Great Recession and Monetary Policy Transmission*

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Abstract

This paper studies the existence of changes in the transmission mechanism of monetary policy on 110 US monthly macroeconomics variables during the Great Recession. Impulse Response Functions for this large dataset are estimated for different states of the economy. I combine three different techniques to deal with the dimensionality problems which emerge from an estimation procedure of this magnitude: (i) factor decomposition, (ii) an identification strategy independent of the number of variables included in the dataset and (iii) a blockwise optimization algorithm for the correct selection of the Bayesian priors. Results show the presence of structural breaks in the forces driving the economy as well as qualitative differences in the reaction of all the variables to monetary policy decisions depending on these changes.

JEL classification: C55, E32, E43, E52.

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1 Introduction

In the last years, since the beginning of the Great Recession in 2008, the Federal Reserve has implemented a set of policy measures in order to stimulate the growth of the US economy. Official interest rates are currently at their lower bound and they will be eventually raised by policymakers. On the other hand, the twenty years previous to the collapse of the financial system were characterized by long expansions, two brief recessions, moderate interest rates and the lowest volatility since the middle of the 20th century. After the magnitude and impact of the financial crisis in 2008, macroeconomic transmission mechanisms may have been affected. Therefore, monetary policy decisions entail doubts about the size, effectiveness and duration of the consequences of ending the monetary stimulus on macroeconomic variables. The response of real economy could be similar to the observed in the period previous to the Great Recession, or, on the contrary, it may overreact after this stage of great volatility.

This paper tries to solve this issue identifying structural changes in the US economy during the Great Recession based on the dynamics of a large dataset of 110 monthly macroeconomics series during the last forty years. I find distinguishable reactions to monetary policy shocks in the different structural phases detected for all the variables included in the dataset.

Conventionally, monetary policy analysis has been carried out by imposing plausible restrictions in Vector Autoregressive (VAR) innovations for the identification of the structural shock of interest. Thus, it is assumed that the innovations of the VAR span the space of the structural shocks. However, if there is a variable containing information related with the structural shock which is not included in the model its innovations will be biased due to the omission of this relevant variable. Given that the number of parameters estimated in a VAR increases as the square of the number of time series included in the model, this approach is not able to deal with large amounts of information and, consequently, the omission of relevant information becomes a plausible problem. In fact, this technical limitation has been argued as explanation for some of the results provided by the structural VAR literature which are not concealable with economic theory: raises of prices as consequence of a contractionary monetary shock, known as the Price Puzzle (Sims, 1992) and monetary policy changes which only affect exchanges rates with a considerable delay instead of contemporaneously, the Delayed Overshooting Puzzle (Eichenbaum and Evans, 1995).

More recently, factor decomposition has been included in the structural analysis literature in order to avoid the *dimensionality problems* of VARs and reconcile theoretical predictions with empirical results. Under the assumption that the whole economy is driven by a reduced set of latent forces, large datasets can be summarized in a small number of factors which explain the most of the co-movement in the macroeconomic data. Due to its considerable smaller cross sectional dimension with respect to the observed data, factors can be included in economic analysis allowing for parsimonious specifications. The advantages of this approach at macroeconomic forecasting with respect to other models have been widely shown[1].

Bernanke, Boivin and Eliasz (2005) use this technique to combine a set of factors with federal funds rate in a VAR for the identification of monetary policy shocks. The inclusion of higher level of information in this model, known as Factor Augmented VAR (FAVAR), solves the Price Puzzle predicting reasonable responses in prices to monetary shocks. Moreover, this approach allows the estimation of the responses to monetary shocks in the large set of variables used for the estimation of the latent factors. Under its identification scheme, factors are computed as linear combination of "slow moving variables", those which are largely predetermined as of the current period, are assumed to be non-affected by federal funds rate. Therefore, the number of identification restrictions depends on the number of factors obtained from the data. Thus, a *second dimensionality problem* arises here. If the researcher choses a large number of underlying factors to closely mirror the observable dataset, the number of necessary restrictions will be larger as well. Given that the factors are statistical tools with no clear economic interpretation, it is difficult to find reasonable criteria to impose identification restrictions describing the relationship between federal funds rate and a relatively large set of estimated factors.

Gambetti and Forni (2010) overcome this limitation by using a Dynamic Factor Model (DFM) approach for structural analysis. These models are based on two sets of equations. A first group describing the contemporaneous relationship between observed data and the static factors, as those estimated in the FAVAR, and a second set of equations specifying the dynamic of the static factors which are driven by the dynamic factors. Given that the number of dynamic factors can be lower than the total of static factors, the quantity of static factors representing the dataset can grows without affects the amount of necessary iden-

[1] See Stock and Watson (2002, 2002b), Giannone, Reichlin and Small (2008) or Rünstler et al (2009) for particular examples.

tification restrictions imposed on the number of dynamic factors[2]. Moreover, under the identification strategy of Gambetti and Forni (2010), restrictions are not imposed in the Impulse Response Functions (IRF) of the factors, which are posteriorly linked with the observable data. Instead, restrictions are directly applied into the IRF of the observed variables to the dynamic shocks. This allows us to estimate the factors for the whole dataset with no need of distinguish between slow and fast moving variables and, consequently, none of the available information is discarded. This framework provides reasonable IRF where Price Puzzle and Delayed Overshooting Puzzle disappear.

Despite the advantages of factor decomposition for structural analysis, previous literature assumes structural stability along time in the relation of the factors with the observed data and in the parameters of the factor´s dynamic. However, this paper shows the existence of instability in a factor model applied to the US economy including data corresponding to the Great Recession.

Banerjee, Marcellino, and Masten (2008) perform a Monte Carlo experiment to explore the consequences of changes in the model parameters on the forecast performance of the factors. They find that the effects of instability in the factors loadings fade away as long as temporal and cross sectional dimensions of the panel is large while, on the other hand, discrete changes in the law of motion of the factors may affect the forecast properties of the models. Stock and Watson (2009) study the effects of structural instability in the US between 1959 and 2006 using subsamples corresponding with Great Moderation period (McConnell and Perez Quiros, 2000). Their conclusions are consistent with those provided by Banerjee, Marcellino and Masten (2008): despite the presence of some instability in the factors loadings, most accurate results are based on factors estimated with the full sample in combination with forecast equation for each subsample. As they point out, this striking result may be due to the presence of instability in law of motion of the factors although "additional analysis is required to confirm this conjecture".

This paper takes these findings as starting point and introduces this conjecture into a structural analysis context by assuming that *i)* the behavior of the whole economy can be explained as a stable function of unobservable forces, the factors, and *ii)* the interaction between those forces evolves differently over time. The study of this particular case of instability, within other considered in Stock

[2]Bernanke, Boivin and Eliasz (2005) estimate 3 or 5 static factors from a dataset of 120 variables while Gambetti and Forni (2010) compute 16 static factors to summarize the behavior of a version of the same dataset containing 112 variables.

and Watson (2009), presents two important advantages. First, it permits the existence of several breaks during large periods of time instead of just one. And second, it allows the identification of structural breaks in real time without using ex-post information to assume when these changes take place. This feature is included into the econometric framework using a model where the dynamic of the factors is governed by a Markov Switching (MS) process. Accordingly with this specification, and contrary to previous linear models, relations in the economy change as a function of a latent variable which captures regime shifts across time.

It is important to notice that a *third dimensionality issue* appears here. Given that the dynamic of the factors differs from one regime to another, the number of parameters to be estimated increases proportionally with the number of regimes. In order to deal with such a problem, this paper follows the estimation strategy proposed by Sims, Waggoner and Zha (2008) for large multiple equation MS models. Traditional maximum likelihood estimation procedures are not reliable for sets of parameters too large with respect to the sample size. To overcome this limitation, they suggest a computationally tractable procedure based on Gibbs sampling where prior Bayesian information is included for the estimation of the posterior distribution of the parameters. Due to the complexity of large multivariate MS models, the posterior distribution presents non Gaussian shapes. For this reason, it becomes crucial to choose starting values for the Gibbs sampler close to the most likely scenario in order to avoid series of posterior draws getting stuck in a low probability region. This is done by implementing a blockwise optimization algorithm for the selection of the starting values. The whole set of parameters to be estimated is partitioned into several blocks. Then, a routine for maximization of the posterior distribution is applied to one of these blocks while keeping the value of the other blocks fixed. This step is iterated from one block to the next until convergence is achieved. This method increases likelihood more efficiently than the application of an optimization routine to whole set of parameters when it is considerably large.

I update the dataset generally used in the literature for the estimation of the factor of the US economy by including the period corresponding to the Great Recession. Results show how the inclusion of this data yields important changes in the amplitude of the linear IRF (with no regimes changes) in all the variables with respect to those estimated with data previous to 2008. Once the MS model is introduced into the empirical analysis two different regimes are identified. IRF belonging to a state characterized by low volatility and expansion periods are very similar to those computed linearly with data previous to the Great Recession. However, the shape and magnitude of the IRF linearly computed with the dataset until 2014 are clearly distorted by the form IRF corresponding to a second state corresponding to periods of high volatility and recessions. These facts stress the important effect of the data corresponding with the last years in the results and the necessity of an identification of separated monetary transmission mechanism taking into account the presence of structural instability.

The rest of the paper is organized as follows. Next section describes the model. Section 3 contains the empirical analysis including data description, estimation process and results. Section 4 concludes.

2 Model and Identification

Consider x_{it} as a macroeconomic series expressed on a monthly basis where $i = 1, \ldots, n$. These n series composing the whole economy may be expressed as a function of a set of r latent variable $f_t^1, \ldots, f_t^r$, the static factors, and an idiosyncratic component ε_{it} only associated with x_{it} or with a set of variables belonging to the same macroeconomic category:

$$x_{it} = \lambda_i^1 f_t^1 + \ldots + \lambda_i^r f_t^r + \varepsilon_{it} \tag{1}$$

Given that the static factors affects the n series, equation (1) is rewritten as

$$X_t = \Lambda F_t + \xi_t \tag{2}$$

where $X_t = x_{1t}, ..., x_{nt}$, $F_t = f_t^1, \ldots, f_t^r$, with $1 \leq r << n$, and $\Lambda_i = \lambda_i^1, ..., \lambda_i^r$.

The law of motion of the static factors, which are only contemporaneously related with the observable series, follows a different autoregressive process across time depending of the value of an unoservable Markov chain state variable $s_t = 1, .., h$. Thus,

$$F_t = A_{1s_t} F_{t-1} + A_{2s_t} F_{t-2} + ... + A_{ps_t} F_{t-p} + \eta_t \tag{3}$$

Finally, the η_t innovations of equation (3) are driven by the set of q dynamics factors u_t loaded by the full rank $r \times q$ matrix B_{s_t} which also depends on the state variable

$$\eta_t = B_{s_t} u_t \tag{4}$$

The number of the static factors, r, is bigger or equal than the number of dynamics factors, q, because F_t consits of current and lagged values of the of the dynamic factors u_t. This is known as the static representation of the DFM[3].

Thus, x_{it} is a function of the dynamic factors and its corresponding idyosincratic component:

$$x_{it} = \Lambda_i (I - A_{1s_t} L - A_{2s_t} L^2 - ... - A_{ps_t} L^p) B_{s_t} u_t + \varepsilon_{it} \tag{5}$$

Notice that, accordingly with equation (5), any variable of interest to the researcher within the large set of available information for a particular economy, eventually depends on a reduced set of q dynamic factors for a given state of the economy. Let us consider the dynamic factors as structural shocks and $\Lambda_i (I - A_{1s_t} L - A_{2s_t} L^2 - ... - A_{ps_t} L^p) B_{s_t}$ as the IRF which measure the reaction of a given variable x_{it} to a marginal change in u_t. Based on this representation of the dynamic of the economy, Gambetti and Forni (2010) define a useful strategy for the identification of the monetary shocks equivalent to those applied in structural VAR literature. Structural shocks in equation (5) are unidentified since they do not meet any requirement based economic theory. However, let us suppose that economic theory supports a set of restrictions in the contemporaneous or short term responses of a reduced set of variables to monetary structural shocks and that these timing restrictions can be summarized into an orthogonal matrix H. In that case, identified structural shocks are found by premultipliying u_t by H and its corresponding IRF are identified postmultiplying them by H'. If the number of variables supporting theory restrictions coincides with the number of dynamic factors, H may be found under a standard triangularization scheme. As highlighted by Gambetti and Forni (2010), the number of identification restrictions can be larger than the number of dynamic shocks. However, this paper follows exactly their identification procedure to help comparison of the results.

[3] See Bai and Ng (2007) for further description.

3 Empirics

3.1 Data

Empirical applications of DFM for the U.S. economy are generally based on similar versions of the dataset used by Stock & Watson (1999). Remarkable examples are, Bernanke, Boivin and Eliasz (2005), Boivin and Ng (2006) or Stock & Watson (2012) among others. For the comparability of the findings with previous results, this dataset is also used here. To be precise, the dataset consists in 110 monthly US series which may be classified into the following categories: real output and income, employment and hours, housing starts and sales, inventories and orders, money and credit, interest rates, exchange rates, price indexes and stock prices. This panel exactly corresponds with the version of the Stock & Watson (1999) dataset used by Gambetti and Forni (2010)[4]. The sample starts in April of 1973 in order to avoid the fixed exchange rate and is updated to November of 2013 to include data corresponding with The Great Recession. Data transformation is carried out in line with previous FAVAR and structural DFM literature.

3.2 Estimation under Structural Instability

As mentioned in the previous section, static factors are not observable by the researcher. However, given that macroeconomic data are very collinear, Principal Component Analysis (PCA) may be applied for the estimation of a reduced set of latent series capturing the bulk of their co-movements. Let be X the $t \times n$ matrix of data, static factors are computed by post multiplying X by a $n \times r$ matrix Λ, containing in its columns the r eigenvectors associated with the r biggest eigenvalues of variance covariance matrix of X. This gives us a summary of the original data in terms of the amount of eigenvectors chosen by the researcher. Obviously, the bigger the number of eigenvectors the lower the loss of information caused by this reduction dimension technique. I apply the criteria proposed by Bai and Ng (2002) for the selection of the optimal number of static factors, r. These criteria, generally used in the factors model literature, are also implemented in Gambetti and Forni (2010). In particular, they chose IC_{p2} criterion within the group of specifications proposed by Bai and Ng (2002)

[4] The Index of Help-Wanted Advertising in Newspaper and its ratio with respect to employment were skipped because more recently they provide poor information about labor market conditions .

which points out 16 as the optimal amount of factors. Nevertheless, once their sample set is updated including data corresponding with the Great Recession, all the six versions of IC and PC suggest a value of r equal to 25.

Due to the properties PCA dimension reduction technique, the relation between the latent factors and the observed data is assumed to be linear and stable along the analyzed period. Accordingly with Banerjee, Marcellino, and Masten (2008) and Stock and Watson (2009), the static factors can be correctly estimated by PCA even under structural instability as long as the temporal and cross sectional dimensions of the panel are large. The results of Banerjee, Marcellino, and Masten (2008) are based on Monte Carlo simulations for datasets of 50 series and 150 observations which are considerably smaller than the dataset used here. Alternatively, Stock and Watson (2009) estimate a set of factors using a whole panel US data between 1959 and 2006 and compare them with two sets of factors based on data before and after 1984 in order to capture the structural changes which take place during the Great Moderation[5]. They find that full sample estimations of the factors span the space of the subsamples factors by comparing their correlations. Accordingly with their results, the number of factors summarizing the full sample containing structural shifts was larger than the amount of factors mirroring the co-movements in the subsamples with more stable patterns. This explains why the number of factors selected by Bai and Ng (2002) criteria applied to the dataset of Gambetti and Forni (2010) is bigger once the dataset contains the Great Recession.

Moreover, in order to identify the main sources of instability in the model, Stock and Watson (2009) apply the Chow test to the regression of the observable variables on full sample estimated factors for the pre and post 1984 periods. The same test is applied to four periods ahead direct forecast equation where the parameters estimated also contains the dynamic of the factor[6]. Surprisingly, they find more evidences of instability in the forecast equation than in the factor loadings equations. Moreover, most accurate results are provided by full sample factors in combination with forecast parameter estimated from split samples. This suggests that the structural instability comes from the dynamic of the factors although, as they highlight, this hypothesis requires a further assessment.

This paper explores this scenario. In order to mirror structural breaks in the transition of the forces driven the economy, it is assumed that the dynamic

[5] See Kim and Nelson (1999), McConnell and Perez Quiros (2000).

[6] See stock and Watson (2009), page 5 for details.

of the factors follows a MS process. This specification presents two advantages with respect to the analysis of Stock and Watson (2009). First, accordingly with the MS specification, the dynamic of the factors depends on an unobservable state variable estimated following standard procedures described below. Thus, structural breaks may be identified based on the currently available data and no ex-post information is required. And second, instead of consider a single break, the state variable evolves along the temporal dimension of the dataset allowing for multiple breaks.

The vector containing the state dependent autoregressive parameters and error variance covariance matrices of equation (3), θ,is computed based on the PCA estimation of the static factors. Notice that, as previously mentioned, these parameters depend on a state variable, s_t, which mirrors changes in the macroeconomics patterns along time. Due to the uncertainty about when these changes take place, s_t is estimated. For this purpose, it is assumed that s_t follows a first order Markov switching process characterized by the probabilities of transition from one regime to another represented by a $h \times h$ Q matrix where h is the number of regimes that may be taken by s_t. Given the big amount of parameters that characterize a multivariate MS model, MLE may produce unreliable results for a relatively small sample size. Instead, estimation is carried out following the procedure proposed by Sims, Waggoner and Zha (2008) for large multivariate MS models based on Bayesian methods. The joint posterior density of θ, $S_T = (s_1, s_2 \ldots, s_T)$ and Q is complicated and, even if it is known, its integration to obtain the marginal distribution of the parameters may be unfeasible. Alternatively, Gibbs sampler is used to calculate the moments of the marginal posterior distributions by sampling iteratively from the conditional posterior distributions:

$$i) \quad p(S_T \mid F_T, \theta, Q)$$

$$ii) \quad p(Q \mid F_T, S_T, \theta)$$

$$iii) \quad p(\theta \mid F_T, S_T, Q)$$

$i)$Under the assumption that s_t follows a first order Markov chain process, it can be shown that[7]:

[7]See Kim and Nelson (1999b) equation 9.14 for details.

$$p(S_T \mid F_T, \theta, Q) = p(s_T \mid F_T, \theta, Q) \prod_{t=1}^{T-1} p(s_t \mid F_t, \theta, Q, s_{t+1})$$

where S_T may be drawn recursively for $t = T-1, T-2, \ldots, 1$. Inititally, for a given initial value of the other MS parameters, Hamilton´s filter is applied forward to estimate $p(s_T \mid F_T, \theta, Q)$. Then $p(s_t \mid F_t, \theta, Q, s_{t+1})$ is generated based on

$$p(s_t \mid F_t, \theta, Q, s_{t+1}) = \frac{p(s_t, s_{t+1} \mid F_t, \theta, Q)}{p(s_{t+1} \mid F_t, \theta, Q)}$$

$$= \frac{p(s_{t+1} \mid s_t, F_t, \theta, Q) p(s_t \mid F_t, \theta, Q)}{p(s_{t+1} \mid F_t, \theta, Q)}$$

$$= \frac{q_{s_{t+1}, s_t} p(s_t \mid F_t, \theta, Q)}{p(s_{t+1} \mid F_t, \theta, Q)}$$

where $q_{s_{t+1}, s_t}$is a transition probability in Q from s_t to s_{t+1}.

ii) Conditional on the others parameters, the transition probability matrix Q is generated from a Dirichlet distribution $D(\alpha_{i,j})$ where $1 \leqslant i, j \leqslant h$. $\alpha_{i,j}$, the hyperparameters which specified the form of the prior distribution, are chosen in order to mirror the duration of the NBER recessions and expansions. Precisely, the expected probability of staying in the same state is

$$Eq_{j,j} = \frac{\alpha_{j,j}}{\sum\limits_i \alpha_{i,j}} = \frac{\alpha_{j,j}}{\alpha_{j,j} + (h-1)}$$

$\alpha_{i,j}$ is set equal to 1 for every $i \neq j$ and, for the two regimes specification, $\alpha_{i,i}$ is assumed to be equal 58.3 and $\alpha_{j,j}$ to 12.16. In this way, the believes about the duration of the regimes are reflecting the average duration in months of the NBER recessions and expansion between 1973.4 to 2013.11 respectively.

iii)The state dependent autoregressive parameters and error covariances are drawn as in the standard Bayesian VAR literature. A is genareted from the multivariate normal posterior and σ_η from an inverse-Wishart posterior for each regime. Priors are set as in the version of the Minnesota prior defined by Sims and Zha (1998).

However, given the complexity of large multivariate MS models, the posterior distribution can present complicate shape. In order to avoid sequences of posterior draws stuck in a low probability region, a correct selection of the starting values for the Gibbs sampler becomes crucial. For this purpose, the set of coefficients to be estimated is partitioned into several blocks containing intercepts, autoregressive parameters, error covariances and the transition matrix. Then, an optimization procedure is applied iteratively for each of these blocks while holding the others constant until likelihood convergence is achieved. This procedure has been shown to increase likelihood more efficiently than the application of a maximization routine to the total set of parameters.

Finally, inference about the MS parameters is carried out after 10,000 iterations of the posterior sampler started with the initial values provided by the blockwise algorithm. To guarantee convergence, the first 3,000 iterations were discarded.

Once the estimation of the parameters in equation (3) is performed, the $r \times q$ matrix loading the dynamic factors B_{st} is computed by applying again the PCA dimension reduction technique to the regime-dependent covariance matrices of the errors.

The scheme developed by Gambetti and Forni (2010) is reproduced for structural identification. The identification restrictions are based on: industrial production, prices, interest rates and exchanges rates. The set of contemporaneous IRF corresponding with these variables in this order in equation (5) are restricted to be lower triangular by a Cholesky decomposition. Identification is carried out by post multiplying the complete set of IRF in (5) by the quotient of the Cholesky factor over the set of contemporaneous IRF of these four variables. In this way, it is assumed that production and prices do not respond to interest rate changes within the same month and that interest rates do not respond contemporaneously to exchange rates while the reaction to a monetary policy shock for the remaining of variables included in the dataset remains unrestricted. This identification scheme requires a number of dynamic factors equal to the number of variables considered for identification ($q = 4$). Results of next section are based on this specification in order to help its comparability with respect to the findings provided by Gambetti and Forni (2010).

3.3 Results

At first, I assess the necessity of distinguish between macroeconomic reactions to monetary policy shock along time. For this purposes, linear IRF for some representative variables of the different categories of the dataset are computed for a rolling window period. In this exercise IRF to a 0.5% increase in federal funds rate are estimated based on a subsample starting in April 1973 and finishing in January 2005. Then, the next monthly observation is added to the subsample and IRF are computed again. This step is iterated until the last available observation corresponding with November 2013 is included. For the sake of space, the rolling window IRF for the variables used for identification, industrial production, prices, federal funds rate and exchange rates, are depicted in Figure 1. For these four variables, it can be seen how IRF are very similar from one month to the next until the moment in which data corresponding with the Great Recession is included. Starting from this period, IRF´s amplitude jumps. Thereafter, there is a second group of IRF with a relatively stable shape month by month until the end of the sample. This pattern is also present in all the other rolling window IRF not presented here[8].

These preliminary results show the existence of structural instability in the DFM and provide evidences of changes and different magnitudes in the macroeconomic transmission mechanism during the Great Recession. In consequence, I apply the MS specification to identify the periods when these structural breaks take place. Figure 2 presents the smoothed probabilities of a *second* state[9] once the estimation procedure described in the previous section is applied. In order to characterize this state, the probabilities are presented together with the periods classified as recessions by the National Bureau of Economic Research (shaded areas) and business cycle volatility (dotted line) defined as in Blanchard and Simon (2001): the standard deviation of GDP growth over the last 20 quarters which is assumed to be constant along the three months of each quarter to match monthly data. The figure shows how structural changes in the dynamic of the factors take place during recessions and periods of high volatility (as the inter-recessions periods between 1973 and 1983 or after the 2007 recession) with the single exception of the early 1990s recession which occurs during a low volatility period.

For illustrative purposes, state dependent IRF are presented with linear IRF computed with data up to November 2007 and with a second set of linear IRF including the Great Recession data. To save space, not all the 110 IRF are offered in this paper. Instead, a set of variables considered as being representative of the broad categories included in the dataset are depicted in figures 3 to 7. Several conclusions emerge from this comparison:

[8] Results are available upon request.

[9] Results are based on a two state specification. The estimated probabilities for a third state in the dynamic of the factors were negligible.

As previously observed in the rolling window exercise, the growth in the amplitude of the linear IRF, once data posterior to 2007 is added, is a consistent pattern which affects all the linear IRF for all the 110 variables in the dataset. These differences are not minor. The increases in the maximum value in the linear IRF including updated data are around the double of those computed with data previous to the last recession. Industrial Production Index (Figure 1, first row, columns 1 and 2) is a clear example of this fact. The reduction in this index estimated with updated data reaches 2.5% while this quantity was around 0.9% with the pre-Great Recession sample. A second remarkable example can be found in the reaction of people unemployed for more than 15 weeks after the contractionary policy shock. Here, the maximum amount estimated in 2007 is of 150,000 and during the Great Recession raises to more than 500,000 people (Figure 6, third row, columns 1 and 2).

Moreover, 75% of the pre-Great Recession linear IRF are similar in shape and amplitude to those estimated for the *first* state. For instance, see Federal Funds Rate (Figure 3, third row, columns 1 and 3) or Purchasing Manager Index (figure 7, second row, columns 1 and 3) where these two IRF are almost identical.

These facts stress the distortionary effect that the inclusion of the Great Recession data causes in the estimates with respect to those computed with the dataset used in Gambetti and Forni (2010) where the most of the sample corresponds with a stable period. The consequences of the inclusion of more observation corresponding with a high volatility period in the linear IRF may be clearly seen in the Producer Price Index and M1 (Figure 4, first and second rows) or in the Unemployment Rate (Figure 6, last row) where the shape of the linear IRF computed based in the whole sample is evidently conditioned by the IRF of the *second* state.

4 Concluding remarks

This paper shows the existence of changes in the macroeconomic transmission mechanisms during the Great Recession by analyzing the presence of structural instability in a Dynamic Factor Model. Based on previous Monte Carlo simulations and empirical results which support the correct estimation of the factors under instability in their loadings, I examine the presence of breaks in the transition of the factors using estimation procedure for large multivariate Markov

Switching models. This specification provides evidences supporting the presence of two different dynamics on the underlying forces driving the US economy during the last forty years.

The reaction of macroeconomic variables to monetary policy changes is estimated, firstly, without take into consideration the presence of structural instability. These responses present heterogeneous results when are compared with those in which the Great Recession data is included. This fact stresses the existence of instability and introduces uncertainty about the selection of the correct sample to mirror the current economic conditions. The estimation process proposed here allows the identification of these structural breaks and the evaluation of the reaction of a large dataset of variables to monetary policy shocks in each of those different structural situations. The comparison of these responses with those ignoring the presence of instability highlights the important consequences of the inclusion of data presenting heterogeneous macroeconomics patterns in the magnitude of the effects of monetary policy changes. The distinction and identification of these changes are crucial in order to avoid misleading predictions.

Therefore, in the existing situation, with no conclusive signs of economic recovery and doubts about duration and impact of the structural effects of the Great Recession on the macroeconomic patterns, this paper provides an appealing framework in order to helps policy decision about the eventual effects of abandoning the zero lower bound of the official interest rates.

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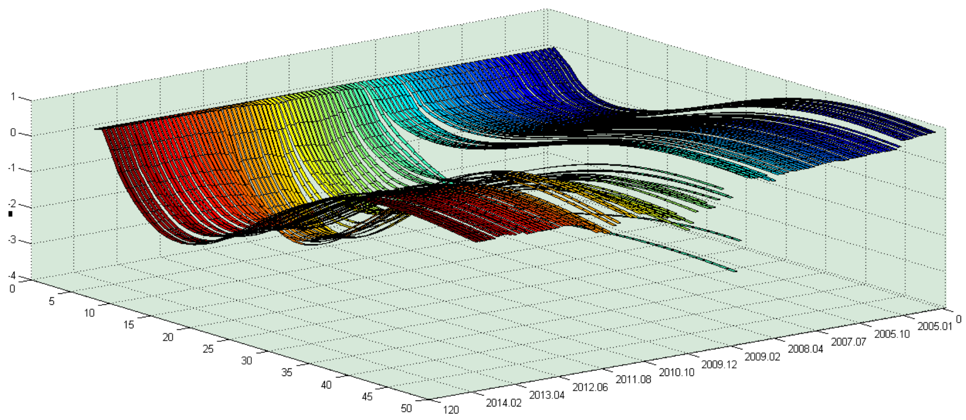

Figure 1.1: 50 months ahead Industrial Production Index rolling window Impulse Response Function from January 2005 to November 2013 for a 50 basis points contractionary monetary policy shock.

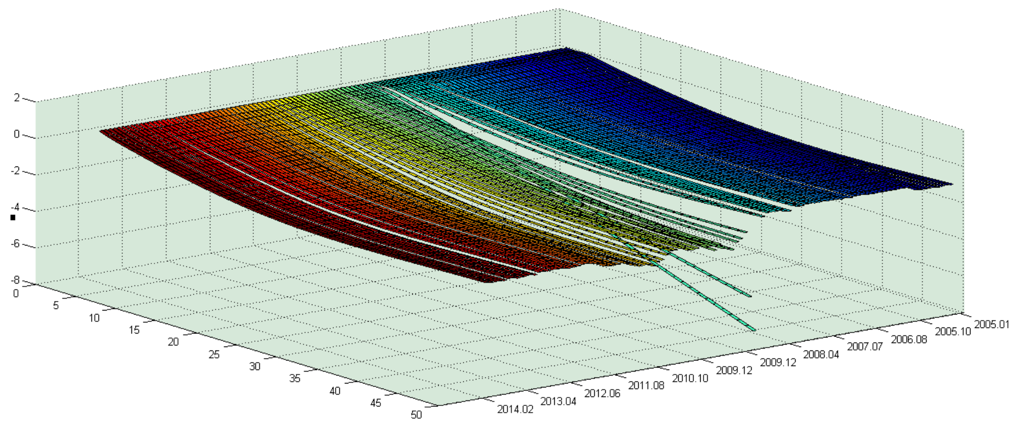

Figure 1.2: 50 months ahead Consumer Price Index rolling window Impulse Response Function from January 2005 to November 2013 for a 50 basis points contractionary monetary policy shock

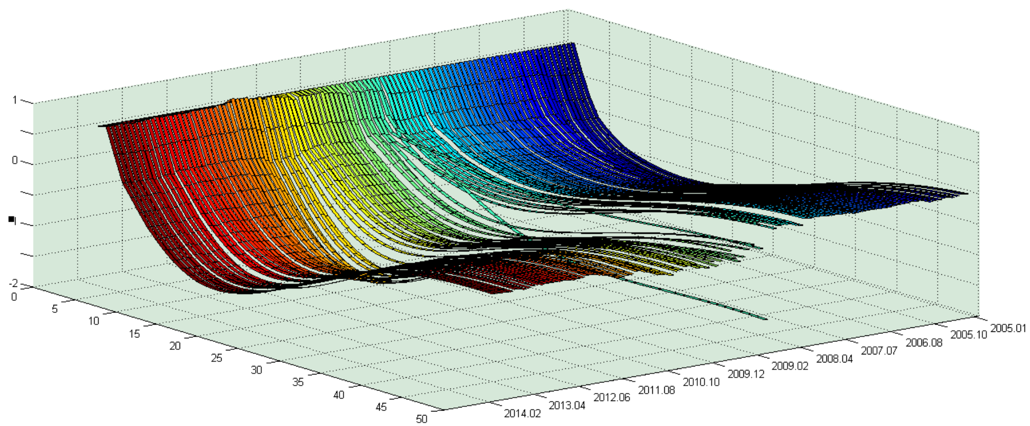

Figure 1.3: 50 months ahead Federal Funds Rates rolling window Impulse Response Function from January 2005 to November 2013 for a 50 basis points contractionary monetary policy shock.

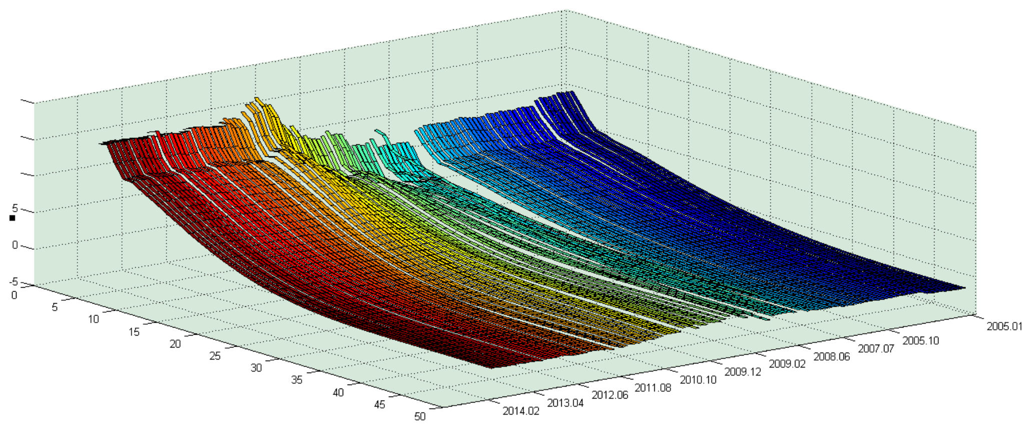

Figure 1.4: 50 months ahead Swiss/US real Exchange Rate rolling window Impulse Response Function from January 2005 to November 2013 for a 50 basis points contractionary monetary policy shock.

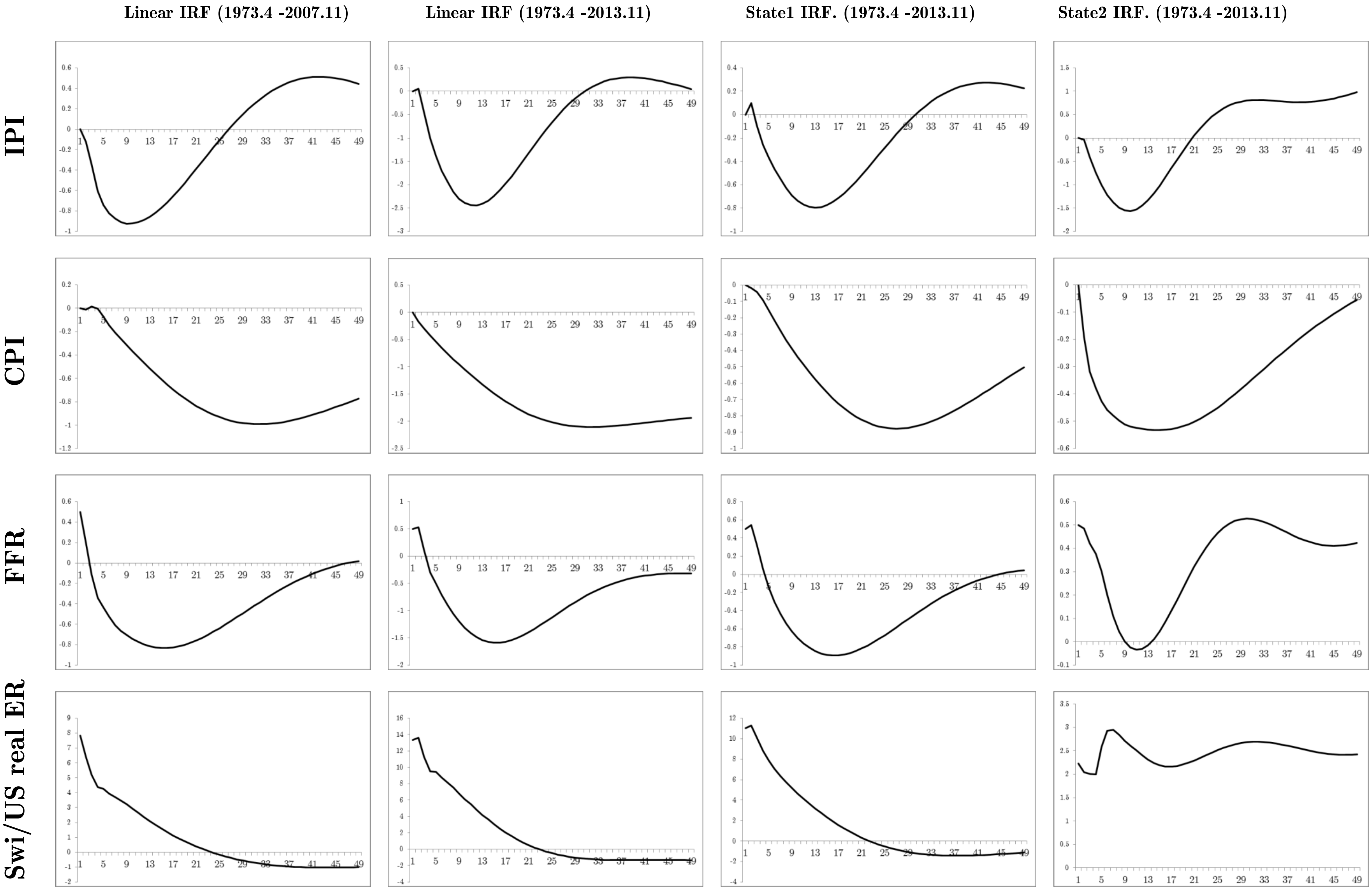

Figure 3. Impulse Response Functions in percentage for identification variables. First column presents linearly IRF for data until November 2007. Second column are linear IRF for the whole sample. Columns three and four are state dependent IRF for the whole sample

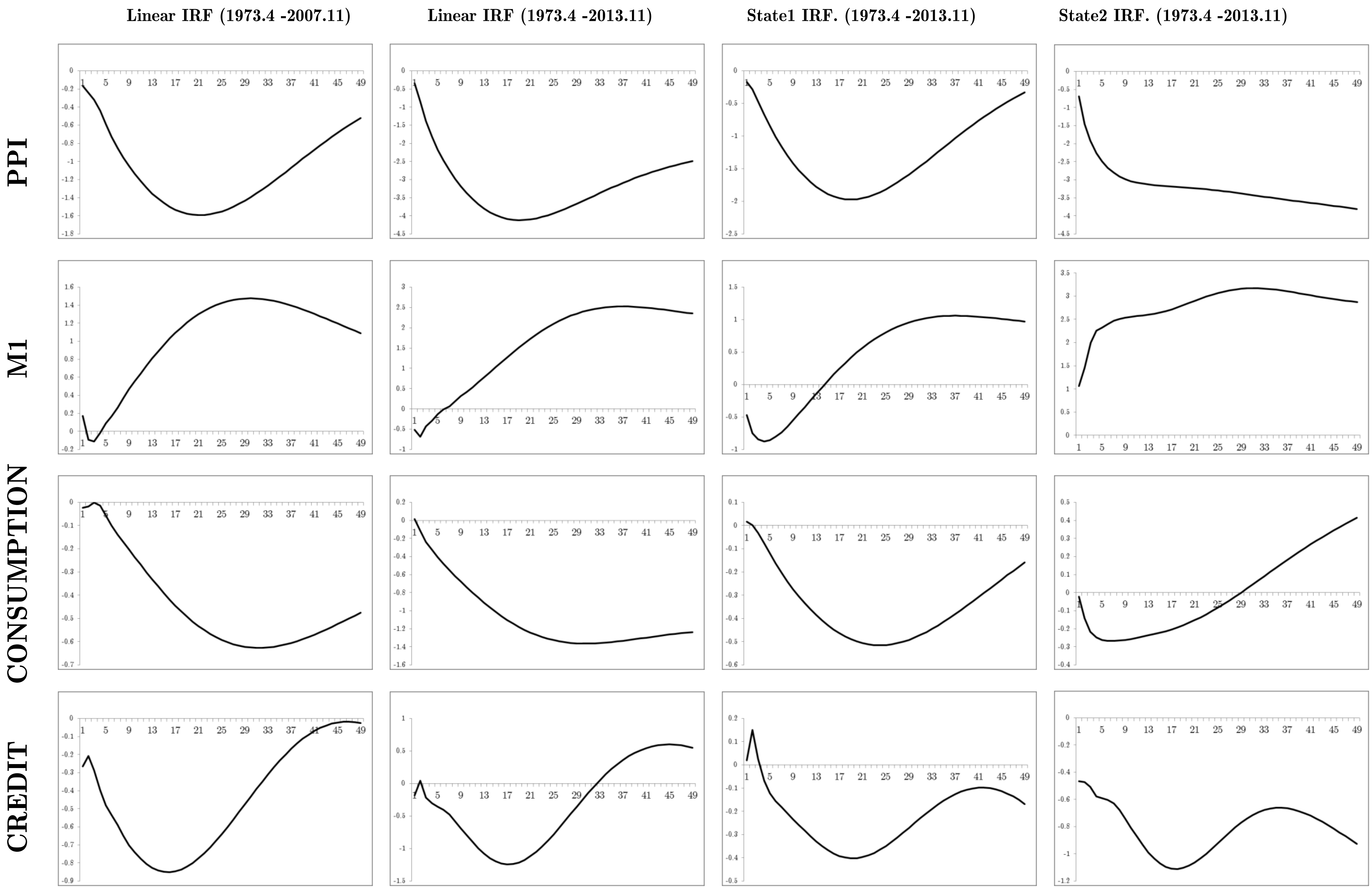

Figure 4. Impulse Response Functions in percentage for Producer Price Index, Money Stock M1, Real Personal Consumption Expenditures and Consumer Credit Outstanding. First column presents linearly IRF for data until November 2007. Second column are linear IRF for the whole sample. Columns three and four are state dependent IRF for the whole sample

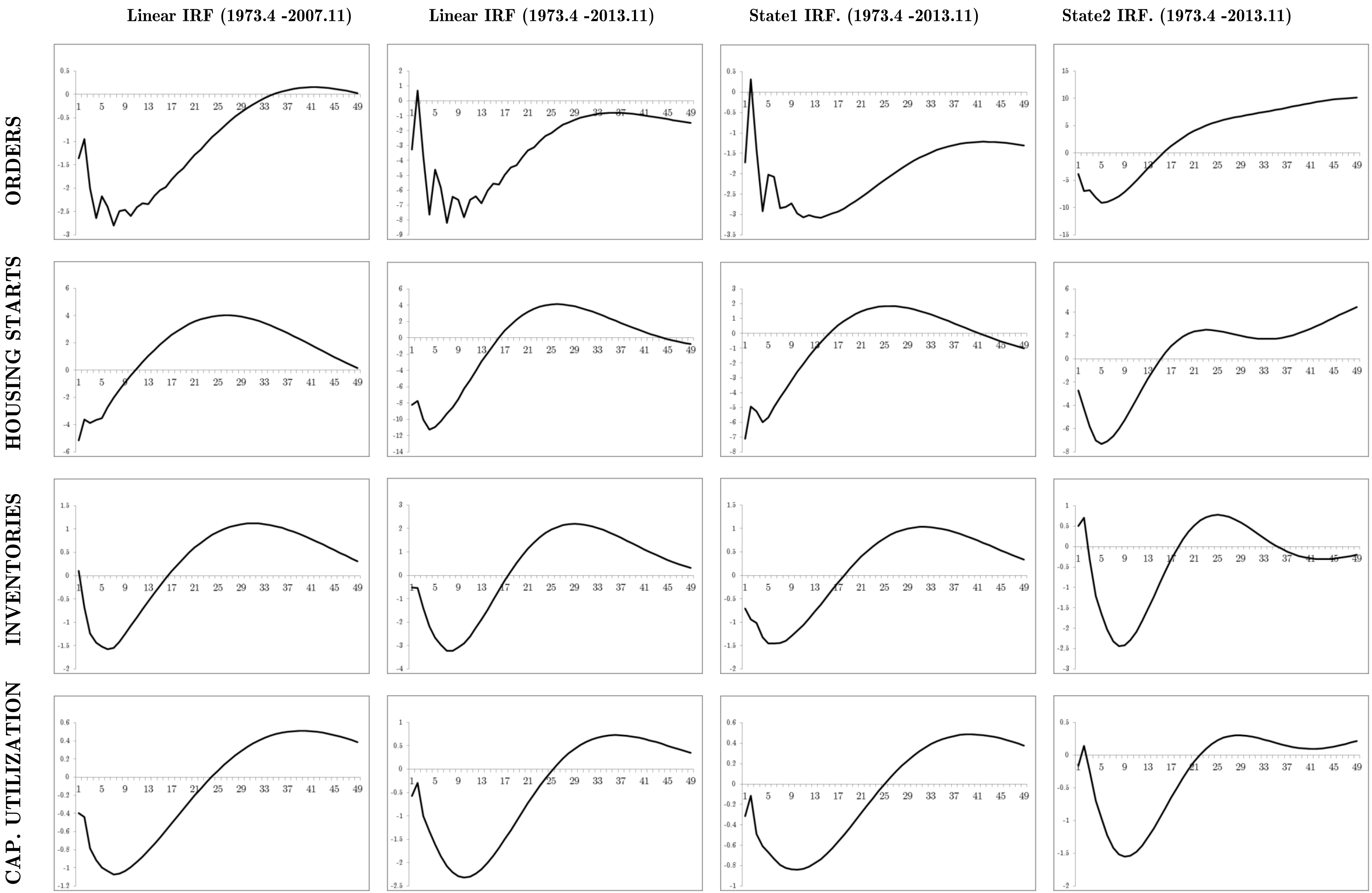

Figure 5. Impulse Response Functions for New Orders: durable goods(%), Nonfarm Housing Starts (%) , NAPM Inventories (index), and Capacity Utilization- Manufacturing(%). First column presents linearly IRF for data until November 2007. Second column are linear IRF for the whole sample. Columns three and four are state dependent IRF for the whole sample.

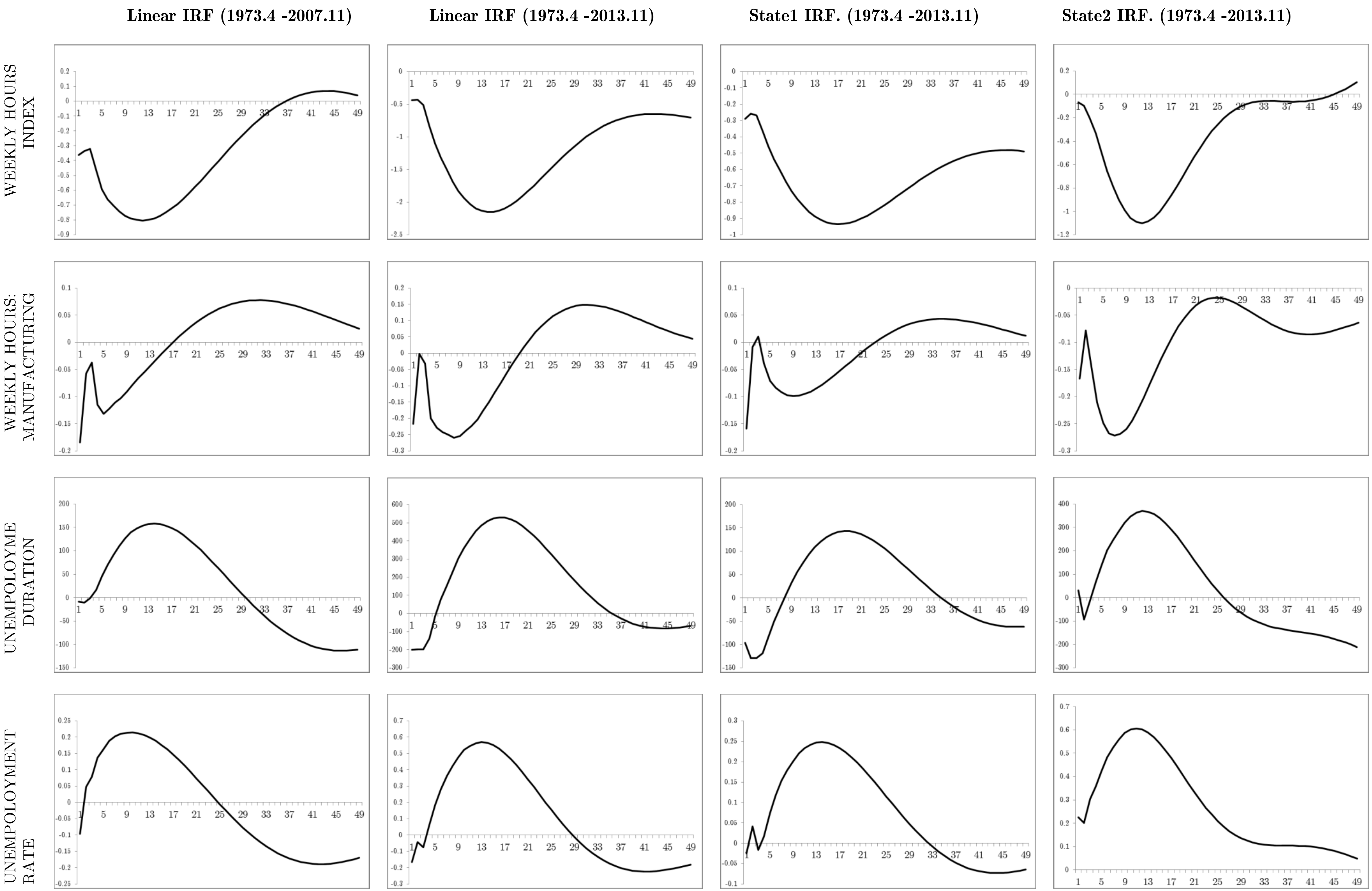

Figure 6. Impulse Response Functions in percentage for Average Weekly Hours Index: Total Private Industries (%), Average Weekly Hours: Manufacturing (hours per week), Unemployment by Duration (thousand people) and Unemployment Rate (%). First column presents linearly IRF for data until November 2007. Second column are linear IRF for the whole sample. Columns three and four are state dependent IRF for the whole sample

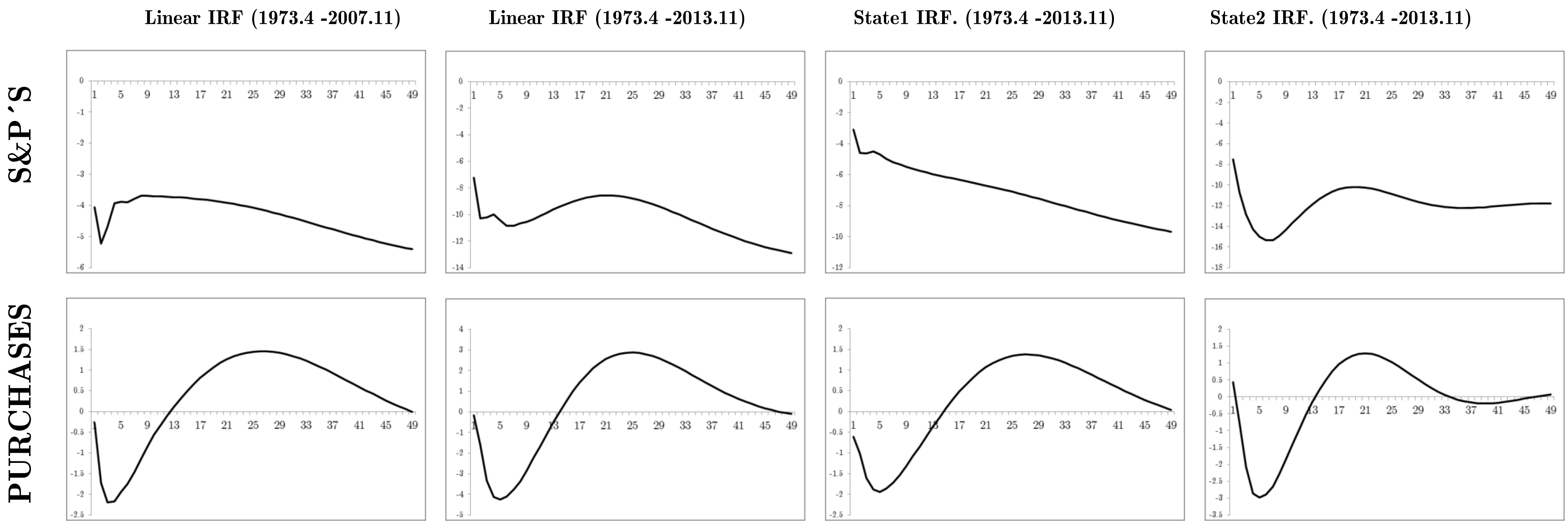

Figure 7. Impulse Response Functions for S&P S Common Stock Price Index (%) and Purchasing Managers Index. First column presents linearly IRF for data until November 2007. Second column are linear IRF for the whole sample. Columns three and four are state dependent IRF for the whole sample

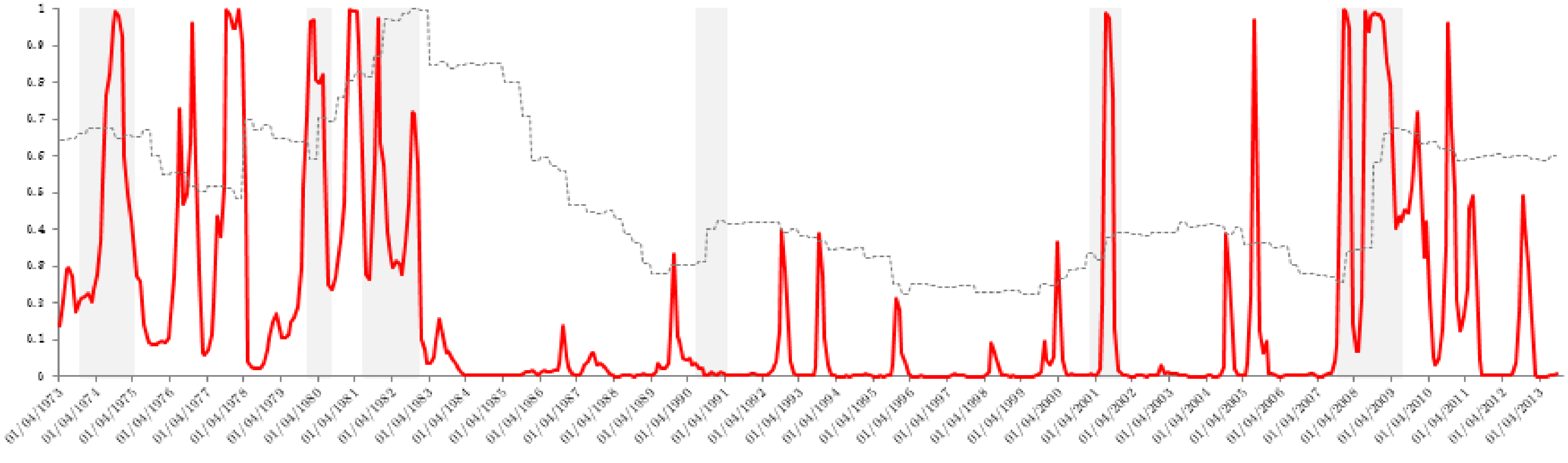

Figure 2. Line: State-2 Smoothed Probabilities. Shaded areas: NBER Recessions. Dotted line: Business Cycle Volatility