The Local Effects of Monetary Policy*

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Abstract

Previous studies have documented disparities in the regional responses to monetary policy shocks; this variation has been found to depend, in part, on differences in the industrial composition of the regional economies. However, due to 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. [JEL codes: C32, E32, E52]

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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 through various regions of the U.S. economy. In this paper, we establish an empirical benchmark for regional asymmetries in the 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 to a monetary policy shock. Furthermore, while repeating the exercise for the state level data, Carlino and DeFina [1999] find substantial within-region and cross-region variability. Other authors (Mihov [2001], Hanson et al. [2006]) have shown these regional asymmetries exist at varying levels of disaggregation, 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 to 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 for the broad credit channel. Owyang and Wall [2006] 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 heterogenous agent VAR to model the propagation from the aggregate sector to the regional sector highlighting the importance of the housing markets.

While the stylized facts supporting the interest rate channel have been preserved, for the most

[1] For example, Carlino and Sill [2001], Carlino and DeFina [2004], 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. Owyang and Zubairy [2008] consider variation in the response to government spending shocks.

part, at all levels of geographical disaggregation, one might be concerned about intrastate variation in industrial mix and demographics. For example, the literature on urban economics has suggested that there is a considerable within-region variation when less granular definitions of regions are embraced (i.e. BEA regions, states, etc). 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 – i.e., the flow of knowledge across geographic space is costly.

In light of these facts, we focus on the city-level properties of monetary-induced recessions. Disaggregating to the city-level provides the additional benefit of a larger panel across which we may measure regional asymmetries. In the first stage of this paper, we will estimate a panel vector autoregression (VAR) to establish the stylized 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, the relevance of which is justified either by the transmission channels of monetary policy or by the potency of the covariate for second order propagation effects, 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 causes 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 VAR), the incidence of shocks (i.e., 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. [2007]).

Our preliminary results show that there is considerable heterogeneity in how the cities respond to monetary policy interventions. The differences are noticeable in the levels and the persistence of the responses, while the cities appear to be more alike with respect to the timing of the recovery. In general, the contractionary effects become insignificant after 3 year. From the transmission channels of monetary policy the interest rate and the equity channels are the prominent ones. There is a mild evidence that the general economic structure has a secondary effect as well.

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

The workhorse of the literature on the identification of monetary policy shocks is the structural VAR. We consider a structural VAR in 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 errors 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 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).

In contrast, the methodology that we consider estimates the structural system (1) directly, allowing us to accommodate the overidentified and near-VAR cases via linear restrictions on the contemporaneous and lagged coefficients in a relatively simple manner.[2] Since this paper focuses on local propagation of aggregate disturbances and, specifically, on monetary policy shocks, there

[2] As discussed in Sims and Zha [1998], the indirect estimation of the contemporaneous effects in the VAR is only valid asymptotically when one considers the case of overidentification.

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):

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

where l_t is the vector of local- or regional-level variables, a_t is the vector of 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 then 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 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 is 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

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

where $y_{i,t}$ is the total non-farm employment for region i and y_t is the level of aggregate output. p_t measures the consumer prices, while $lead_t$ accounts for the index of 10 leading indicators in the VAR.[4] The federal funds rate r_t proxies the monetary policy dynamics. $m2_t$ money stock, tr_t

[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 to the alternative methods that generate error bands. In addition, Monte Carlo studies considered in Kilian and Changa [2000] suggest that the confidence bands calculated this way are likely to be more accurate in high-dimensional VAR models.

[4]In order to identify monetary innovations in the VAR framework the literature has incorporated some measure of future expectations in the empirical specification (Sims [1992a] and Hanson [2004]) and so do we.

total reserves and nbr_t total non-borrowed reserves capture the behavior of the aggregate financial sector in response to monetary policy. All variables but the interest rate are in logarithms. The interest rate enters in percentage points.

In order to achieve identification, we assume that the 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 as well as the measures of future expectations are in the contemporaneous feedback rule of the central banker, monetary policy has no contemporaneous effect on either of these aggregate variables. These restrictions, together with the general restrictions outlined previously, yield an overidentified system.

The quarterly values of total non-farm employment for metropolitan areas are taken from the Current Employment Statistics Survey released by the Bureau of Labor Statistics and cover the period of 1972:I - 2004:IV. 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.[5] The resulting final sample includes 105 metropolitan areas.

The aggregate output is measured with quarterly values of a seasonally adjusted annual rate real GDP. The quarterly values of the composite index of 10 leading indicators measure the dynamics of future expectations. We use CPI for all urban consumers: all items less food and energy as a measure of consumer prices and the effective Federal Funds Rate for the policy interest rate. M2 money stock, Board of Governors total reserves adjusted for changes in reserve requirements and non-borrowed reserves of depository institutions complete the list of the aggregate series. Except for the composite index of 10 leading indicators, the values for the rest are taken from the FRED (Federal Reserve Economic Data) database of the St. Louis Fed. Unless explicitly mentioned, the aggregate series are available in monthly frequencies, where the value for the month corresponding to the end of the quarter is taken as the appropriate quarterly value. All the aggregate series but the interest rate are seasonally adjusted.

In a number of previous studies, the BEA regions have been used as the level of disaggregation to measure the asymmetries within the U.S. economy. Our sample of metropolitan areas are representative of the cross-section of BEA regions: 6 percent of the metropolitan areas are from

[5]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 accounted as part of the New York, Philadelphia, Pennsylvania-New Jersey, and Washington, District of Columbia-Maryland-Virginia-West Virginia metropolitan areas.

Table 1: **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	0.1	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

the New England region, while 16 percent from the Mideast, 18 percent from the Great Lakes, 7 percent from the Plains, 26 percent from the Southeast, 10 percent from the Southwest, 3 percent from the Rocky Mountains, and 14 percent from the Far West.[6]

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 $F_{kxm} = [G_1 \, ... \, G_p \; C]'$, where $k = mp + 1$. The system in (1) can be rewritten as

$$z_t' A = x_t' F + \epsilon_t', \tag{3}$$

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

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 zeros. The prior postulates the following prior distributions:

$$\begin{aligned} a_i &\sim N(0, \bar{S}_i), \\ f_i|a_i &\sim N(\bar{P}_i a_i, \bar{H}_i), \end{aligned} \tag{4}$$

[6]These numbers are broadly consistent with the populations of each region. Additional details about the BEA regions are in the notes to Table 2.

for $i = 1, ..., m$. Given the setup of (3), 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 [1992b]. Values for the six hyperparameters are shown in Table 1 and 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 (4), together with the likelihood function, yield marginal posterior pdfs for b_i and g_i defined by

$$p(b_1, ..., b_m|X, Y) \propto |det[U_1 b_1|...|U_m b_m]|^T exp\left(-\frac{T}{2}\sum_{i=1}^{n} b_i' S_i^{-1} b_i\right) \quad (5)$$

$$p(g_i|b_i, X, Y) = \varphi(P_i b_i, H_i), \quad (6)$$

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, generate 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_is, starting with some arbitrary initial values of $\{b_1^* \; ... \; b_{i-1}^* \; b_i^* \; b_{i+1}^* \; ... \; b_m^*\}$. The initial 5000 draws are discarded to eliminate the effect of the initial values. The results presented are based on the remaining 10000 accumulated draws. Once the appropriate distribution of A is at hand, obtaining a distribution for F via (6) is a straightforward task.

Table 2: **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	NOR	SE	BIR	SE
OKC	SW	DEM	PL	RCP	SE	CGR	SE
PHP	ME	DET	GL	SAT	SW	CHT	SE
SFR	FW	DYS	GL	SJO	FW	COL	GL
WIL	ME	HON	FW	SLC	RM	CTI	GL
		JAX	SE	TUL	SW	CVL	GL
Cluster 2		KNC	PL			FRE	FW
ANA	GL	LAC	ME			FWA	GL
DEN	RM	LAX	FW			GNS	SE
JAS	PL	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			ORL	SE
BOI	RM	ROH	ME			RSB	FW
FTL	SE	SAC	FW			SDI	FW
GRR	GL	SPD	NE			WPB	SE
KAL	GL	STL	PL			YNG	GL
LSV	SW	STO	FW				
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, Planes, Southeast, Southwest, Rocky Mountain and Far West regions accordingly.

4 City-level Impulse Responses

For the most part, the empirical results for the first stage regressions can be summarized in the city-level impulse responses to a monetary shock. Here, we present these results for representative metropolitan areas. The full sample of impulse responses are available in the Appendix.

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.[7] We use the $k-$means algorithm to collect the 105 city-level responses into 6 mutually-exclusive groups. The specific $k-$means algorithm utilized minimizes the total squared Euclidean distance of the metro areas in each cluster from the cluster mean over the number of groups exogenously specified.[8]

The composition of the clusters are presented in Table 2. The majority (62 percent) of the metropolitan areas belong to either Cluster 3 or Cluster 5. 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 five out of the eight BEA regions.

Table 3 summarizes the average behavior of the mode of the employment responses of each of the clusters. The first column presents the average depth of a recession per cluster. 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 average recession trough represents a 0.19 percentage point decline in the employment. The average trough occurs between years two and four. The average total cost of the recession – measured by the average of the total absolute deviation of employment from the steady state equilibrium – is higher for clusters with higher average trough.

The last three columns of Table 3 show the average behavior of the impulse responses across the clusters at one, two, and four years 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 year 4. On the other hand, the monetary-induced recessions in cities in Cluster 3 are persistent

[7]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.

[8]The algorithm is iterative: it randomly chooses the center points for the clusters, sequentially reallocates the metropolitan areas, and recalculates the center points until the optimality condition is satisfied. The choice for the number of clusters is less trivial. 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.

Table 3: **Properties of the MA Clusters**

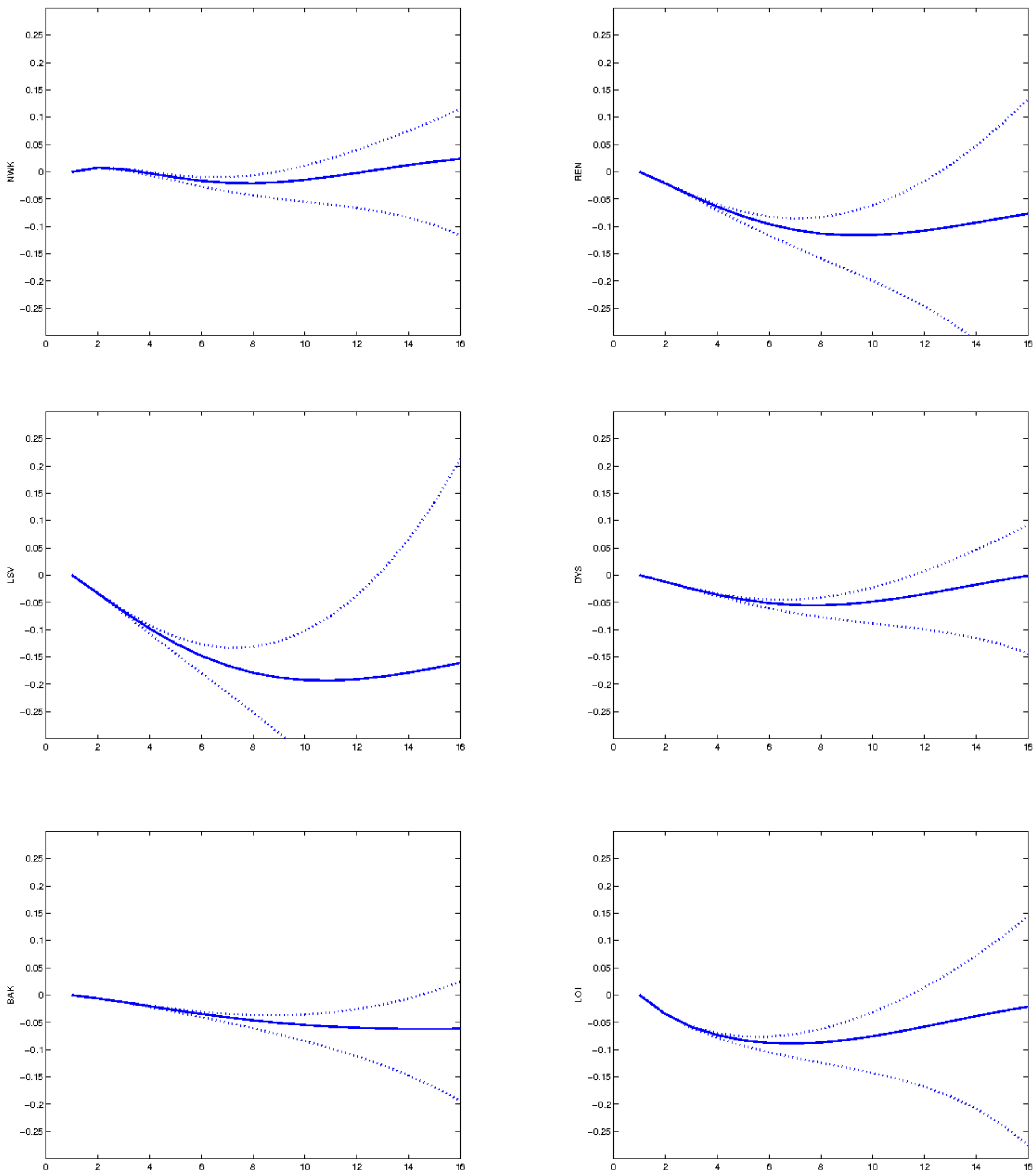
	Max	Period	Total	Period 4	Period 8	Period 16
Cluster 1	-0.03	9.27	0.29	0.01	-0.01	-0.00
Cluster 2	-0.12	9.50	1.35	-0.07	-0.11	-0.08
Cluster 3	-0.19	9.29	2.18	-0.11	-0.19	-0.12
Cluster 4	-0.05	8.53	0.52	-0.03	-0.05	-0.01
Cluster 5	-0.07	12.92	0.70	-0.01	-0.05	-0.06
Cluster 6	-0.09	8.17	0.95	-0.06	-0.09	-0.03

– on average, a 0.6 percentage point employment contraction after 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 initally – 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.

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; Las Vegas, NV-AZ; Dayton-Springfield, OH; Bakersfield, CA; Louisville, KY-IN) are depicted in Figure 1.[9] 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 shape of the responses of Dayton-Springfield and Louisville, as well as Reno and Las Vegas are very similar to each other with some differences in both the magnitudes and the recovery times. The employment responses for Newark and Bakersfield are comparable in magnitude, the latter exhibiting more persistent level effects.

[9] While constructing the coverage areas, we account for serial correlation and cross correlation of the impulse responses. As suggested by Sims and Zha [1999], we use the principal component decomposition – an eigenvalue-eigenvector decomposition that eliminates the redundancy between the data elements, making the new covariance matrix diagonal. In addition, we can filter the "noise" in the data, where the "noise" would be associated with the eigenvalues that account for a small share of a total variance. For our results, we have used the first principal component only which accounts for the 32% of the total joint variation.

Figure 1: **Employment response to monetary shock - representative cities**



5 Why do Asymmetries Exist?

In the previous section, we documented the asymmetries across the metropolitan areas, both in the depth and duration of monetary-induced recessions. In the 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 observed asymmetric responses of real activity (local employment for our analysis) to an aggregate monetary policy innovation. The distinctive economic and financial structures of the local economies, as well as the local-level policy, matter. For now, we abstract from the latter and concentrate on the importance of economic structure. The discussion relies on the hypothesis that certain features of the economy are, to a great extent, responsible for the impact or short-run 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 the cost channel.[10] Other aspects of the economy predominantly affect the propagation mechanism, thus determining the properties of the longer-term employment response.

According to the traditional interest rate channel, a rise in the long-term real interest rate leads to an increase in the cost of borrowing, triggering a decline in investment spending, aggregate demand, and equilibrium employment. Investments include business fixed investments, i.e., business expenditures on structures and equipment; residential fixed investments, i.e. residential spending on housing; and inventories. The interest rate elasticity of each of these can vary at a local level because cities differ in industry mix, contractual agreements governing the housing market, etc. Industries such as construction and manufacturing are presumed to be more sensitive to the interest rate fluctuations because they rely heavier on borrowing and inventories; thus, the cities where these industries dominate would be expected to contract more as long-term real interest rates increase. 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 [2006]).

The equity channel of monetary policy works through a wealth effect. As interest rates decrease, equities become a more attractive alternative to bond holding, thus their demand and accordingly prices increase. As equities appreciate, agents in general become wealthier and, based on the life-

[10]For a more elaborate discussion see Mishkin [1996].

cycle theory of consumption, they spend more thus increasing equilibrium output and employment. Now, the types of equities that have the potency to create unequal effects locally via equity channel are housing and land prices. The reason behind this is that the 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.

The transmission mechanism of the exchange rate channel is the following: As interest rates rise, the currency appreciates (in real terms provided prices are sticky). As a result, exports contract and imports increase, while domestic real activity decreases. Regional asymmetries arise due to the proportion of traded and non-traded sectors on a city level. Manufacturing and mining are largely traded industries, while construction and services are largely non-traded.

Differences in the financial structure are important for the credit channel of monetary policy. Under a narrow credit channel (or bank lending channel), a contractionary monetary policy decreases bank reserves and deposits and, therefore, the amount of funds available for lending (Kashyap and Stein [1994]), curtailing investment and real activity. Either borrowers lack options to substitute loans for alternative funding or banks lack opportunities to raise funds for lending, except through deposit liabilities. Thus, more small firms and more small banks translate into greater regional sensitivity to monetary policy.[11]

The broad credit channel emphasizes general credit market imperfections and is not limited to the 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 the external financing becomes more expensive, investments and real activity decline.

Under the cost channel of monetary policy, interest rate movements result in supply side effects – output contracts and prices increase. The effect of the cost channel is believed to be more acute in the manufacturing sector when a rigidity makes marginal cost depend on interest rates (Barth and Ramey [2001] and Christiano et al. [1997]). For example, when factors of production are paid before the sales revenues are received, firms borrow to finance their working capital.

[11]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 exhibit more interest rate sensitivity compared to the large ones.

Monetary policy transmission channels are the primary sources of monetary business cycles. Nevertheless, the general economic structure of the cities has the potency to create second-order propagation effects. When a city is more industrially diverse, it can absorb the effects of the monetary (and other) shocks more easily. A similar argument can apply to the labor force: If a city's population is more educated, the labor force can shift across sectors, reducing the effect of a monetary shock on city-level employment. The overall flexibility of the labor markets matter as well. If a greater proportion of the labor force is unionized, then the adjustment process for employment will be less accentuated, since firing the workers will be harder. In addition, as Altissimo et al. [2006] documents for the case of the Euro Area, more labor intensive industries exhibit greater price stickiness. When the prices are rigid, the firms respond to contractionary shocks by curtailing output and employment.

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.[12] Specifically, we consider a cross-sectional regression in the following form:

$$l_r = \alpha + x\beta + \upsilon, \tag{7}$$

where l_r 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; υ is the residual.

When using a classical approach to test the elasticity of the employment response with respect to different covariates, one is open to the criticism that statements about the significance of the covariate can be made only if the estimation uncertainty associated with the generated regressor is taken into account. Because we already have a distribution for the impulse responses, we can find the point estimate of the regression coefficient β associated with every draw in our sampler. The end result will be an empirical distribution for the βs that is uncovered from the original estimation. With a sufficient number of draws, a proper coverage area for the regression parameters can be constructed.

[12] 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.

5.3 Covariate Data

Industry shares are important for various channels of monetary transmission. Accordingly, the shares of total employment in manufacturing, services, finance, insurance, and real estate are included in x. House prices are included to account for the wealth effects. The housing prices are measured with the log of the housing price indexes reported by the Office of Federal Housing Enterprise Oversight (OFHEO), which tracks the average housing price changes in repeated transactions.[13] The log of the value of loans to small businesses, as well as the log of the Herfindahl-Hirschman Index (HHI) that measures banking concentration identify the narrow credit channel. The log of the average establishment size is included to identify the broad credit channel. The log of the industry diversity index and the fraction of population 25-years-of-age-or-older with a bachelor's degree are included to account for the general economic flexibility of the city. The percentage of the total labor force covered by union contracts approximates for the labor market rigidities. Finally, the BEA regional dummies are included to reveal the regional fixed effects, if any.

The 1990 values of many of the covariates are those ones used in Owyang et al. [2006]. The amount of the loans to small businesses are taken from the Federal Financial Institutions Examination Council's Community Reinvestment Act (CRA).[14] To further identify the bank-lending or narrow credit channel, we use the value of loans to businesses with gross annual revenues no greater than $1 million.

5.4 Empirical Results

Table 4 shows the estimation results for various regressors.[15] The horizontal lines in the table are intended to give some broad themes to the covariates based on the theoretical outline above. One of the principle determinants of the magnitude of the monetary-induced recession is the city's average growth rate; fast growing cities experience, on average, deeper recessions. As shown in column 1, when the absolute value of the employment response is taken as a dependent variable, both banking concentration and manufacturing share are significant within one and two years after

[13] It should be noted that our housing data are based on the post-2004 MSA classifications. Thus, at times, its geographic definitions definitions do not exactly overlap with the geographic definitions of the other covariates.

[14] In the CRA methodology, small business loans are "loans of up to $1 million that either are secured by nonfarm or nonresidential real estate or are for commercial and industrial purposes."

[15] Since the policy disturbance is contractionary, the values of the regressors would be negative, except for the total cost of the regression. For ease of exposition, we take the absolute value of the employment responses; thus, in the empirical results below, a positive coefficient reflects greater interest rate sensitivity.

the monetary contraction. Contrary to the findings of Carlino and DeFina [1998], Owyang and Wall [2006] both the manufacturing share, as well as the banking concentration appears to be mildly significant for the the depth and total cost of monetary-induced recession.

In addition to industry shares, employment in cities in the Southeast region appear to be significantly more sensitive to interest rate changes at short horizons. The fixed effects associated with the Planes and Great Lakes regions are only mildly significant. None of the covariates that are included in order to capture the overall flexibility of the economy and thus its ability to absorb shocks are significant.

Table 4: **Testing the Transmission Hypothesis**

Covariate	Max	Total	Period 4	Period 8	Period 16
constant	-0.38	-3.98	-0.24	-0.45	-0.27
average growth	0.08	1.01**	0.05**	0.09**	0.08*
recession freq	-0.03	-0.25	0.01	-0.02	-0.03
manufacturing	0.26*	2.91*	0.17**	0.32*	0.21*
finance etc.	-0.30	-3.06	-0.17	-0.22	-0.23
services	0.19	2.57	0.11	0.26	0.21
house prices	0.01	0.01	0.00	0.01	-0.00
HHI	0.09*	1.03*	0.05**	0.10**	0.08*
small business loans	0.01	0.15	0.00	0.01	0.01
establishment size	-0.05	-0.74	-0.04	-0.07	-0.05
industrial diversity	0.02	0.05	0.02	0.04	-0.01
college grad	-0.05	-0.84	-0.06	-0.09	-0.06
labor unions	0.08	1.11	0.08	0.07	0.07
NE	0.03	0.26*	0.01*	0.03	0.02
ME	-0.01	-0.11	0.00	-0.00	-0.02
GL	0.01	0.12	0.02*	0.02	-0.00
PL	0.01	0.13	0.02*	0.02	0.00
SE	0.01	0.12	0.03**	0.01	-0.01
SW	0.01	0.07	0.00	-0.00	0.00
RM	0.03	0.38	0.01	0.03	0.03

Notes: ** indicates that the coefficient for the specific covariate falls into 95% coverage area, while * indicates that it falls into the 68% coverage area.

6 Conclusion

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

Using a VAR with city-level data, we find significant and important cross-metro-area variation in the response of employment to a monetary policy shock. Perhaps as expected, this variation extends to cities even in close geographic proximity, even within the same state. However, in second stage regressions testing the channels through which monetary policy affects employment, our results confirm that manufacturing share remains an important determinant for the responsiveness to interest rate innovations. In addition, we find evidence for the credit channel, more specifically for the degree of banking concentration at the local level. These findings suggest that the manner in which monetary policy propagates through the economy is primarily through stimulating/contracting interest-sensitive investment on the firm side.

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A The Reference Prior

The standard deviation for all elements in the jth row of $\bar{S}_i$ are 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 $\lambda_0\lambda_4$.[16] The role of the hyperparameters is presented in Table 1. 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 $t = 1, ..., m$

$$z_{jt} = \begin{cases} \mu_5 \bar{z}_{0j} & j = t \\ 0 & \text{otherwise} \end{cases}$$

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

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 type observation. For $s = 1, ..., k$ and $j = 1, ..., m$ this initial observation is constructed such that $z_j = \mu_6 \bar{z}_{0j}$ and

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

[16]For example, suppose $m = 2$ and $p = 2$. It follows from the discussion above that for $i = 1, 2$, $\bar{S}_i = diag(\begin{bmatrix} \lambda_0/\sigma_1 & \lambda_0/\sigma_2 \end{bmatrix})$, $\bar{P}_i = \begin{bmatrix} I_2 & 0_2 & 0 \end{bmatrix}'$ and $\bar{H}_i = diag(\begin{bmatrix} \lambda_0\lambda_1/\sigma_1 & \lambda_0\lambda_1/\sigma_2 & \lambda_0\lambda_1/(\sigma_1 2^{\lambda_3}) & \lambda_0\lambda_1/(\sigma_2 2^{\lambda_3}) & \lambda_0\lambda_4 \end{bmatrix})$, where $diag(v)$ represents a matrix with elements of v on the main diagonal and zeros everywhere else.

B Tables and Figures

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

Abbreviation	Metropolitan Area	Abbreviation	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

Figure 2: Impulse response functions - VAR(1) - aggregate variables

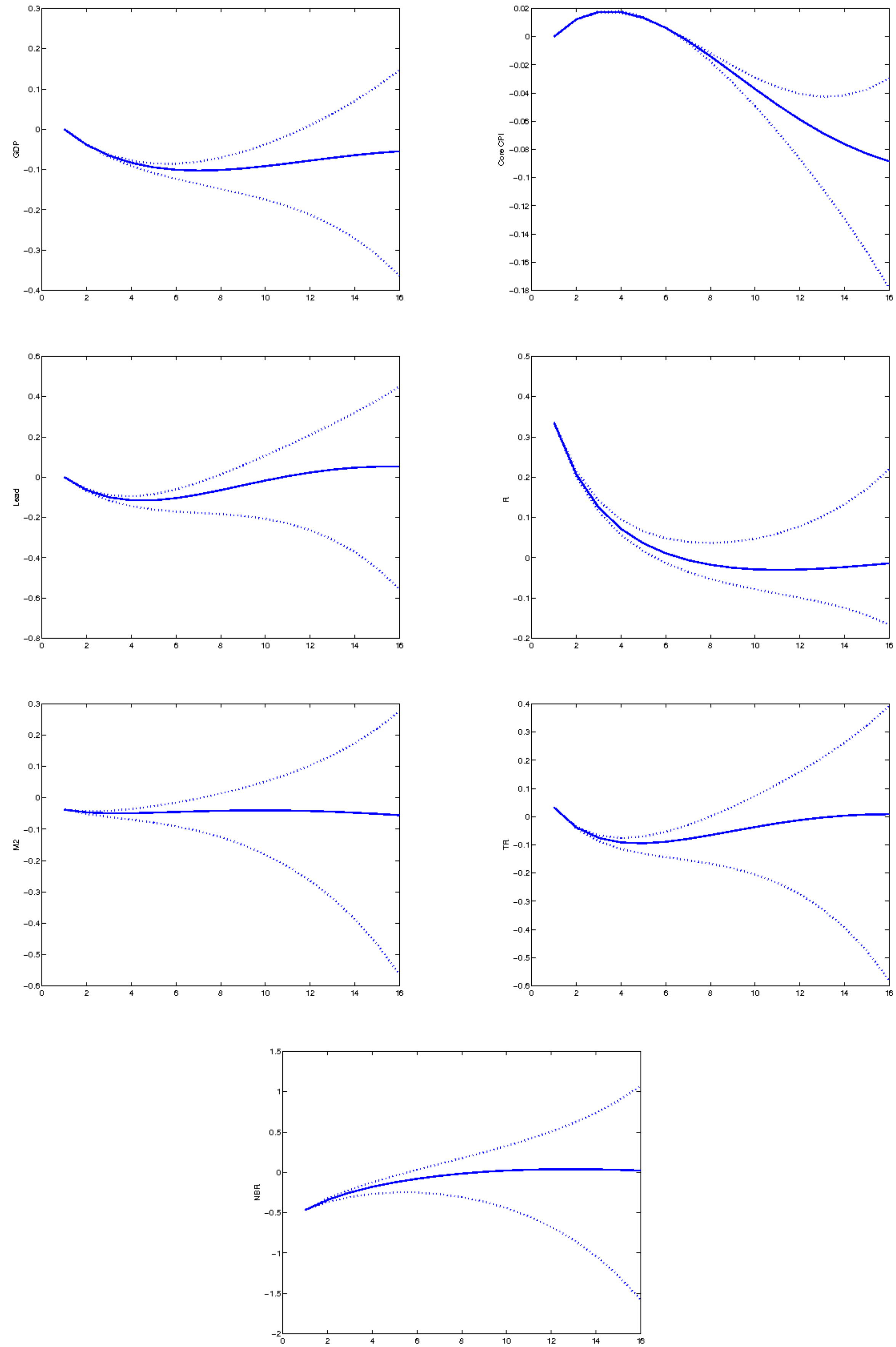

Figure 3: Impulse response functions - VAR(1) - city level employment

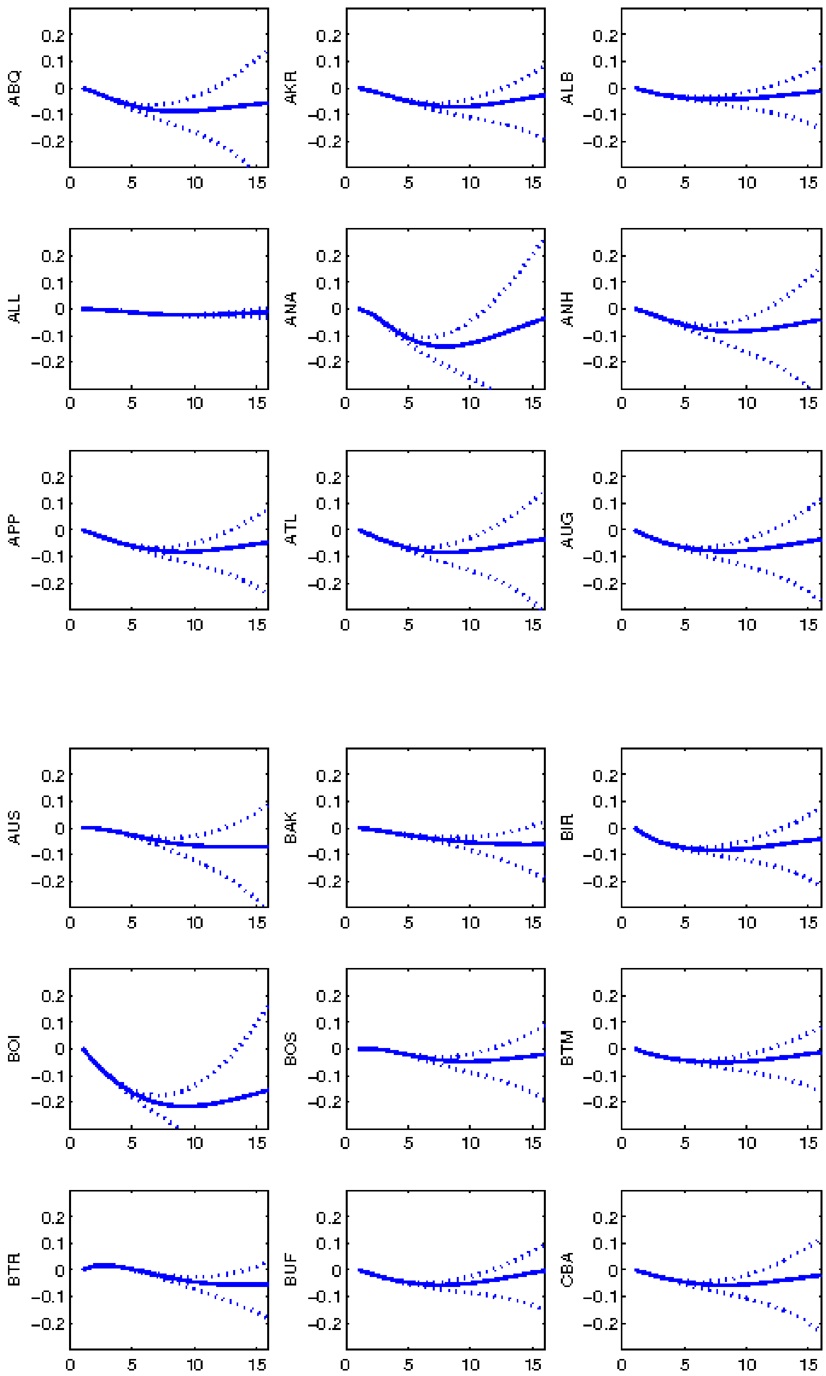

Figure 4: Impulse response functions - VAR(1) - city level employment (cont.)

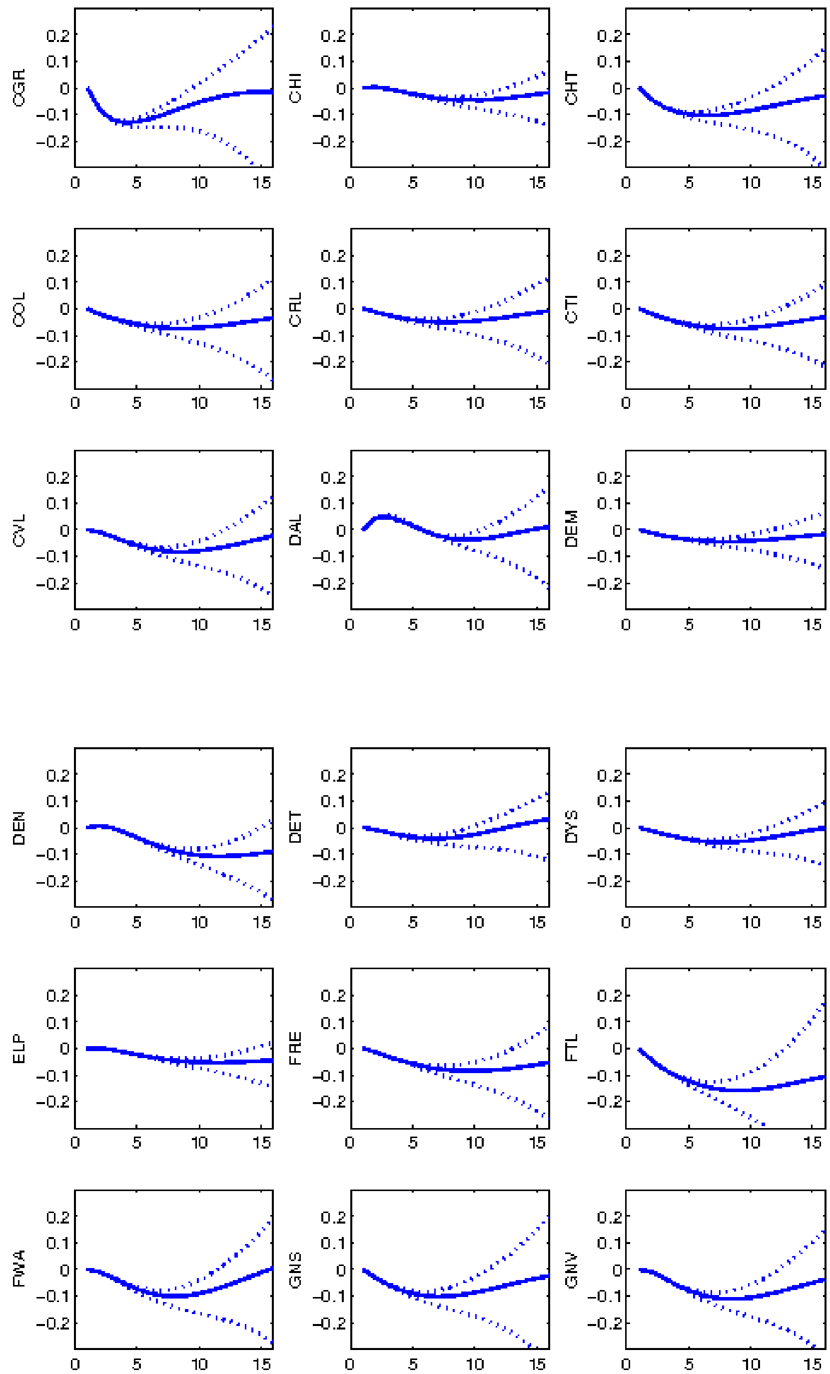

Figure 5: Impulse response functions - VAR(1) - city level employment (cont.)

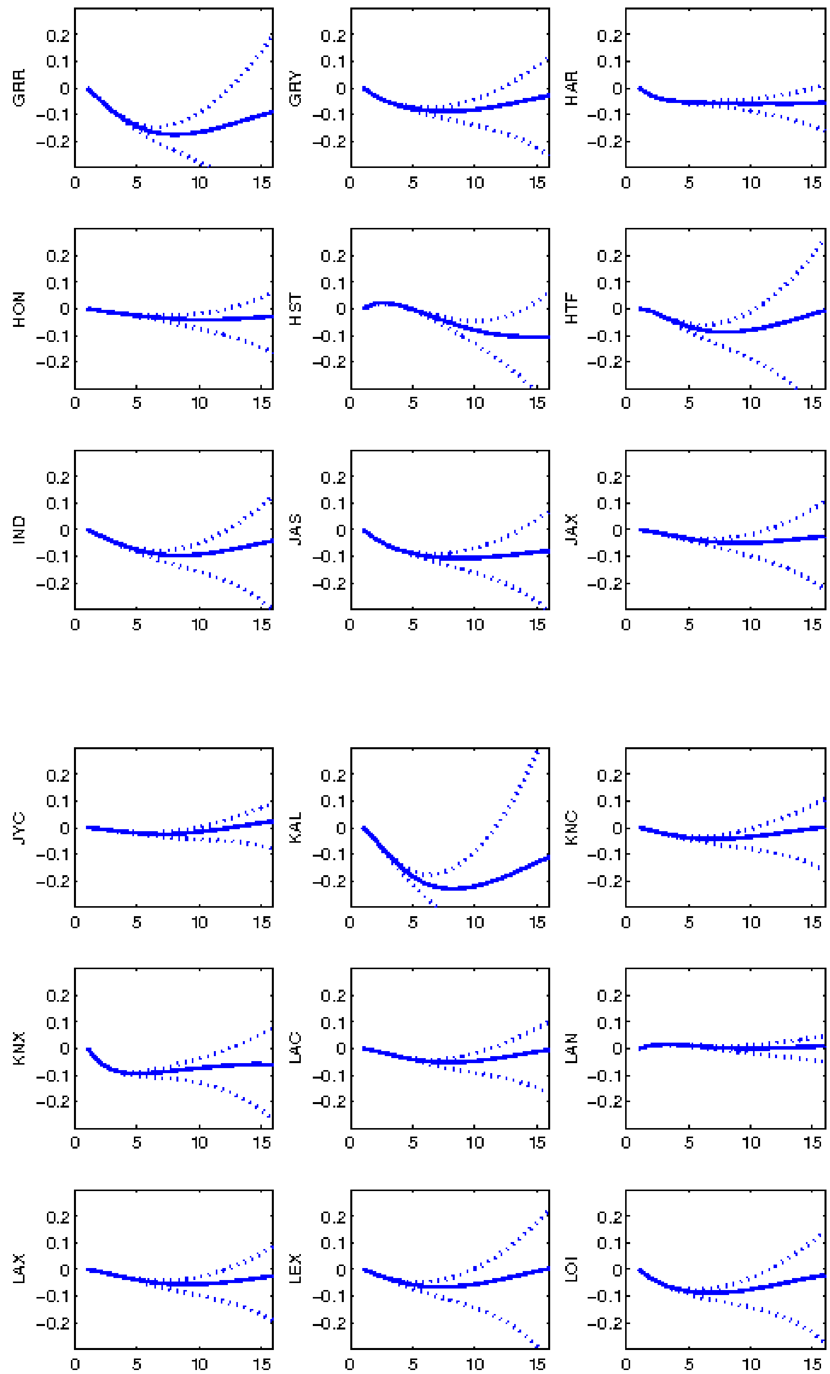

Figure 6: Impulse response functions - VAR(1) - city level employment (cont.)

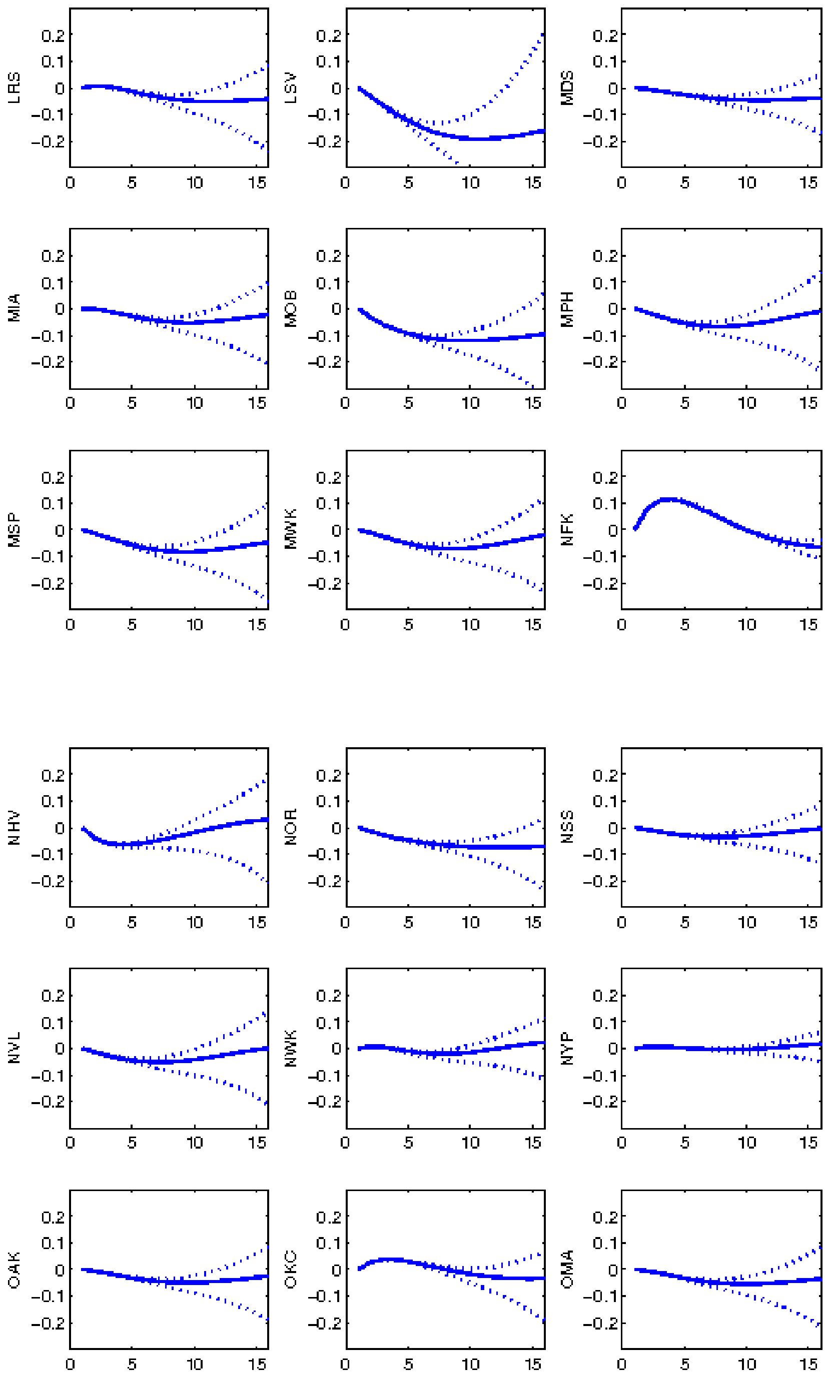

Figure 7: Impulse response functions - VAR(1) - city level employment (cont.)

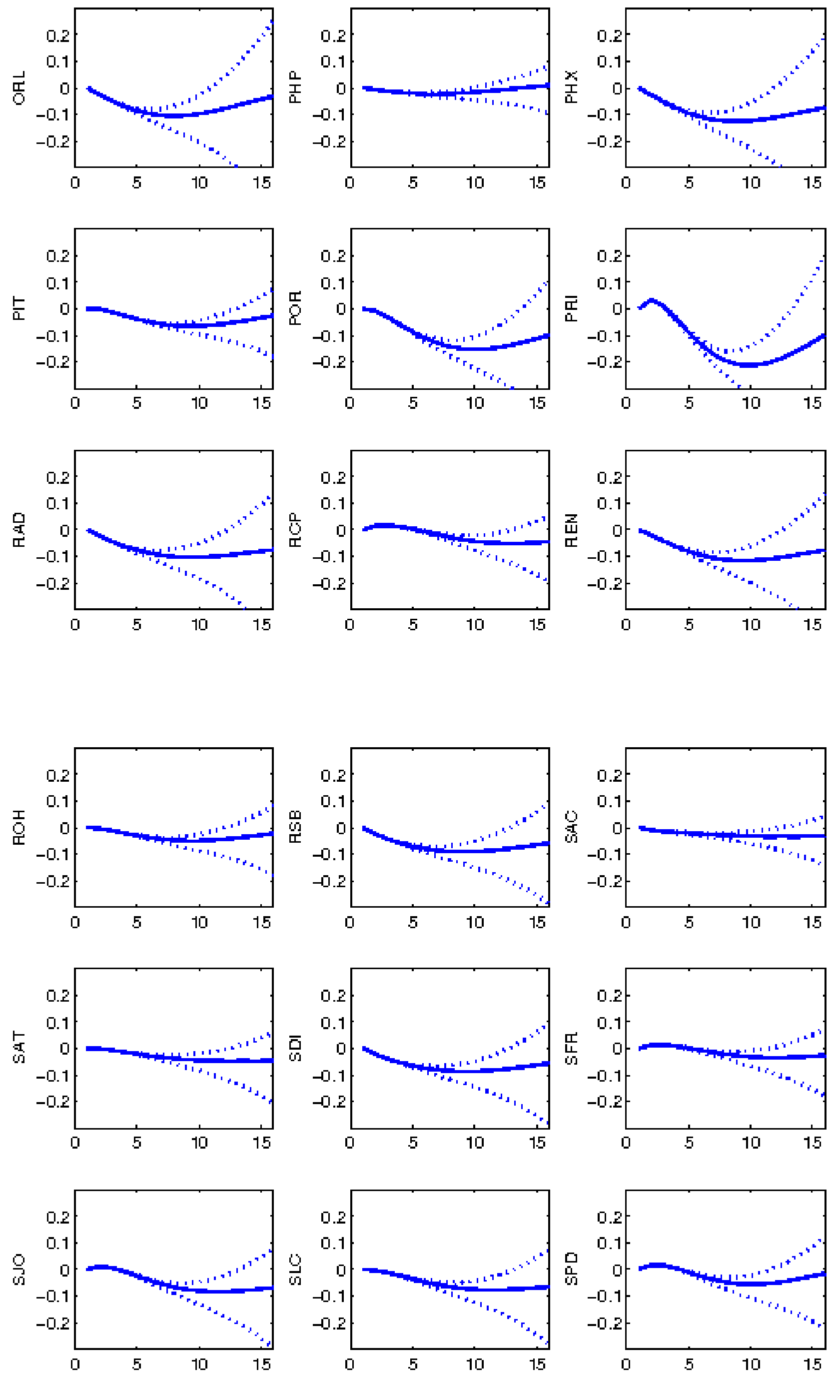

Figure 8: Impulse response functions - VAR(1) - city level employment (cont.)