The evolution of monetary policy effectiveness under macroeconomic instability

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Abstract

This paper studies the evolution of the monetary policy transmission mechanisms in the US following the Great Recession. The implementation of a modified Dynamic Factor Model enables the identification of two different structural scenarios based on the information contained in a large dataset of 110 variables. Impulse Response Functions to an increase of official interest rate for this large dataset are estimated for each structural context. Three techniques are combined 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 a structural break in 2008 and the higher responsiveness of the economy to monetary policy after that date.

JEL classification: C55, E32, E43, E52. Keywords: Large Dataset, Factor Models, Structural Change, Great Recession, Monetary Policy.

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1 Introduction

The evolution of the US economy has been characterized by large periods of expansion, brief recessions and very low volatility since the middle of the eighties. However, the bankruptcy of Lehman Brothers in 2008 led to the collapse of the financial system, a severe increase in volatility and a dramatic slowdown of the economic activity. Production, employment and prices fell drastically with no similar precedents in recent economic history. In order to alleviate the liquidity shortage of the financial system and to counteract its consequences in the real economy, the Federal Reserve (Fed) implemented exceptional monetary policies, lowering official interest rates to the zero lower bound.

Some years after the bankruptcy of Lehman Brothers, with signs of economic recovery, policymakers must decide about the manner and timing of tightening monetary conditions. After the sudden macroeconomic changes that took place during the Great Recession, it seems reasonable to consider the presence of changes in the effects of the monetary policies and their transmission mechanism. Thus, monetary policy decision making entails new doubts, since the response of real economy to an increase of the official interest rates could be similar to those observed during the period of stability before 2008 or, on the contrary, it may have changed following this period of great volatility and the dramatic effects of the financial crisis in the credit markets.

Thus, the aim of this paper is to evaluate if monetary policy transmission mechanisms have been altered after the Great Recession and, if this is the case, to figure out if the modification in these mechanisms is permanent. To address this issue, we use historical data to identify the presence of changes in the reactions of a large set of 110 macroeconomic indicators to monetary policy during the last forty years in the US. The endogenous identification of these structural changes allows us to provide reliable predictions of the consequences of an increase in the official interest rates, given the structural characteristics of the economic context at a given date. To this end, we propose the combination of several estimation techniques to exploit the information contained in this large data set and to deal with the dimensionality problems inherent to a specification of this magnitude.

Results based on the combination of these methodologies show the presence of two distinguishable structural scenarios over the last forty years and differences in the reactions of macroeconomic indicators to monetary policy shocks in each of them. One state coincides with periods of economic growth and low volatility and the other with periods of recessions and high volatility. State-dependent responses are compared with those linearly estimated, ignoring the presence of different structural scenarios before and after 2008. The inclusion of data corresponding to the Great Recession leads to important changes in the amplitude of the linear responses. The state-dependent responses belonging to the state characterized by low volatility and expansions are very similar to those computed linearly with data previous to 2008. However, the shape and magnitude of the responses linearly computed with a dataset updated until 2016 are distorted by the form of the IRF for the state of high volatility and recessions. These facts suggest that full sample linear estimates may lead to inaccurate results, especially if the economy have recently suffered an episode of high volatility, and they stress the need to identify different monetary policy reactions in the presence of structural breaks.

The rest of the paper is organized as follows. The next section reviews the literature related with this topic making emphasis on the methodologies for the empirical analysis of the monetary policy transmission mechanisms and the situations where the effectiveness of monetary policy may be altered. Section 3 describes the model. Section 4 contains the data description and estimation process. Section 5 includes the results. Finally, section 6 concludes.

2 Literature Review

From a methodological point of view, empirical analysis of the monetary policy transmission mechanism has been conventionally carried out by the estimation of Vector Autoregressive (VAR) models. In this framework, monetary policy shocks have been identified by imposing short run restrictions in the VAR innovations to specify the contemporaneous effect of the monetary policy variable on other macroeconomic indicators[1]. Thus, it is assumed that the innovations in the VAR span the space of the structural shocks. However, if there is a variable containing information related to the structural shock which is not included in the model, the estimations will be biased due to its omission. 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 put forward as an explanation for some of the results provided by the structural VAR literature which are not compatible with economic theory: prices increases as a consequence of a contractionary monetary shock, known as the Price Puzzle (Sims, 1992) and monetary policy changes which only affect exchange rates after a considerable delay instead of contemporaneously, the Delayed Overshooting Puzzle (Eichenbaum and Evans, 1995).

This conflict between empirical results and economic theory has been addressed by exploring alternative identification strategies or adding some other variables in the set of equations of the VAR. Alternatively, factor decomposition has been recently included in the structural analysis literature to solve the *dimensionality problems* of VARs and reconcile theoretical predictions and 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 most of the co-movement in the macroeconomic data. Due to their 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 to macroeconomic forecasting over other

[1] Brandt and Freeman (2009) also estimate a VAR model to identify structural relationships between economic and political variables using Bayesian methods.

models have been widely shown[2].

Bernanke, Boivin and Eliasz (2005) use the above technique to combine a set of factors with federal funds rate (FFR) in a VAR to identify monetary policy shocks. The inclusion of a higher level of information in this model, known as Factor Augmented VAR (FAVAR), solves the Price Puzzle by predicting reasonable responses of 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 their identification scheme, factors are computed as linear combination of "slow moving variables", those which are largely predetermined as of the current period and are assumed to be non-affected by FFR contemporaneously. In addition, 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 chooses a larger 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 FFR and a relatively large set of estimated factors.

Gambetti and Forni (2010) overcome this limitation by using a Dynamic Factor Model (DFM) for structural analysis. This model is based on two sets of equations: one describing the contemporaneous relationship between observed data and the static factors, like those estimated in the FAVAR, and another set of equations specifying the dynamics of the static factors with innovations driven by a smaller group of dynamic factors. In this setting, the number of static factors capturing the behavior of the observed data may grow without affecting the amount of identification restrictions, since they are imposed on the dynamic factors[3]. Moreover, with the identification strategy of Gambetti and Forni

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

[3]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.

(2010), restrictions are not imposed on the Impulse Response Functions (IRF) of the factors, which are posteriorly linked with the observable data, but are directly applied to the IRF of the observed variables to the dynamic shocks. This allows us to estimate the factors for the whole dataset with no need to distinguish between slow and fast moving variables and, consequently, none of the available information is discarded. In addition, this framework provides reasonable IRF where not only the Price Puzzle but also the Delayed Overshooting Puzzle are solved.

Despite the advantages of the implementation of these dimension reduction techniques for structural analysis, these approaches assume an invariant relationship between monetary policy and macroeconomic developments along time. However, this paper shows that this assumption becomes less realistic for long periods of time and provides evidence of instability in the results of a factor model applied to the US economy once data is updated to include the Great Recession period. This result casts some doubts on the adequacy of this recent data, corresponding to a more volatile period, for the characterization of the current economic context and adds uncertainty to the selection of the correct sample.

Recent literature has devoted attention to the possible presence of instability in DFMs. 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 are large, while, on the other hand, discrete changes in the law of motion of the factors may affect the forecasting properties of the model. Stock and Watson (2009) study the effects of structural instability in the US between 1959 and 2006 using subsamples corresponding to the Great Moderation period (McConnell and Perez-Quiros, 2000). Their conclusions are consistent with those of Banerjee, Marcellino and Masten (2008): despite the presence of some instability in the factors loadings, the most accurate results are based on factors estimated with the full sample in combination with forecast equations for each subsample. Given that the forecast equations implicitly contain the dynamics of the factors, Stock and Watson (2009) suggest that the better results of this combination may be explained by the presence of instability in the parameters describing the law of motion of the factors.

In this case, the implementation of a model that captures variations in the law of motion of the factors becomes an appealing solution. This can be achieved by using an specification where the dynamics of the factors is governed by a Markov Switching (MS) process. This implies to assume that the behavior of the whole economy can be explained as a stable function of unobservable factors, as often done, but also that the interaction between those forces evolves differently over time. According to this specification, relations in the economy change as a function of a latent variable which captures regime shifts across time classifying the subsample periods corresponding to each regime. The analysis of this case of instability, within those considered in Stock and Watson (2009), presents two advantages. First, it allows for the existence of several breaks during long periods of time, instead of just one. Second, it enables the identification of structural breaks in real time without using ex-post information to assume when these breaks took place.

It is important to note that the estimation of this model, where breaks in the dynamics of factors are allowed, is non-trivial and that a *third dimensionality problem* appears here. Given that observable data are summarized in several factors and that these factors follow different processes from one regime to another, the number of parameters to be estimated is considerably larger and increases proportionally with the number of regimes. In order to deal with this problem, Sims, Waggoner and Zha (2008) proposed an estimation strategy for large multiple equation MS models. Traditional maximum likelihood estimation procedures may become imprecise for sets of parameters that are too large with respect to the sample size. To overcome this limitation, the above authors 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 may present 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.

Thus, the combination of these methodologies allows us to describe the evolution of the effects of monetary policy as a function of a latent state variable. In this regard, our paper is related to previous literature that has evaluated the evolution of monetary policy effectiveness as a function of other variables as central bank transparency, measures of economic uncertainty or banking conditions. Papadamou et al. (2015) evaluate the effectiveness of monetary policy for a panel of emerging economies depending on their level of central bank transparency and find that the transmission mechanism of the monetary policy is more effective under high transparency. Since Bloom et al. (2007) and Bloom (2009), an important strand of literature has devoted increasing attention to the effects of uncertainty on economic activity (Bachmann et al. 2013), employment and investment (Baker et al. 2016), the differences in the economic consequences of uncertainty shocks when the economy is at the Zero Lower Bound (Caggiano et al. 2017) as well as the role of uncertainty on the alteration of the monetary policy transmission mechanisms (Aastveit et al. 2017, Aye et al. 2017 or Pellegrino, 2018). The latter line of research, where monetary policy interacts with uncertainty, have found that monetary policy changes tend to be less effective when uncertainty is high. From a theoretical point of view, this can be explained because uncertainty affects some channels for the transmission of monetary policy as the *investment-based channel* and the *consumption-based channel*[4]. Under high uncertainty economic agents postpone their decisions about investment or increase their precautionary savings delaying consumption expenditure. This "wait-and-see" behavior weakens the transmission of monetary policy since economic agents become less sensitive to variations in the monetary policy stance.

[4]See Boivin et al. (2010) for a review of the literature focused on the different channels for the transmission of monetary policy.

Furthermore, there are other mechanisms for the transmission of the monetary policy based on the presence of imperfections in the credit markets (the *credit view*) as the *bank lending channel* and the *bank capital channel.* As stressed by Van den Heuvel (2012), these channels predict that the effects of monetary policy may be stronger if banks are less liquid or worse capitalized. In fact, the empirical findings of Van den Heuvel (2012) show that lending and output are more reactive to monetary policy when the banking sector shows a low capital-asset ratio. In addition, Boivin et al. (2010) point out structural changes in the economy related to institutional changes in the credit markets as one of the primary sources for the variation in the effects of monetary policy. In order to evaluate the evolution of monetary policy transmission mechanisms in the US, Boivin et al. (2010) estimate a FAVAR for two subsamples between 1962:1–1979:9 and 1984:1–2008:12, since many restrictive regulations in the credit markets of the US were removed in the 1980s, and find that after 1984 output, inflation and credit initially respond less to monetary policy and may show more persistent effects in the long term. We contribute to these findings applying an estimation procedure that allows us to endogenously identify the presence of this structural break (and others) to determine the date when the sample must be split for the correct identification in the changes of the monetary policy transmission mechanisms. This is done by combining the DFM of Gambetti and Forni (2010), instead of the FAVAR for the reasons explained above, with the methodology to estimate large multivariate MS models proposed by Sims, Waggoner and Zha (2008) to identify changes in the dynamics of the latent factors. The next two sections describe this model and the estimation process.

3 Model and Identification

Consider x_{it} as a macroeconomic series expressed on a monthly basis where $i = 1, \dots, n$. These n series are representative of the whole economy and may be expressed as a function of a set of r latent variables $f_t^1, \ldots, f_t^r$, the static factors, and an idiosyncratic component ε_{it} associated only 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 affect 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 Λ is a $n \times r$ matrix.

The law of motion of the static factors, which are only contemporaneously related to the observable series, follows a different autoregressive process over time depending on 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) show state-dependent covariance matrices and 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

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

As previously mentioned, the static factors are only contemporaneously related with the observable variables. Bai and Ng (2007) show that the dynamic relationship of the observables variables with current and lagged values of latent factors may be captured using a specification where the innovations in autoregressive dynamics of the static factors is driven by a set of q dynamic factors, where $q \leq r$, as described in equation (4). This is known as the static representation of the DFM [5].

Thus, knowing that x_{it} is related with the static factors through Λ_i in (2), the parameters describing the law of motion of the static factors in (3) and the relationship between the static and dynamic factors in (4), we can express x_{it} as a function of the dynamic factors and its corresponding idyosincratic component:

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

Notice that, according to 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 $\Lambda_i (I - A_{1s_t} L - A_{2s_t} L^2 - ... - A_{ps_t} L^p)^{-1} B_{s_t}$ 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 dynamics of the economy, Gambetti and Forni (2010) define a recursive strategy for the identification of the monetary policy shocks equivalent to those applied in the standard structural VAR literature. Structural shocks in equation (5) are unidentified since they do not meet any requirement based on economic theory. However, let us suppose that economic theory does support a set of restrictions in the contemporaneous responses of a reduced set of variables to monetary policy shocks and that these restrictions can be summarized into an orthogonal matrix H. In this case, identified structural shocks are found by premultipliying u_t by H and its corresponding IRF are identified by 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.

[5] See Bai and Ng (2007), section 3, for a detailed description.

4 Data and Methodology

Empirical applications of DFM for the U.S. economy are generally based on the initial dataset used by Stock & Watson (1999). Noteworthy examples are, Bernanke, Boivin and Eliasz (2005), Boivin and Ng (2006), Gambetti and Forni (2010) or Stock & Watson (2012) among others. In this paper, we use the same set of series in Gambetti and Forni (2010)[6] for comparability with their results. In detail, the dataset consists of 110 monthly US series which may be classified into the following categories: real output and income, employment and hours, housing starts and permits, inventories and orders, money and credit, interest rates, exchange rates, price indexes and stock prices. Series were downloaded from the Federal Reserve Bank of St. Louis database (FRED), the Bureau of Labor Statistics, Quandl, International Financial Statistics database from the IMF, Datasetream and Monthly Monetary and Financial Statistics database from the OECD. The sample starts in April of 1973 in order to avoid the fixed exchange rate and is updated to May of 2016 to include data corresponding to the Great Recession. Data transformation is carried out in line with previous FAVAR and structural DFM literature[7]. Table 1 compares the descriptive statistics of some of the main indicators included in the categories listed above for two different subsamples. First subsample finishes in November 2007 matching the period analyzed in Gambetti and Forni (2010) while the last columns of the table provide the same statistics for a second subsample including the Great Recession from December 2007 until the end of the sample.

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 X be the $t \times n$ matrix of data, static factors

[6]The Index of Help-Wanted Advertising in Newspaper and its ratio with respect to employment were removed from the dataset because, given that nowadays the most of the vacancies are advertised online, they provide poor information about the current labor market conditions.

[7]Detailed description of dataset is available upon request.

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 the variance covariance matrix of X. This gives us a summary of the original data in terms of the number of eigenvectors chosen by the researcher. Obviously, the higher the number of eigenvectors the lower the loss of information caused by this reduction dimension technique. We 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), who, within the group of specifications proposed by Bai and Ng (2002), chose one criterion which points to 16 as the optimal number of factors. Nevertheless, once the sample set is updated including data corresponding to the Great Recession, the criterion suggested by Bai and Ng (2002) determine an optimal 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. According to 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 up to 50 series and 150 temporal observations which are considerably smaller than the dataset used here. Elsewhere, Stock and Watson (2009) estimate a set of factors using a whole panel of US data between 1959 and 2006 and compare them with two sets of factors based on subsamples before and after 1984 in order to capture the structural changes which took place during the Great Moderation[8]. By comparing their correlations, they find that full sample estimations of the factors span the space of the subsamples factors. According to their results, the number of factors summarizing the full sample containing structural shifts was larger than the number of factors mirroring

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

the co-movements in the subsamples with more stable patterns. This explains why the number of factors selected by the Bai and Ng (2002) criterion applied to the dataset of Gambetti and Forni (2010) is higher once the dataset includes 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 dynamics of the factor[9]. They find more evidence of instability in the forecast equation than in the factor loadings equations. Furthermore, most accurate predictions are provided by full sample factors in combination with forecast parameter estimated for each subsample. As they point out, these results suggest that the main source of structural instability comes from the dynamics of the factors.

Taking into account these findings, and in order to identify the presence of breaks in the dynamics of the factors driving the economy, we assume that the evolution of the factors follows a MS process. This specification presents two advantages with respect to the analysis of Stock and Watson (2009). First, according to the MS specification, the dynamics of the factors depends on an unobservable state variable estimated following the standard procedures described below. Thus, structural breaks may be identified based on the data currently available and no ex-post information about the dates of the breaks is required. Second, instead of considering 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

[9] See stock and Watson (2009) for details.

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 large number of parameters that characterize a multivariate MS model, MLE may produce inaccurate 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 sampling is used to calculate the moments of the marginal posterior distributions by sampling iteratively from the next 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[10]

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

where S_T may be drawn recursively for $t = T-1, T-2, \ldots, 1$. First, 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

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

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

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

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

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. 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, beliefs about the duration of the regimes reflect 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 may present non-Gaussian shapes. In order to avoid sequences of posterior draws stuck in a low probability region, a correct selection of the starting values for the Gibbs sampling becomes crucial. For this purpose, as suggested by Sims, Waggoner and Zha (2008), the set of coefficients to be estimated was partitioned into several blocks. Then, for the initial guess of the coefficients, an optimization procedure is applied iteratively from one block to another, while keeping the others constant, until likelihood convergence is achieved. It has been shown that this iterative procedure increases the likelihood efficiently when the number of parameters is large.

Finally, inference about the MS parameters was carried out after 10,000 iterations of the posterior sampler starting 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) was performed, the $r \times q$ matrix loading for the dynamic factors B_{st} was computed by applying the PCA dimension reduction technique to the regime-dependent covariance matrices of the errors.

Structural identification was achieved by reproducing the scheme developed by Gambetti and Forni (2010). The identification restrictions were based on: industrial production, consumer price index, FFR and Swiss/US real exchange rate. The set of contemporaneous IRF of these four variables, in this order, were restricted to be lower triangular using a Cholesky decomposition. First, we computed the Cholesky factor of the matrix containing these four conterporaneous IRF. Identification was then carried out by post multiplying the set of IRF in (5) by the product of the inverse of the matrix containing the contemporaneous IRF of the four identification variables and the Cholesky factor. In this way, it is assumed that production and prices do not respond to interest rates within the same period and that interest rates do not respond contemporaneously to exchange rates. Finally, this identification strategy requires a number of dynamic factors equal to the number of variables selected for identification (q=4). Results in the next section are based on this specification following Gambetti and Forni (2010).

Finally, confidence bands for the IRF are obtained through Monte Carlo simulations[11].

[11] Standard block bootstrap methods to obtain the confidence bands are unfeasible due to the high computational load of the estimation procedure implemented here. Even for a small reasonable number of

We generate 10,000 draws of the dynamic shocks from a $N \sim (0,1)$ distribution to simulate the distribution of the IRF.

5 Results

First, we analyzed the need to evaluate the evolution of the macroeconomic reaction to monetary policy shocks along time. For this, we selected some representative variables of the different categories in the dataset and estimated their linear IRF assuming that the model parameters remain invariant along the sample. Then, we compared these linear IRF across a progressively extended sample period. In this exercise, IRF to a 0.5% increase in FFR were estimated based on a subsample starting in April 1973 and finishing in January 2005. Then, the next monthly observation was added to the subsample and IRF were computed again. This step was iterated until the observations corresponding with November 2013 were included. Thus, this exercise mirrors the evolution of the results obtained with the arrival of new data and the decisions that must be faced by the researcher about the correct sample in the characterization of the current economic conditions under the possible presence of structural instability. For the sake of space, only the progressively extended sample period IRF corresponding to three of the variables used in the identification of the monetary policy shocks (industrial production, prices and exchange rates) are depicted in Figure 1.

IRF are very similar from one month to the next until the moment in which the data corresponding to the Great Recession is included. Starting from this period, IRF amplitude jumps. Thereafter, there is a second group of IRF with a relatively stable month by month shape until the end of this exercise in November 2013, some years after the end of the Great Recession. This pattern is also present in the other progressively extended sample period IRF not presented here.

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iterations, say 500, that would require more than one year of computation time. See Pesaran et al. (2004) for an alternative example where the computational load of bootstrapping techniques is acknowledged for the estimation of large-scale models.

These preliminary results show the existence of structural instability in the DFM and provide evidence of shifts in the macroeconomic reactions to monetary policy during the Great Recession. Figure 2 emphasizes the sample effects on the measurement of the consequences of a contractionary monetary policy shock. The picture shows IRF for several variables estimated ignoring the presence of structural instability under two possible decisions regarding the sample selection: *i)* estimation must be carried out based on data previous to 2008, assuming that the Great Recession is over, and that the more volatile data corresponding to that period lead to results which are not representative of the current economic context or, *ii)* considering that full sample information must be included because the larger our dataset, the more precise our estimates will be.

As an illustrative example, and given the particular attention devoted to the developments in the labor market for the monetary policy decision making, the IRF in the upper part of Figure 2 emphasizes the sample effects of this decision on the estimated response of unemployment rate to a contractionary monetary policy shock. As can be observed, there are important differences in the results depending on this decision. Under sample selection decision *i)*, using data until November 2007, the maximum increase in unemployment rate will be around 0.2% while this figure rises to 0.6% when using full sample information.

As stressed by Ume (2018), housing market activity is also a main concern to policymakers given that it is an important channel in the transmission of monetary policy. Ume (2018) analyzes the effects of monetary policy shocks on several measures of housing market activity before the financial crisis. Hence, the middle and lower graphs of Figure 2 reproduce the comparison previously done with unemployment rate for the two variables commonly included in the datasets of Gambetti and Forni (2010) and Ume (2018): new privately owned housing units started and new private housing units authorized by building permits. As in the case of unemployment rate, housing starts and housing permits show a different reaction to monetary policy shocks depending on the sample selection decision and have a higher initial responsiveness when IRF are computed with full sample data. Although estimated under different methodologies, the pre-Great Recession IRF for the housing market indicators provided here are qualitatively similar to those estimated by Ume (2018) under a recursive scheme[12] for a very close sample period: housing starts and housing permits decrease following the contractionary monetary policy shock and show a recovery after some periods. Thus, these IRF have similar shapes in both works although the initial decrease and the following recovery after the contractionary shock are more pronounced once estimated with the DFM as it happens in Gambetti and Forni (2010).

Therefore, to incorporate this knowledge about the existence of structural instability and to solve the concerns regarding the correct sample for characterization of the current economic context, we apply the MS specification described previously. The estimation of this model allows us to identify the periods when the structural breaks take place and to classify the data into different subsamples for each state of the economy according to those dates. Figure 3 presents the MS smoothed probabilities of a second state[13]. The probabilities are presented together with the periods classified as recessions by the NBER and the business cycle volatility is defined as in Blanchard and Simon (2001): the standard deviation of GDP growth over the last 20 quarters[14].

Since the seminal work of Hamilton (1989), MS probabilities of a regime change in economic time series have been widely used to capture macroeconomic shifts. This univariate methodology has been applied, among other examples, to forecast exchange rates (Engel, 1994), to model short-term interest rates (Dahlquist and Gray, 2000) and to iden-

[12] Ume (2018) estimates a set of IRF for four different indicator of the housing market under different identification strategies. We compare our results with those based on a recursive procedure given that we follow the recursive identification method proposed by Gambetti and Forni (2010) for the reasons described above.

[13] Results are based on a specification for the presence of two states. A three-state MS model was also estimated. However, the smoothed probabilities for a third state in the dynamic of the factors were negligible and this specification was discarded.

[14] This measurement of volatility is assumed to be constant along the three months of each quarter to match data at a monthly frequency.

tify changes in the dynamics of personal consumer expenditures (Lettau et al. 2008) or productivity shocks (D'Addona and Giannikos, 2014). In this works, the interpretation of the regime probabilities is straightforward in the sense that they are related to a single variable.

Chauvet (1998) combined a MS model with the reduction dimension properties of the small-scale factor model proposed by Stock and Watson (1991) to summarize information from four indicators of economic activity and characterize the business cycle with the resulting MS probabilities. Camacho et al. (2018) estimate the probabilities of recession in real time by means of the model proposed by Chauvet (1998), mixing four monthly series related to production, employment, income and sales (as in Chauvet ,1998) with quarterly GDP and modifying the estimation procedure to deal with "ragged ends" that accounts for the different delays in the release of each series. The regime probabilities of these two examples provide a good characterization of the NBER expansion and recessions periods given that, as stressed by Chauvet (1998), they focus on the series used by the NBER and by the Department of Commerce to the construction of its coincident indicator. However, the probabilities depicted in Figure 3 take information from a big dataset of variables that is considered in the large-scale dynamic factor literature as a comprehensive description of the US economy. Thus, these probabilities are able to identify variation in the economic patterns coming from different sources or macroeconomic categories. Figure 3 shows how most structural changes take place during recessions and periods of high volatility (like the inter-recessions periods between 1973 and 1983 or after the 2007 recession), with the single exception of the mild recession in the early 1990s which occurs during a low volatility period. Additionally, the smoothed probabilities also capture transitory shocks to the US economy from several macroeconomic categories. For instance, the smoothed probabilities show a peak in summer 2005 coinciding with Hurricane Katrina (see Edelstein and Kilian (2009) for a detailed description of the economic consequences of this shock on energy prices). They also capture the "downturns in private inventory investment, in federal government spending, in exports, and in state and local government spending" that lead the Bureau of Economic Analysis to measure a decrease in the annual growth rate of GDP during the last quarter of 2012 in its advance estimate release (Bureau of Economic Analysis, 2013). There is also a peak at the end of 2015 coinciding with the Chinese stock market crash that affected commodity prices and the US markets.

For illustrative purposes, state-dependent IRF are presented with linear IRF computed with data up to November 2007 and with a second group of linear IRF that includes the Great Recession data. These sets of linear IRF reflect the two possible decisions about the sample period described above. To save space, not all the 110 IRF are included here. Instead, a set of variables considered as being representative of the broad categories of the dataset are depicted in Figures 4 to 7. Several conclusions emerge from this comparison.

As previously observed in the progressively extended sample period exercise and in the particular case of the reaction of the unemployment rate and housing market indicators, there is an increase in the amplitude of the linear IRF once data posterior to 2007 is added. The differences in the results depending on the sample selection are noteworthy. The maximum values in the linear IRF including updated data are around double of those computed with data previous to the last recession. See Industrial Production Index (Figure 4, first row, columns 1 and 2) as a representative example of this fact, where the maximum reduction in this index estimated with updated data reaches 2.5%, while this figure is around 0.9% with the pre-Great Recession sample. Moreover, pre-Great Recession linear IRF tend to be similar in shape and amplitude to those estimated using the MS specification for the state of expansions and low volatility. Purchasing Manager Index (Figure 6, third row, columns 1 and 3) or Capacity Utilization (Figure 7, third row, columns 1 and 3) are two noteworthy examples. These facts stress the effect that the inclusion of the Great Recession data causes on the linear estimates with respect to those computed with data up to 2008 given that most of the pre-Great Recession sample belongs to the state of expansion and low volatility.

The consequences of the inclusion of more observations corresponding to a high volatility period on the linear IRF are clearly seen in Producer Price Index (Figure 5, third row) or in the Unemployment Rate (Figure 7, first row), where the shape of the linear IRF computed for the whole sample is evidently influenced by the state-dependent IRF for periods of high volatility and recessions. Therefore, if the economy has recovered to a state of stability and growth, the full sample linear estimates would be inaccurate and the assessment about the current state of the economy becomes crucial in identifying the correct responses.

6 Concluding remarks

This paper shows the existence of changes in the monetary policy transmission mechanisms during the Great Recession by analyzing the presence of structural instability in a Dynamic Factor Model. Based on the empirical results of previous literature, which point to the dynamics of the factors as the main source of instability, we examine the presence of breaks in the autoregressive behavior of the factors, using an estimation procedure for large multivariate Markov Switching models. This specification provides evidence supporting the presence of two different dynamics on the underlying factors driving the US economy over the last forty years.

First, the response of macroeconomic variables to monetary policy changes is estimated linearly without taking into consideration the presence of structural instability, using data previous to 2008. These linear responses present a sizeable increase in their magnitude once they are computed with updated data including the Great Recession period. This finding confirms the existence of instability. Furthermore, this introduces uncertainty regarding the selection of the correct sample for the representation of the current economic conditions and for the estimation of the macroeconomic reaction to monetary policy after the financial crisis. The estimation process applied here enables the identification of structural breaks, the classification of the data corresponding to each structural scenario and the evaluation of the responses of a large dataset of variables to monetary policy shocks for each particular structural context.

We identify a structural break coinciding with the Great Recession and find that macroeconomic indicators tend to be more reactive to monetary policy shocks after that break. In addition, our findings show that this change in the monetary policy transmission mechanisms is not permanent since the US economy recovers to the previous state after some years. This suggests that, even under high uncertainty, when monetary policy becomes less influential (Aastveit et al. 2017, Aye et al. 2017 or Pellegrino, 2018) as explained by the *investment* and *consumption channels*, the dramatic consequences of the financial crisis on the credit markets during the Great Recession intensified the effects of the monetary policy (the *credit view*), in line with Boivin et al. (2010) and Van den Heuvel (2012). On the one hand, our findings are similar to those in Boivin et al. (2010) since we identify a regime change at the beginning of the eighties and the comparison of the reaction of the economic indicators to a contractionary monetary policy shocks before and after that break yields similar conclusions to theirs with the economic indicators being more likely to react less to monetary policy shocks after that break. On the other hand, we also identify a structural change coinciding with the Great Recession and find a higher responsiveness of the economy to monetary policy shocks after that date. This may be explained by the effects of the financial crisis and the deterioration of the banking conditions as predicted by the bank lending and the bank capital channels analyzed in Van den Heuvel (2012). In this regard, Boivin et al. (2010) also suggest that these channels might have become more important in the transmission of the monetary policy after the financial crisis due to shrinkage of the credit provided via the securities market, that was an alternative to the credit provided by banks.

The combination of the methodologies applied here allows us to identify the correct sample for the estimation of the monetary policy transmission mechanisms during periods of change in the state of the economy in a feasible manner when dealing with large datasets. Nevertheless, more has to be known about the specific causes driving these changes in the economy as the consequences of macroeconomic risk and uncertainty on the influence of monetary policy. The estimation of more complex large-scale models that identify separately regime switches in both autoregressive behavior and volatility of the underlying factors driving the economy can shed some light on these questions and help to evaluate the effect of macroeconomic risk. We leave this as an open question that can be addressed in future research.

The comparison of the state-dependent responses with those linearly estimated shows how reactions to monetary policy computed ignoring the presence of structural instability may provide misleading results, especially, after a recent change in the macroeconomic conditions. Thus, if the financial crisis had not permanently affected the structural conditions and the economy had recovered after that episode of high volatility, the inclusion of recent data for the estimation of the monetary policy effects disregarding a new structural situation would lead to inaccurate estimates. Consequently, distinguishing and identifying these structural breaks is crucial to avoid misleading predictions. For these reasons, given the doubts about duration and impact of the structural effects of the Great Recession on the macroeconomic patterns, this paper provides an appealing framework to support decision making in the move towards a tightening of monetary policy conditions.

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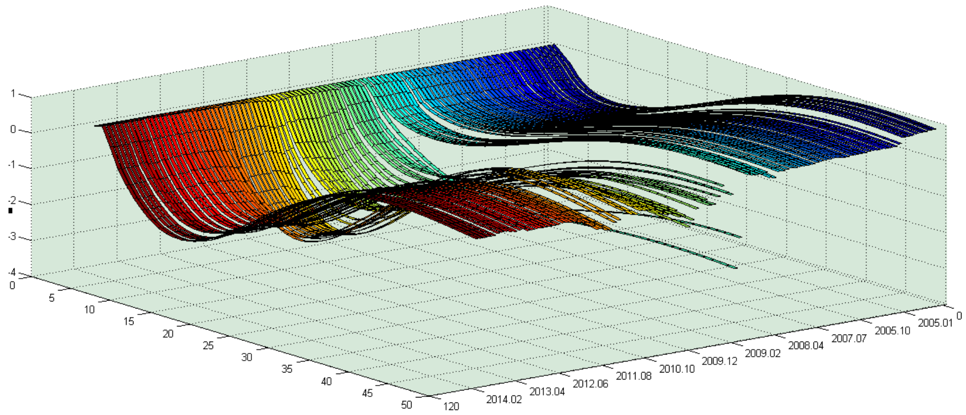
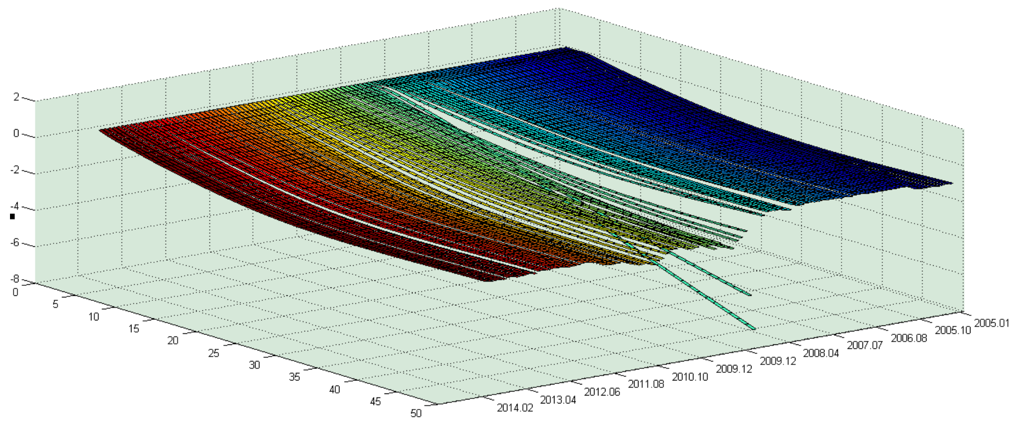
Tables and Figures

Series	Transformations	Pre Great Recession (1973.4 - 2007.11)				Post Great Recession (2007.12 - 2016.5)			
		mean	sd	max	min	mean	sd	max	min
Industrial Producion Index	2	0,002	0,007	0,021	-0,036	0,000	0,008	0,014	-0,044
Consumer Price Index	2	0,004	0,003	0,018	-0,005	0,001	0,003	0,010	-0,018
Swiss/US real Exchange Rate	1	0,225	0,157	0,716	-0,110	0,022	0,066	0,149	-0,207
Consumer Credit	2	0,005	0,007	0,029	-0,070	0,005	0,009	0,074	-0,035
S&P'S common stock price index	2	0,007	0,035	0,110	-0,136	0,001	0,046	0,119	-0,255
Producer Price Index	2	0,003	0,007	0,043	-0,019	0,001	0,010	0,024	-0,039
Housing Starts	1	7,324	0,212	7,729	6,682	6,682	0,276	7,100	6,170
ISM Inventories Index	0	45,845	6,215	66,500	24,600	47,461	5,327	56,500	31,000
ISM Purchasing Managers Index	0	52,050	6,522	69,900	29,400	51,984	5,493	59,900	33,100
Unemployment Rate	0	6,193	1,434	10,800	3,800	7,407	1,701	10,000	4,700
Average Weekly Hours Index	2	0,001	0,005	0,030	-0,029	0,000	0,004	0,011	-0,013
Capacity Utilization	1	80,785	3,470	88,729	70,843	75,904	3,367	81,096	66,710
Housing Permits	1	7,273	0,245	7,724	6,564	6,722	0,280	7,217	6,240
Federal Funds Rate	0	6,673	3,526	19,100	0,980	0,393	0,779	4,240	0,070

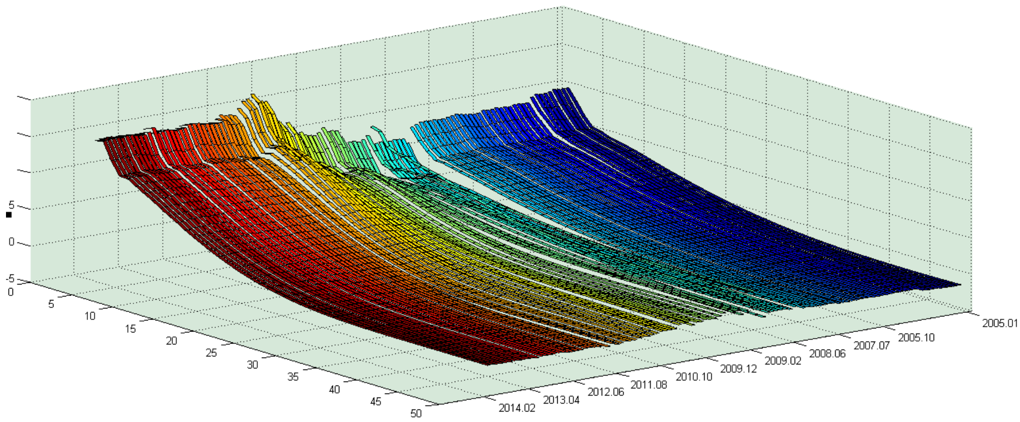
Table 1. Descriptive Statistics for selected macroeconomics indicators for two subsamples: 1973.4 -2007.11 and 2007.12 - 2016.5. Transformation codes: 0=levels; 1=logs; 2=differences of logs.



Industrial Production Index



Consumer Price Index



Swiss/US real Exchange Rate

Figure 1. 50 months ahead Industrial Production Index, Consumer Price Index and Swiss/US real Exchange Rate progressively extended sample period linear Impulse Response Functions from January 2005 to November 2013 for a 50 basis points contractionary monetary policy shock.

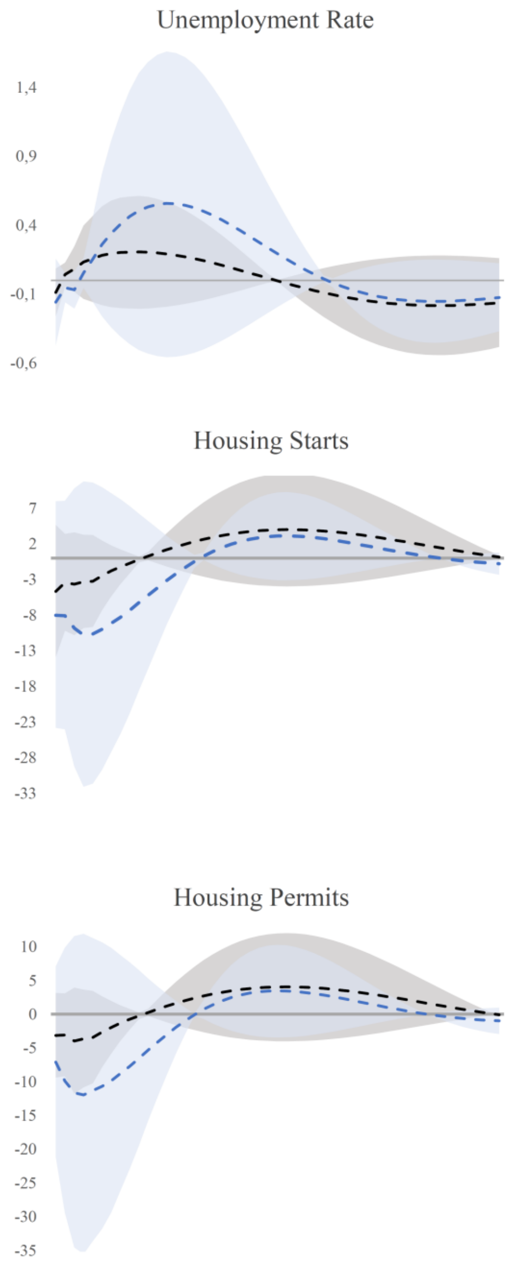


Figure 2. 50 months ahead Unemployment Rate, Housing Starts and Housing Permits Impulse Response Functions for a 50 basis points contractionary monetary policy shock. Black dashed line: sample from April 1973 to November 2007. Blue dashed line: sample from April 1973 to May 2016. Shaded areas: ± 1 standard deviation confidence bands.

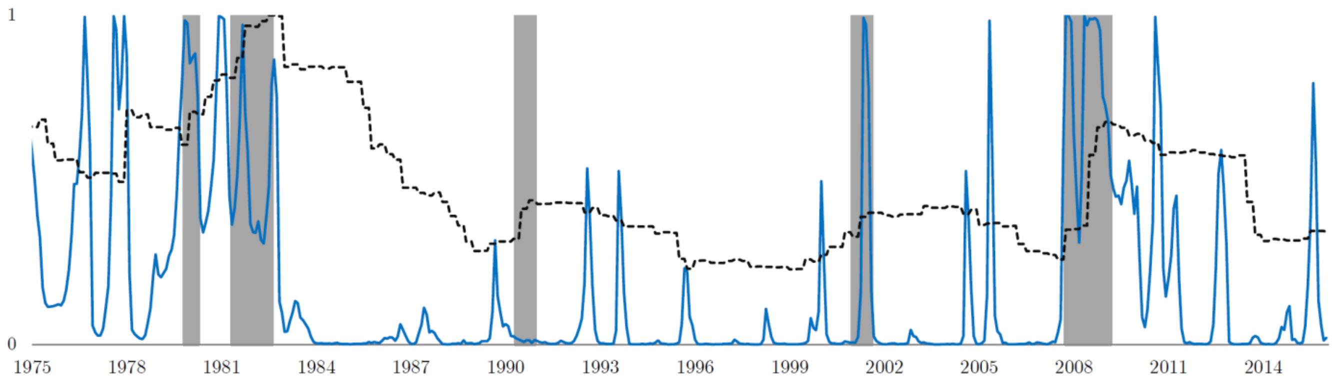


Figure 3. Blue Line: Second State Smoothed Probabilities. Shaded areas: NBER Recessions. Dashed line: normalized Business Cycle Volatility

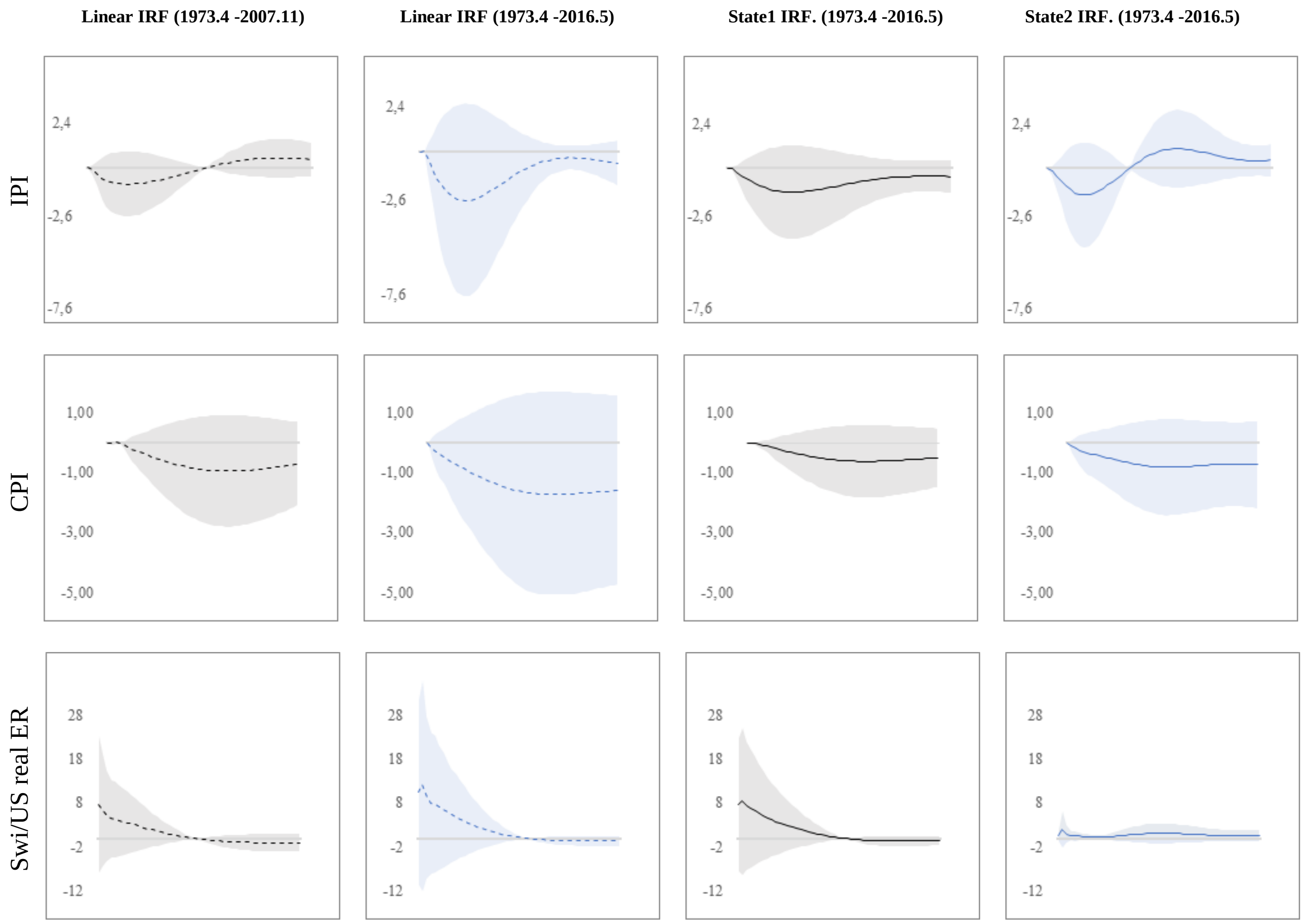


Figure 4. 50 months ahead Industrial Production Index, Consumer Price Index and Swiss/US real Exchange Rate Impulse Response Functions for a 50 basis points contractionary monetary policy shock. Black dashed line: sample from April 1973 to November 2007. Blue dashed line: full sample from April 1973 to May 2016. Black solid line: full sample state dependent estimates corresponding with stages of low volatility and expansions. Blue solid line: full sample state dependent estimates corresponding with stages of high volatility and recessions. Shaded areas: ± 1 standard deviation confidence bands.

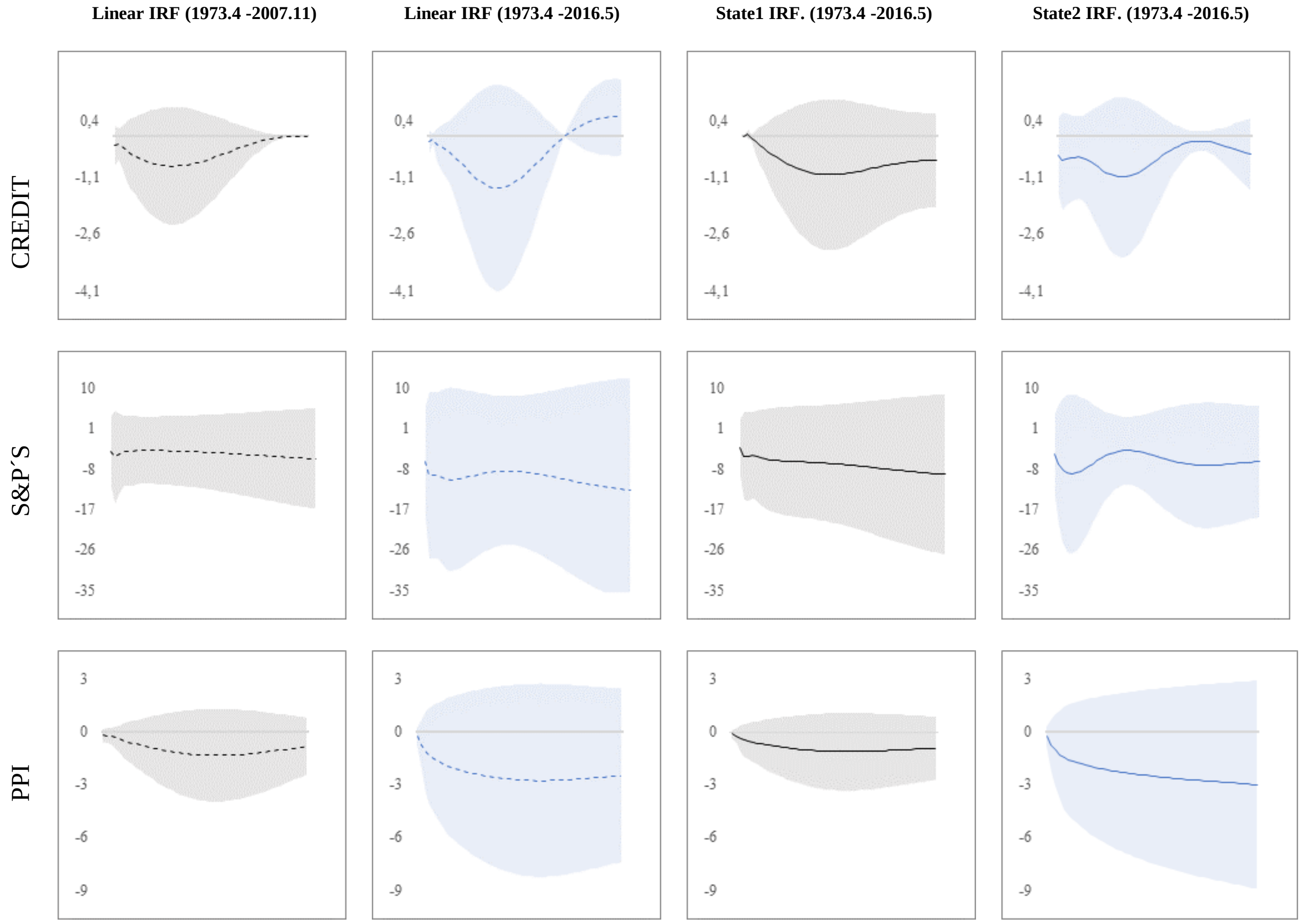


Figure 5. 50 months ahead Consumer Credit Outstanding, S&P S Common Stock Price Index (%) and Producer Price Index Impulse Response Functions for a 50 basis points contractionary monetary policy shock. Black dashed line: sample from April 1973 to November 2007. Blue dashed line: full sample from April 1973 to May 2016. Black solid line: full sample state dependent estimates corresponding with stages of low volatility and expansions. Blue solid line: full sample state dependent estimates corresponding with stages of high volatility and recessions. Shaded areas: ± 1 standard deviation confidence bands.

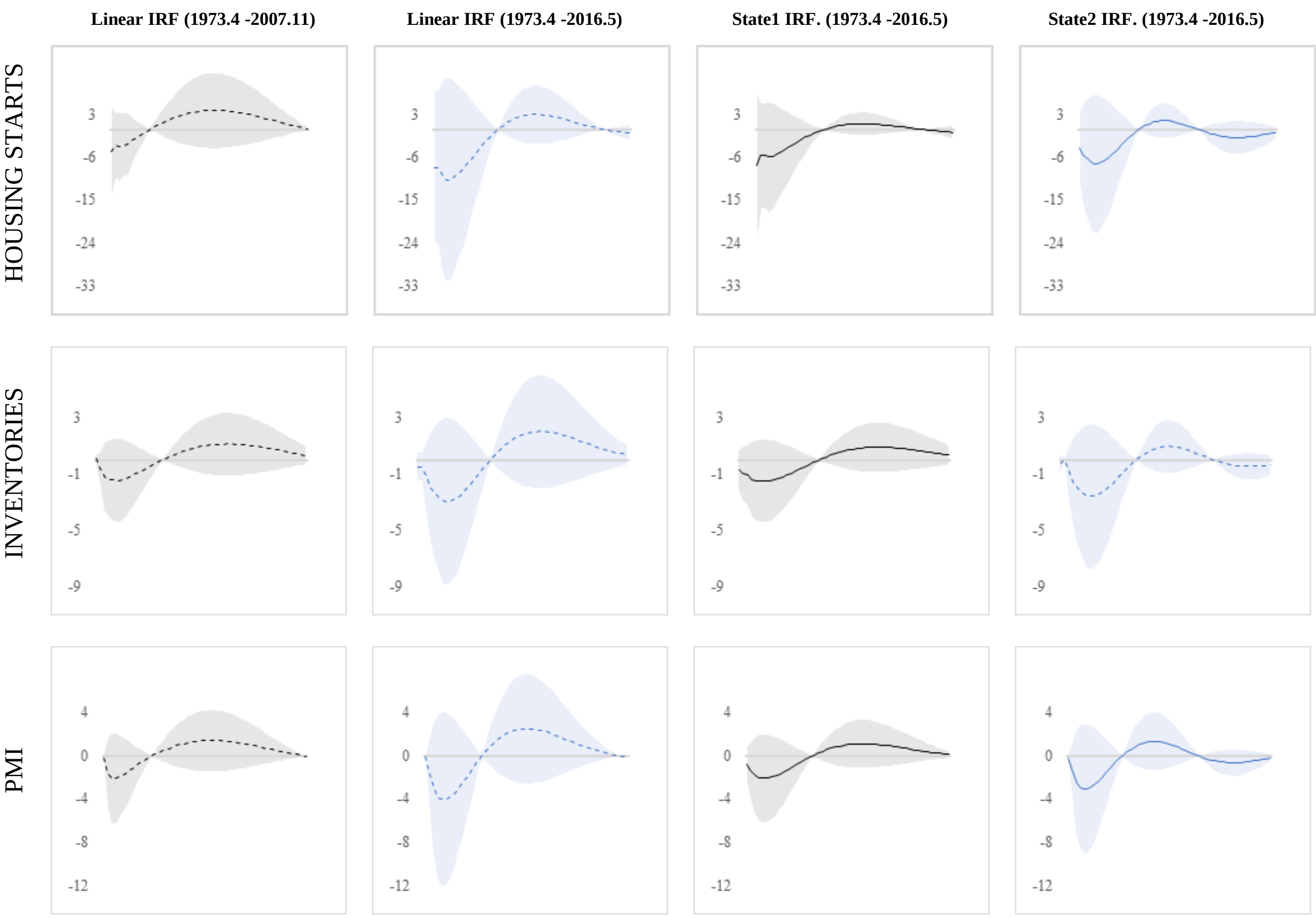


Figure 6. 50 months ahead Nonfarm Housing Starts (%), ISM Manufacturing Inventories Index and Purchasing Managers Index Impulse Response Functions for a 50 basis points contractionary monetary policy shock. Black dashed line: sample from April 1973 to November 2007. Blue dashed line: full sample from April 1973 to May 2016. Black solid line: full sample state dependent estimates corresponding with stages of low volatility and expansions. Blue solid line: full sample state dependent estimates corresponding with stages of high volatility and recessions. Shaded areas: ± 1 standard deviation confidence bands.

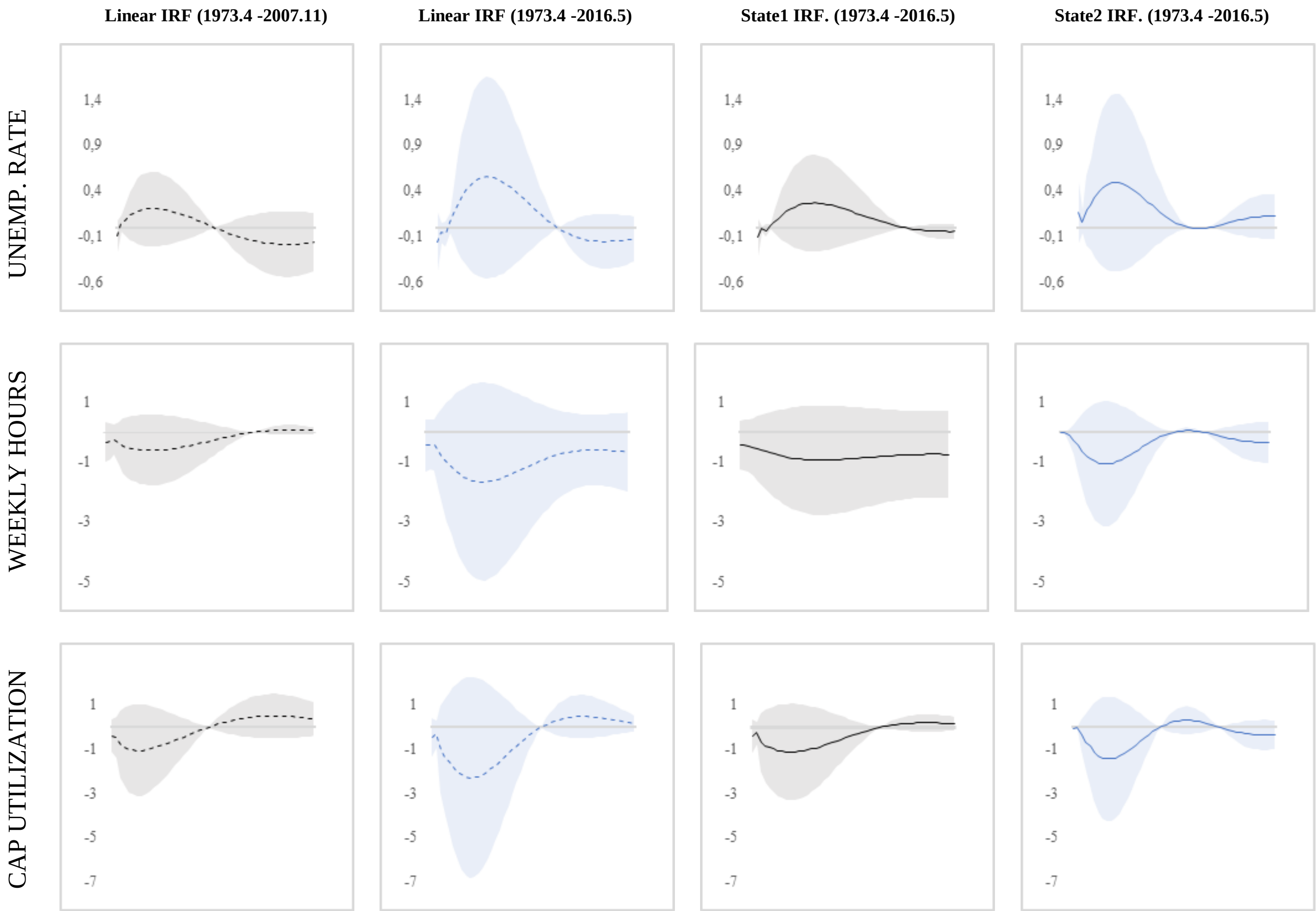


Figure 7. 50 months ahead Unemployment Rate (%), Average Weekly Hours Index: Total Private Industries (%) and Capacity Utilization- Manufacturing (%) Impulse Response Functions for a 50 basis points contractionary monetary policy shock. Black dashed line: sample from April 1973 to November 2007. Blue dashed line: full sample from April 1973 to May 2016. Black solid line: full sample state dependent estimates corresponding with stages of low volatility and expansions. Blue solid line: full sample state dependent estimates corresponding with stages of high volatility and recessions. Shaded areas: ± 1 standard deviation confidence bands.