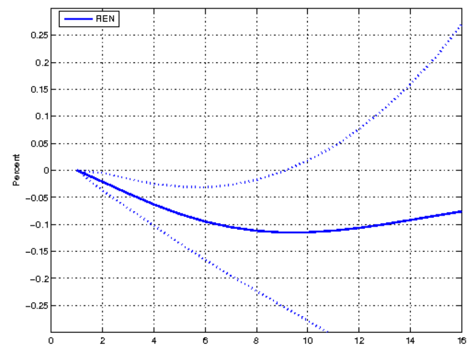
(b) All Cities and Clusters

Notes: The modal impulse response at the trough.

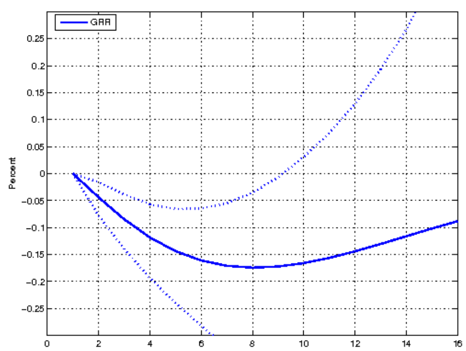
Figure 4: **Employment response to monetary shock - representative cities**



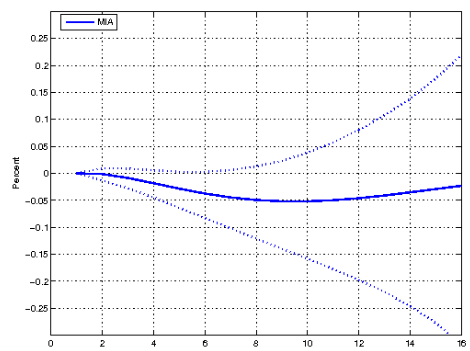
(a) Newark



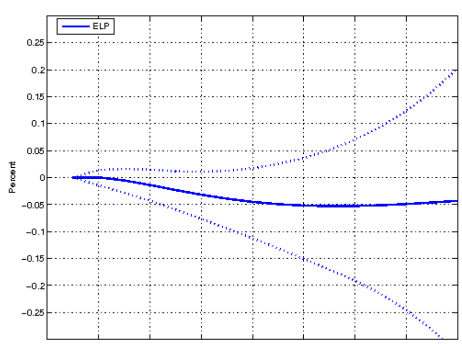
(b) Reno



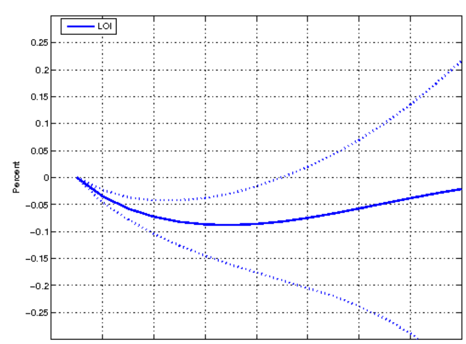
(c) Gary



(d) Miami



(e) El Paso



(f) Louisville

Notes: Modal impulse response and 16th and 84th percentiles of the impulse response function distributions.