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Abstract

This paper studies the role of the Federal Reserve's policy in the recent boom and bust of the housing market, and in the ensuing recession. By estimating a Structural Dynamic Factor model on a panel of 109 US quarterly variables from 1982 to 2010, we find that, although the Federal Reserve's policy between 2002 and 2004 was slightly expansionary, its contribution to the recent housing cycle was negligible. We also show that a more restrictive policy would have smoothed the cycle but not prevented the recession. We thus find no role for the Federal Reserve in causing the recession.

JEL Classification: C32, E32, E52, R2
Keywords: Structural Factor Model, Business Cycle, Monetary Policy, Housing

1 Introduction

In early 2006 residential investment and house prices in the US collapsed. In September-October 2008, as the banks' huge losses based on the "sub-prime mortgage bubble" were revealed, a furious storm hit the stock market. The banking crisis was so profound that public intervention was necessary to prevent major financial institutions (Fannie Mae, Freddie Mac, and Citibank among others) from defaulting. From the financial market, the contagion spread to the real economy and the rest of the world, resulting in a severe global recession.

Policy analysts and economists began debating the causes of the crisis, pointing to the late 1990s financial deregulation, to the Federal Reserve's policy after the events of 9/11, and to the real estate market bubble.

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In the literature, debate has centered on the role of the Federal Reserve in influencing the boom and bust of the housing market,[1] and the ensuing recession, without, however, reaching a consensus. On the on hand, Taylor (2007) and Leamer (2007) argue that the Federal Reserve intentionally led an expansionary policy between 2003 and 2004; additionally, Taylor (2007) and Leamer (2009) show that this policy contributed to the housing boom, and that a more restrictive policy would have consistently smoothed the housing cycle. On the other hand, while Bernanke (2010) argues that the Federal Reserve's policy was not expansionary, Jarociñski and Smets (2008) and Bean et al. (2010), among others, show that, although the Federal Reserve's policy was slightly expansionary, its contribution to the housing boom and to the ensuing recession was negligible.

Compared to this literature, which is based on the estimation of small-scale models, we adopt a different approach. In this paper, we estimate a Structural Dynamic Factor model, a model that does not suffer the curse of dimensionality when used to analyze a large number of variables. Our goal is to understand whether the Federal Reserve's policy after 9/11 influenced the real estate market bubble, and the ensuing recession.

As pointed out by Bernanke and Boivin (2003) and Giannone et al. (2005), considering a large number of variables is crucial when studying monetary policy. In fact, since the Federal Reserve bases its decisions upon the observation of a large number of variables, a small number of variables may not suffice to estimate accurately the Federal Reserve's policy rule. This is a relevant issue when performing structural analysis.

Theoretically, structural analysis is based on the assumption that the information set used by both the econometrician and economic agents is the same. Should this not be the case–if the econometric model includes less information than that used by agents–then estimation both of structural shocks, and of their impact on the economy, and hence of the Central Bank policy rule, is problematic (Lippi and Reichlin, 1993, 1994). Empirically, results in Bernanke et al. (2005), Forni et al. (2009), Bańbura et al. (2010), and Forni and Gambetti (2010a) confirm that this is also a relevant problem: as the number of variables included in the model increases, the estimated impulse response functions change considerably. It is therefore clear that, in order to disentangle *systematic* (i.e. the policy/feedback rule) and *unsystematic* (i.e. shocks) monetary policy, we have to include all the variables that the Federal Reserve considers in its decision making, thus motivating the use of Factor models.

Our empirical analysis is carried out on a panel of 109 US quarterly variables from 1982 to 2010. We show that the Federal Reserve's policy between 2002 and 2004 was slightly expansionary, but that its contribution to the housing boom was negligible. Finally, we show that a more restrictive policy such as the one suggested by Taylor (2007) would have smoothed the cycle, but we do not find evidence that such a policy would have been able to prevent the recession.

The rest of the paper is organized as follows: Section 2 describes the methodology, while in Section 3 we present model estimation. In Section 4, by means of two different counterfactual exercises, we study the Federal Reserve's policy after 9/11. Finally, in Section 5 we present

[1] There is, indeed, a wide consensus that, besides local dynamics, macroeconomic shocks are an important source of housing market fluctuations (Del Negro and Otrok, 2007; Moench and Ng, 2011; Stock and Watson, 2009). There is also well–documented evidence that monetary policy shocks can influence the housing market (Jarociñski and Smets, 2008; Eickmeier and Hofmann, 2011), especially in liberalized markets (Calza et al., 2011), and possibly through a credit channel (Iacoviello and Minetti, 2008). Finally, the literature agrees that shocks in the housing market have important spillover effects on the rest of the economy (Moench and Ng, 2011; Iacoviello and Neri, 2010) especially through collateral effects (Iacoviello, 2005).

our conclusions.

2 Methodology

Since the seminal contributions of Giannone et al. (2005), Bernanke et al. (2005), Stock and Watson (2005), and Forni et al. (2009), Factor models have been used for macroeconomic analysis. Due to the strong comovement among macroeconomic time series, Factor models offer a realistic and parsimonious representation of the data, since they assume that a small number of macroeconomic shocks drives the bulk of comovement in the data. Moreover, Factor models can be easily estimated with the method of principal components (Forni et al., 2000; Stock and Watson, 2002; Bai, 2003) or Maximum Likelihood (Doz et al., 2011) under general assumptions on the cross-correlation of the idiosyncratic errors. Finally, and more importantly, when used to analyze large databases, Factor models do not suffer the curse of dimensionality.

Factor models are based on the idea that fluctuations in the economy are due to a few structural shocks that affect all the variables, and to several idiosyncratic shocks (generally of much less interest) resulting perhaps from measurement error or sectorial or regional dynamics, that influence one or a few variables. Therefore, each stationary time series x_{it}, $i = 1, \ldots, N$ and $t = 1, \ldots, T$, in the dataset can be decomposed into the sum of two mutually orthogonal components which account for the two sources of fluctuations: the *common* component χ_{it}, which is a linear combination of $r \ll N$ *common* factors F_{kt}, $k = 1, \ldots, r$, driven by $q \leq r$ *common* shocks u_{jt}, $j = 1, \ldots, q$, and an idiosyncratic component ξ_{it}. Formally, let x_t be an $N \times 1$ vector of stationary variables. Then

$$x_t = \chi_t + \xi_t, \quad \text{for} \quad t = 1, \ldots, T, \tag{1}$$

$$\chi_t = \Lambda F_t, \tag{2}$$

$$A(L) F_t = G u_t \tag{3}$$

where, Λ is an $N \times r$ matrix of factor loadings, $A(L)$ is a matrix lag polynomial, and G is an $r \times q$ matrix of rank q. The common shocks and the idiosyncratic components are assumed to be uncorrelated at all leads and lags, while the idiosyncratic components are allowed to be both serially and cross-sectionally correlated albeit by a limited amount (approximate factor structure).[2]

Doz et al. (2011) prove that model (1)-(3) can be consistently estimated by (Quasi) Maximum Likelihood under different sources of misspecification of the cross-sectional and serial correlation of the idiosyncratic components. Let $u_t \sim \mathcal{N}(0, Q)$, and $\xi_t \sim \mathcal{N}(0, R)$, where R is a diagonal matrix, then (1)-(3) can be cast into a state space representation and a consistent estimation of the model parameters involving the Kalman Smoother and the EM algorithm can be obtained.[3]

[2] This is the Structural Dynamic Factor model first introduced by Giannone et al. (2005), Stock and Watson (2005), and Forni et al. (2009) which is a development of the model originally proposed by Stock and Watson (2002) and Bai (2003), and it is a particular case of the Generalized Dynamic Factor model by Forni et al. (2000) and Forni and Lippi (2001). Other similar models were also proposed by Sargent and Sims (1977), Geweke (1977), Chamberlain and Rothschild (1983), and Bernanke et al. (2005). For a formal treatment of the model, we refer the reader to Forni et al. (2009).

[3] For a detailed explanation of this estimation method, we refer the reader to Doz et al. (2011). Here we just sketch the algorithm. Let $\widehat{F}^{(j)}$ and $\widehat{\theta}^{(j)} = \{\widehat{\Lambda}^{(j)}, \widehat{A}(L)^{(j)}, \widehat{G}^{(j)}, \widehat{R}^{(j)}, \widehat{Q}^{(j)}\}$ be the estimate of the factors

In this paper we are interested in disentangling the policy/feedback rule and monetary policy shocks, i.e. *systematic* and *unsystematic* monetary policy. Rewrite (1)-(3) as

$$x_t = C(L)u_t + \xi_t \tag{4}$$

where $C(L) = \Lambda A(L)^{-1}G$ is the impulse response function. However, it is well known that in (4) impulse responses and common shocks are identified only up to multiplication by a $q \times q$ rotation matrix H. Hence, in order to achieve identification, it is necessary to impose economically meaningful restrictions such as those in Forni et al. (2009) and Forni and Gambetti (2010a).

In order to identify the monetary policy shock we use sign restrictions (Canova and de Nicolò, 2003; Uhlig, 2005), an identification strategy also used in the context of Factor models by Eickmeier (2009) and Forni and Gambetti (2010b,c). Specifically, at each iteration we draw a vector of $q(q-1)/2$ angles ω from a uniform distribution on $[0, 2\pi)$, which, by means of Givens transformation, are used to construct an orthogonal matrix $H(\omega)$ of dimension $q \times q$. We then compute the associated impulse responses and if they satisfy a prescribed set of sign restrictions (to be specified in Section 3.3) we accept the draw, otherwise we discard it. We stop this procedure once K draws are accepted.[4]

3 Empirical Analysis

3.1 Data

The analysis is carried out on a panel of 109 quarterly series from 1982:3 to 2010:4 describing the US economy. The variables cover 12 different categories: Industrial Production, Consumer Price Indexes, Producer Price Indexes, Monetary Aggregates, Banking, GDP and Components, Housing Sector, Productivity & Cost, Interest Rates, Employment and Population, Business/Fiscal, Financial Markets. All variables are transformed to reach stationarity and then standardized to have zero mean and unit variance thus preventing possible scale effects when extracting the factors. The complete list of variables and transformations is reported in Appendix A.

We focus on a sample starting in the early 1980s for a number of reasons. First, it is well known that in the mid–eighties the US experienced a structural break, the so-called "great moderation".[5] Second, as suggested by Clarida et al. (2000) among others, from the

and of the parameter obtained at the j-th iteration. Then at the $j+1$-th iteration the algorithm works as follows: (i) an estimate of $\widehat{F}^{(j+1)}$ given $\theta^{(j)}$ is obtained by means of the Kalman Smoother; (ii) an estimate of $\theta^{(j+1)}$ given $\widehat{F}^{(j+1)}$ is obtained by maximizing the expected likelihood; (iii) this procedure is repeated until convergence.

[4]In order to build confidence intervals for impulse response functions we use a bootstrap algorithm. In detail, at each iteration d, we bootstrap the estimated common shocks u_t^d and we generate new static factors as $F_t^d = \widehat{A}^*(L)^{-1}\widehat{G}u_t^d$, where the * indicates that we correct for the distortion induced by the VAR estimation on the static factors, as in Kilian (1998). We then estimate the parameters of equation (3) and identify the monetary policy shock, thus obtaining new bootstrapped impulse response functions. Collecting together all admissible impulse responses (those on the sample and those on the bootstrap) gives a distribution of impulse responses from which we can obtain point estimates and confidence bands by computing the median and the relevant percentiles.

[5]With the term "great moderation" the literature identifies the decline in output growth and inflation variability which has occurred in the US since the mid–1980s. Although there is not yet a consensus on whether the great moderation is a consequence of "good luck", i.e. a decline in the volatility of structural

early 1980s the Federal Reserve's monetary policy rule was more oriented towards maintaining price stability.

Third, from the early 1980s a number of institutional changes have occurred in the housing finance sector, such as abrogation of the so-called Reg Q (a deposit rate ceiling) and the state laws capping the mortgage rate. Moreover, the loan crisis in the late 1980s changed the housing finance sector substantially, causing it progressively to shift from a system based on bank deposits to a system based on the mortgage market (Bernanke, 2007). These institutional changes might have changed the contribution of monetary policy to the housing market.[6]

Fourth, although Stock and Watson (2002) demonstrate that the space spanned by the static factors can be consistently estimated also in the presence of *limited time variation* in the factor loadings, in the presence of a structural break the number of factors is over-estimated, and the factor loadings are inconsistently estimated (Breitung and Eickmeier, 2011).

For all these reasons, we start our sample in the early 1980s–specifically 1982:3–when the Federal Reserve changed its policy rule and switched from targeting Nonborrowed Reserve to targeting the federal funds rate (Clarida et al., 2000).

3.2 Model Parameters

The literature has suggested different strategies to determine the number of common factors (Bai and Ng, 2002; Onatski, 2009).[7] Table 1 shows the results of the Bai and Ng (2002) IC_1 criterion and of the Onatski (2009) test together with the share of variance explained by the i-th eigenvalue (in decreasing order) of the spectral density matrix of x, and the percentage of variance explained by i-th eigenvalue of the variance covariance matrix of x. As we can see from Table 1, the Bai and Ng (2002) criterion suggests the presence of 7 static factors, while the Onatski (2009) test suggests the presence of 4 common shocks. Moreover, 7 static eigenvalues account for 65% of the total variance, which is roughly the same share of variance accounted for by the first 4 dynamic eigenvalues (67%). Hence, we will use as a benchmark specification the one with $r = 7$ and $q = 4$.[8] However, in Appendix B we provide robustness

shocks, or of "good policy", i.e. a change in the propagation mechanism of the shocks, the recent literature has favored the hypothesis of good policy. Galí and Gambetti (2009) provide evidence consistent with a decline in the size of non-technology shocks and with better countercyclical policies in response to these shocks. Giannone et al. (2008) strongly reject the good luck hypothesis in favor of changes in the propagation mechanism by showing that most of the analyses of the great moderation suffer from an omitted variable problem since they are carried out by means of small scale models.

[6]There is indeed rich evidence pointing in this direction: Calza et al. (2011) show that residential investment and house prices are more responsive to policy shocks in developed/flexible mortgage markets rather than in regulated/fixed markets. Mojon (2007) shows that monetary policy contributed to the decoupling of household investment and the other components of GDP. Iacoviello and Neri (2010) show that the spillovers from the housing market to the rest of the economy became increasingly important after the 1980s, and Goodhart and Hofmann (2008) show that the link between house prices, broad money, private credit, and the macroeconomy became stronger after 1985.

[7]Other criteria to determine the number of common factors suggested in the literature and not used in this paper are: Bai and Ng (2007); Hallin and Liška (2007); Amengual and Watson (2007); Onatski (2010); Alessi et al. (2010); Kapetanios (2010).

[8]Notably, 4 common shocks are in line with results in recent Factor models applications on large US datasets (Forni and Gambetti, 2010a,c). Indeed, the stochastic dimension of the US economy is a matter of debate. Earlier contributions (Giannone et al., 2005; Watson, 2005) conclude for 2 common shocks, while later contributions (Stock and Watson, 2005; Bai and Ng, 2007) conclude for a larger number (6-7) of shocks. Stock and Watson (2005) reconcile the two findings by explaining that, although the first two common shocks (a demand and a supply shock, Giannone et al. 2005) account for the bulk of comovement in the data and hence for forecasting they may suffice, for structural analysis a larger number of common shocks is desirable.

analyses for different parameter configurations.

The model is estimated with the Quasi Maximum Likelihood estimator of Doz et al. (2011) by imposing the restriction that the idiosyncratic term of the federal funds rate is equal to zero.[9] With this restriction, our model is a special case of the Dynamic Factor model, which nests the Factor Augmented VAR of Bernanke et al. (2005). On the one hand, compared to a standard Factor model, the main advantage of our approach is to impose a plausible restriction (see footnote 9). On the other hand, compared to a FAVAR, the main advantage of our approach is estimation efficiency since, as shown in Doz et al. (2011), the Quasi Maximum Likelihood estimator is more efficient in small samples compared to the two-step estimator based on principal components and OLS, which is used for FAVAR estimation. Furthermore, as a standard Dynamic Factor model, and in contrast to a FAVAR, our approach does not impose the restriction $r = q$, a restriction not supported by US data (see among others Bai and Ng, 2007, Amengual and Watson, 2007, Forni and Gambetti, 2010a, and the discussion in the previous paragraph).

Table 2 shows the percentage of variance explained by the common shocks. As we can see, 4 common shocks explain on average 56% of the entire variance of the database, 71% of GDP and 86% of Industrial Production, 68% of consumer prices and of Commodity Prices, and most of the fluctuations in the labor market. Looking at the housing market, common shocks account for nearly 60% of residential investment, and slightly more than 50% of building permits, while they account for only a small percentage of variation in house prices, thus indicating that prices are mainly driven by local dynamics.

3.3 Identification

Identification of monetary policy shocks is achieved by making use of the following assumptions: after a contractionary monetary policy shock, the federal funds rate increases, while GDP, consumer prices, commodity prices, non-borrowed reserves, and M1 decrease. These restrictions are imposed for the first three lags. Results are robust if restrictions are imposed on a smaller, or a larger number of lags.

Figure 1 shows the median impulse response function for selected variables together with 68% confidence bands,[10] where the shock is normalized so that at impact it raises the federal

[9]Recall that the idiosyncratic component captures either possible measurement error, or the effect of specific shocks such as regional or sectorial specific shocks. Hence, by imposing this restriction, we are assuming that (i) the federal funds rate is not measured with error, and (ii) that the federal funds rate moves only in response to common/macroeconomic shocks, or, in other words, that the Federal Reserve does not respond to sectorial or regional shocks but only to macroeconomic shocks. The first assumption is not, in fact, an assumption, since the federal funds rate is not measured with error, and the second assumption is extremely plausible (see also Giannone et al., 2005).

Similar restrictions could be imposed on other variables as well. However, we believe that this restriction is plausible only for the federal funds rate. For example, it is natural to think of imposing this restriction also on other interest rates since they are not measured with error. However, assuming a zero idiosyncratic component for all interest rates would also mean assuming that the yield curve is entirely determined by macroeconomic shocks, an assumption that is not supported by the economic literature (Ang and Piazzesi, 2003; Evans and Marshall, 2007).

[10]In order to compute confidence intervals, we use the procedure described in footnote 4 with 500 bootstrap draws. To keep computations feasible, for each sample we save $K = 25$ rotation matrices, and then we select just one rotation matrix as suggested by Fry and Pagan (2011). Fry and Pagan (2011) point out that for each sample the distribution of the $H(\omega)$ that satisfies the sign restrictions represents model uncertainty. However, when computing impulse responses with confidence bands, what matters is sampling uncertainty, not model uncertainty. Hence, Fry and Pagan (2011) suggest selecting for each sample just one rotation, namely the one

funds rate by 50 basis points. After a contractionary monetary policy shock, the federal funds rate slowly reverts to its baseline level (around 10 quarters), consumer prices decrease at impact to around -0.2% and in 5 quarters revert to their baseline, while GDP slowly decreases as far as -0.6%. Finally, the housing market is strongly influenced by monetary policy shocks: Residential investment decreases to a low of -4%, Real House Prices decrease significantly to -1%, and building permits decrease as far as -6%.

4 The Federal Reserve's Policy after 9/11 and the Housing Bubble

Since financial markets in September-October 2008 crashed, policy analysts and economists have debated the causes of the crisis, among which the Federal Reserve's policy after the events of 9/11 is the one that has attracted the most attention.

In a number of papers and speeches, John Taylor (2007, 2009, 2011) argues that the Federal Reserve's loose monetary policy between 2003 and 2004 is responsible for the recession. Taylor (2007) shows that the low interest rates in 2003 and 2004 contributed to the housing boom, and that a higher rate would have consistently smoothed the housing cycle. Taylor (2009) shows that the low interest rate led to excessive risk taking. Finally, Taylor (2011) concludes that this period of loose monetary policy led both to the "great recession", and to the end of the "great moderation".

Similarly, Leamer (2007) provides evidence that "eight of the ten [US] recessions were preceded by sustained and substantial problems in housing" (p. 164), and suggests that the Federal Reserve's loose monetary policy contributed to the boom and bust of the housing market. Lastly, Iacoviello and Neri (2010) estimate that monetary policy accounts for 15% of the boom in real house prices, whereas it accounts for almost the entire residential investment bust.

On the other hand, Jarociñski and Smets (2008) show that, although low interest rates in 2003 and 2004 contributed to the boom in the housing market, the effect on the economy was rather limited. Similarly, Dokko et al. (2011) provide evidence that monetary policy was not the primary contributing factor to the fluctuations in the housing markets, while Eickmeier and Hofmann (2011) reveal that monetary policy contributed only at a very late stage to the dynamics in the housing and credit markets. Finally, Bean et al. (2010) show that the low policy rates were a factor in the crisis, but only a *modest* factor.

To sum up, the literature has not reached a consensus on the role of the Federal Reserve in influencing the boom and bust of the housing market, nor in the ensuing recession. In this Section, we use our model to analyze Federal Reserve's policy after 9/11, and to understand whether it played any role in causing, or in contributing to, the recession.

We perform two different and complementary counterfactual exercises: the first based on structural shocks, and the second based on conditional forecasts.[11] In the first exercise, we modify a specific shock, namely the monetary policy shock; in the second exercise, in order to impose the desired counterfactual path of the policy rate, we estimate the most likely combination of macroeconomic shocks that would have generated such a path. The

that produces the impulse response closest to the median response.

[11] To quote a few recent contributions, counterfactuals based on structural shocks are used in Baumeister and Benati (2010) and Bean et al. (2010), while counterfactuals based on conditional forecast are used in Jarociñski and Smets (2008) and Giannone et al. (2012)

main advantage of the first exercise is that it is linked directly to the policy, while the main advantage of the second is that it is not dependent on the identifying assumptions. The main drawback of both exercises is that they may be subject to the Lucas (1976) critique. However, if counterfactuals are produced by means of "modest policy interventions" (Leeper and Zha, 2003), i.e. by adding *small* shocks to the model, so that the regime switch is not foreseen by economic agents, then the exercise is free of the Lucas (1976) critique.

4.1 Counterfactuals Based on Structural Shocks

Taylor (2007) argues that between 2003 and 2004 the Federal Reserve intentionally ran an expansionary policy. By estimating a standard Taylor rule, he shows that the federal funds rate "was well below what experience during the previous two decades of good economic macroeconomic performance [...] would have predicted" (p. 464), and he also suggests what would have been the correct interest rate.

On the other hand, Bernanke (2010) criticizes Taylor (2007) by arguing that the Federal Reserve kept the interest rate low between 2003 and 2004 for a number of reasons ("jobless" recovery after the 2001 recession, slow growth of GDP, and risk of deflation), and that, at that time, there was consensus among economists on the Federal Reserve's policy.[12] He then concludes that the Federal Reserve's policy, "though certainly accommodative, does not appear to have been inappropriate, given the state of the economy and policymakers' medium-term objectives" (p. 19).

With our model, we can test which of the two arguments is correct. As we argued in the introduction, since we are working in a data-rich environment, we are able to disentangle better than Taylor (2007) and Bernanke (2010), who both use only small scale models, *systematic* (i.e. the policy/feedback rule) and *unsystematic* (i.e. shocks) monetary policy.

The left plot of Figure 2 shows the estimated median monetary policy shocks from 1990 to 2010 together with 68% confidence bands.[13] Similarly to Del Negro and Otrok (2007), we find that between 2002 and 2004 monetary policy shocks were mainly negative, thus indicating an expansionary monetary policy.

Figure 3 shows the actual federal funds rate (thick line), the path of the federal funds rate suggested by Taylor (2007) (dotted line), and the counterfactual interest rate obtained by setting to zero all the estimated monetary policy shocks (thin line). In other words, the thin line is the median trajectory of the federal funds rate that would have happened if the Federal Reserve had followed the estimated monetary policy rule between 2002:2 and 2006:3.

The result in Figure 3 supports the argument of Bernanke (2010) since the counterfactual federal funds rate is almost identical to the actual one, and since it is far away from the path suggested by Taylor (2007). This result indicates that not only was monetary policy not *too loose*, but also that the interest rate suggested by Taylor (2007) would have required a restrictive monetary policy (right plot in Figure 2).

[12]In addition, Bernanke (2010) warns against drawing conclusions based on estimated Taylor rules since "simple policy rules [...] are only rules of thumb, [which] necessarily leave out many factors that may be relevant to the making of effective policy in a given episode" (p. 5). Moreover, Poole (2007) shows that a standard Taylor rule tracks well the federal funds rate only up to the end of the 90s, but not from 2000 onwards. He explains that this result depends on a number of technical reasons, such as the fact that the FOMC changed its inflation objective by measuring the inflation rate as PCE inflation rather than CPI inflation.

[13]Note that the median and the confidence bands are not obtained with the bootstrap algorithm, rather they are obtained by simply saving the first 500 rotations that satisfy the sign restrictions on the actual sample. We do so because what matters in counterfactual analysis is model uncertainty, not sample uncertainty.

It is however legitimate to ask whether a different (i.e. more restrictive) monetary policy would have been helpful. In addition, is the Federal Reserve responsible for the recession? Figure 4 and Figure 5 try to throw light on these questions. Figure 4 shows the paths of GDP, Residential Investment, Building Permits, and Real House Prices that would have happened if the Federal Reserve had just followed the estimated policy rule between 2002:2 and 2006:3, while Figure 5 shows the paths of the same variables that would have occurred if the Federal Reserve had followed the path suggested by Taylor (2007).

Figure 4 shows that if the Federal Reserve had simply followed the estimated policy rule, nothing would have changed. By contrast, Figure 5 shows that if the Federal Reserve had run a "contractionary" policy as suggested by Taylor (2007), then between 2002 and 2004 GDP and the housing variables would have experienced a smaller, and often negative, growth rate. However, such a policy would have not been able to prevent the recession. This result supports the argument that during the crisis, mechanisms that did not depend on monetary policy–or, at least, on conventional monetary policy–were taking place.[14] Hence, we find no role for the Federal Reserve in the recession.

To conclude, in contrast to Taylor (2007) and in agreement with Bernanke (2010), we show that the Federal Reserve deviated from the policy rule in an expansionary sense, but that the path of the interest rate implied by the estimated policy rule is almost identical to the actual one. On the other hand, we find that a different policy, such as that suggested by Taylor (2007), would have smoothed the housing cycle. However, (i) the policy suggested by Taylor (2007) would have required an intentionally restrictive monetary policy, and (ii) it would have not been able to avoid the recession.

4.2 Counterfactuals based on Conditional Forecasts

In this subsection, we answer questions similar to those of the previous subsection but with a different methodology. The methodology we use is the conditional forecast methodology (Doan et al., 1984; Waggoner and Zha, 1999) implemented by means of the algorithm suggested by Bańbura et al. (2011), which is suitable for any (large) model with a state-space representation.

The methodology of conditional forecasts estimates the most likely combination of macroeconomic shocks that would have generated the counterfactual interest rate. With this counterfactual exercise, we can study the Federal Reserve's policy after 9/11 from a different perspective than that adopted in Section 4.1. In Section 4.1, the difference between the actual and the counterfactual interest rate is due only to monetary policy shocks. Here, instead, this difference is the result of all q macroeconomic shocks. This means that we do not require that this difference be only the result of *unsystematic* monetary policy, but of *systematic* monetary policy as well.

In practice, to estimate a conditional forecast, we need first to modify the database by setting to missing value all the variables that we want to forecast, and by leaving unaltered all the variables we want to condition on. Then, once the database is modified, we proceed as follows: 1. we estimate the model on the benchmark database thus obtaining an estimate of the parameters ($\widehat{\theta}$), of the common factors ($\widehat{F}_t$), and of the common ($\widehat{\chi}_t$) and the idiosyncratic

[14] As explained by Taylor (2009), once the housing bubble had burst, the crisis became mainly a counterparty risk problem rather than a liquidity problem. In particular, Taylor (2009) argues that the use of sub-prime mortgages led to excessive risk taking, and that this risk was put to the market through mortgage-backed securities of great complexity, the risk of which was underestimated by the rating agencies. This counterparty risk problem started nonlinear phenomena that cannot be explained by our model.

($\widehat{\xi}_t$) components; 2. given $\widehat{\theta}$, we estimate new factors ($\widetilde{F}_t$) and new common components ($\widetilde{\chi}_t$) by running the Kalman Smoother on the new database; 3. we obtain the conditional forecast as $\widetilde{x}_t = \widetilde{\chi}_t + \widehat{\xi}_t$.

As in Section 4.1, the main question we want to answer here is the following: what would have happened if the Federal Reserve had followed a different policy? That is, we compute the forecast of all the variables in the database conditional on the Federal Reserve following the path of the interest rate suggested by Taylor (2007).[15] Figure 6 shows the actual growth rate (shaded area), and the conditional forecast (straight line) for different variables. Confirming the results of Figure 5, Figure 6 shows that a higher interest rate (*i*) would have hardly influenced GDP growth, (*ii*) would have slightly mitigated the housing market boom, but (*iii*) would have not prevented the recession.

We conclude this Section by using conditional forecasts to answer one last question related to those addressed so far: can we explain business cycle fluctuations from 2002 onwards based only on the observed federal funds rate? That is, we compute the forecast of all the variables in the database conditional only on the actual federal funds rate. Figure 7 shows the actual growth rate (shaded area), and the conditional forecast (straight line) for different variables. The results in Figure 7 show that the conditional forecast matches quite well the period between 2002 and 2007, but that it has a poor fit starting from mid 2008. This result indicates that after 2007 mechanisms different from those acting before 2007 prevailed in characterizing the business cycle, which is in line with the results of Section 4.1, according to which the Federal Reserve played no role in the recession.

5 Conclusions

In this paper, we estimate a Structural Dynamic Factor model on a panel of 109 US quarterly variables from 1982 to 2010. We use the estimated model to study the role of the Federal Reserve's policy in influencing the recent boom and bust of the housing market, and the ensuing recession. Results of two different and complementary counterfactual exercises (the first based on structural shocks, and the second based on conditional forecasts) show that: (*i*) the Federal Reserve ran an expansionary policy between 2002 and 2004; however, (*ii*) the federal funds rate that would have happened if the Federal Reserve had followed the estimated monetary policy rule is almost identical to the actual one; hence, (*iii*) if the Federal Reserve simply had followed the estimated policy rule, almost nothing would have changed.

We also consider the effect of an alternative policy (restrictive according to our model) such as the one suggested by Taylor (2007). Results show that if the Federal Reserve had followed such a policy, the business cycle would have been smoothed. However, we do not find evidence that the policy suggested by Taylor (2007) would have been able to prevent the recession. As explained by Taylor (2009), once the housing bubble had burst, the economy was driven by mechanisms (such as counterparty risk for example) that did not depend on monetary policy. Hence, we find no role for the Federal Reserve in causing the recession.

[15] Practically, this exercise is implemented by setting to missing value all interest rates except the federal funds rate, and by substituting for the actual federal funds rate the path suggested by Taylor (2007).

References

Alessi, L., M. Barigozzi, and M. Capasso (2010). Improved penalization for determining the number of factors in approximate static factor models. *Statistics and Probability Letters 80*, 1806–1813.

Amengual, D. and M. W. Watson (2007). Consistent estimation of the number of dynamic factors in a large N and T panel. *Journal of Business and Economic Statistics 25*, 91–96.

Ang, A. and M. Piazzesi (2003). A no-arbitrage vector autoregression of term structure dynamics with macroeconomic and latent variables. *Journal of Monetary Economics 50*(4), 745–787.

Bai, J. (2003). Inferential theory for factor models of large dimensions. *Econometrica 71*, 135–171.

Bai, J. and S. Ng (2002). Determining the number of factors in approximate factor models. *Econometrica 70*, 191–221.

Bai, J. and S. Ng (2007). Determining the number of primitive shocks in factor models. *Journal of Business and Economic Statistics 25*, 52–60.

Bańbura, M., D. Giannone, and M. Lenza (2011). Conditional forecasting with large vector auto-regressions: an application to the Euro Area. Université libre de Bruxelles.

Bańbura, M., D. Giannone, and L. Reichlin (2010). Large bayesian vector auto regressions. *Journal of Applied Econometrics 25*, 71–92.

Baumeister, C. and L. Benati (2010). Unconventional monetary policy and the great recession - estimating the impact of a compression in the yield spread at the zero lower bound. Working Paper 1258, E.C.B.

Bean, C., M. Paustian, A. Penalver, and T. Taylor (2010). Monetary policy after the fall. Paper presented at the Federal Reserve Bank of Kansas City Annual Conference Macroeconomic Challenges: The Decade Ahead, Jackson Hole, Wyoming, August 28.

Bernanke, B. S. (2007). Housing, housing finance, and monetary policy: a symposium sponsored by the Federal Reserve Bank of Kansas City: opening remarks. *Proceedings*, 1–20. Federal Reserve Bank of Kansas City.

Bernanke, B. S. (2010). Monetary policy and the housing bubble. Speech at the Annual Meeting of the American Economic Association, Atlanta, Georgia, January 3.

Bernanke, B. S. and J. Boivin (2003). Monetary policy in a data-rich environment. *Journal of Monetary Economics 50*, 525–546.

Bernanke, B. S., J. Boivin, and P. S. Eliasz (2005). Measuring the effects of monetary policy: A Factor-Augmented Vector Autoregressive (FAVAR) approach. *The Quarterly Journal of Economics 120*, 387–422.

Breitung, J. and S. Eickmeier (2011). Testing for structural breaks in dynamic factor models. *Journal of Econometrics 163*, 71–74.

Calza, A., T. Monacelli, and L. Stracca (2011). Housing finance and monetary policy. *Journal of the European Economic Association*. forthcoming.

Canova, F. and G. de Nicolò (2003). On the sources of business cycles in the G-7. *Journal of International Economics 59*, 77–10.

Chamberlain, G. and M. Rothschild (1983). Arbitrage, factor structure, and mean-variance analysis on large asset markets. *Econometrica 51*(5), 1281–304.

Clarida, R., J. Galí, and M. Gertler (2000). Monetary policy rules and macroeconomic stability: Evidence and some theory. *Quarterly Journal of Economics 115*, 147–180.

Del Negro, M. and C. Otrok (2007). 99 luftballons: Monetary policy and the house price boom across U.S. states. *Journal of Monetary Economics 54*, 1962–1985.

Doan, T., R. B. Litterman, and C. Sims (1984). Forecasting and conditional projection using realistic prior distributions. *Econometric Reviews 3*, 1–100.

Dokko, J., B. M. Doyle, M. T. Kiley, J. Kim, S. Sherlund, J. Sim, and S. Van Den Heuvel (2011). Monetary policy and the global housing bubble. *Economic Policy 26*, 237–287.

Doz, C., D. Giannone, and L. Reichlin (2011). A quasi maximum likelihood approach for large approximate dynamic factor models. *Review of Economics and Statistics*. forthcoming.

Eickmeier, S. (2009). Comovements and heterogeneity in the Euro Area analyzed in a non-stationary dynamic factor model. *Journal of Applied Econometrics 24*, 933–959.

Eickmeier, S. and B. Hofmann (2011). Monetary policy, housing booms, and financial (im)balances. *Macroeconomic Dynamics*. forthcoming.

Evans, C. L. and D. A. Marshall (2007). Economic determinants of the nominal treasury yield curve. *Journal of Monetary Economics 54*(7), 1986–2003.

Forni, M. and L. Gambetti (2010a). The dynamic effects of monetary policy: A structural factor model approach. *Journal of Monetary Economics 57*, 203–216.

Forni, M. and L. Gambetti (2010b). Fiscal foresight and the effects of goverment spending. Discussion Papers 7840, C.E.P.R.

Forni, M. and L. Gambetti (2010c). Macroeconomic Shocks and the Business Cycle: Evidence from a Structural Factor Model. Discussion Papers 7692, C.E.P.R.

Forni, M., D. Giannone, M. Lippi, and L. Reichlin (2009). Opening the Black Box: Structural Factor Models versus Structural VARs. *Econometric Theory 25*, 1319–1347.

Forni, M., M. Hallin, M. Lippi, and L. Reichlin (2000). The Generalized Dynamic Factor Model: Identification and Estimation. *The Review of Economics and Statistics 82*, 540–554.

Forni, M. and M. Lippi (2001). The Generalized Dynamic Factor Model: Representation Theory. *Econometric Theory 17*, 1113–1141.

Fry, R. and A. R. Pagan (2011). Sign restrictions in structural vector autoregressions: A critical review. *Journal of Economic Literature 49*, 938–960.

Galí, J. and L. Gambetti (2009). On the sources of the great moderation. *American Economic Journal: Macroeconomics 1*(1), 26–57.

Geweke, J. (1977). The dynamic factor analysis of economic time series. In D. J. Aigner and A. S. Goldberger (Eds.), *Latent Variables in Socio-Economic Models*. Amsterdam: North Holland.

Giannone, D., M. Lenza, and L. Reichlin (2008). Explaining the great moderation: It is not the shocks. *Journal of the European Economic Association 6*, 621–633.

Giannone, D., M. Lenza, and L. Reichlin (2012). Money, credit, monetary policy and the business cycle in the Euro Area. Discussion Papers 8944, C.E.P.R.

Giannone, D., L. Reichlin, and L. Sala (2005). Monetary policy in real time. In M. Gertler and K. Rogoff (Eds.), *NBER Macroeconomics Annual 2004*. MIT Press.

Goodhart, C. and B. Hofmann (2008). House prices, money, credit, and the macroeconomy. *Oxford Review of Economic Policy 24*, 180–205.

Hallin, M. and R. Liška (2007). Determining the number of factors in the general dynamic factor model. *Journal of the American Statistical Association 102*, 603–617.

Iacoviello, M. (2005). House prices, borrowing constraints, and monetary policy in the business cycle. *American Economic Review 95*, 739–764.

Iacoviello, M. and R. Minetti (2008). The credit channel of monetary policy: Evidence from the housing market. *Journal of Macroeconomics 30*, 69–96.

Iacoviello, M. and S. Neri (2010). Housing market spillovers: Evidence from an estimated DSGE model. *American Economic Journal: Macroeconomics 2*, 125–164.

Jarociñski, M. and F. Smets (2008). House prices and the stance of monetary policy. *Federal Reserve Bank of St. Louis Review 90*, 339–366.

Kapetanios, G. (2010). A testing procedure for determining the number of factors in approximate factor models with large datasets. *Journal of Business and Economic Statistics 28*, 397–409.

Kilian, L. (1998). Small-sample confidence intervals for impulse response functions. *The Review of Economics and Statistics 80*, 218–230.

Leamer, E. E. (2007). Housing *is* the business cycle. *Proceedings*, 149–233. Federal Reserve Bank of Kansas City.

Leamer, E. E. (2009). Homes and cars: Why are the cycles in homes and consumer durables so similar? *The B.E. Journal of Economic Analysis & Policy 9*, Article 5.

Leeper, E. M. and T. Zha (2003). Modest policy interventions. *Journal of Monetary Economics 50*(8), 1673–1700.

Lippi, M. and L. Reichlin (1993). The dynamic effects of aggregate demand and supply disturbances: Comment. *American Economic Review 83*, 644–52.

Lippi, M. and L. Reichlin (1994). VAR analysis, nonfundamental representations, Blaschke matrices. *Journal of Econometrics 63*, 307–325.

Lucas, R. J. (1976). Econometric policy evaluation: A critique. *Carnegie-Rochester Conference Series on Public Policy 1*, 19–46.

Moench, E. and S. Ng (2011). A hierarchical factor analysis of U.S. housing market dynamics. *Econometrics Journal 14*, C1–C24.

Mojon, B. (2007). Monetary policy, output composition and the great moderation. Working Paper Series 07, Federal Reserve Bank of Chicago.

Onatski, A. (2009). Testing hypotheses about the number of factors in large factor models. *Econometrica 77*, 1447–1479.

Onatski, A. (2010). Determining the number of factors from empirical distribution of eigenvalues. *Review of Economics and Statistics 92*, 1004–1016.

Poole, W. (2007). Understanding the Fed. *Federal Reserve Bank of St. Louis Review 89*, 3–14.

Sargent, T. J. and C. A. Sims (1977). Business cycle modeling without pretending to have too much a-priori economic theory. In C. A. Sims (Ed.), *New Methods in Business Cycle Research*. Minneapolis: Federal Reserve Bank of Minneapolis.

Stock, J. H. and M. W. Watson (2002). Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association 97*, 1167–1179.

Stock, J. H. and M. W. Watson (2005). Implications of dynamic factor models for VAR analysis. Working Paper 11467, NBER.

Stock, J. H. and M. W. Watson (2009). The evolution of national and regional factors in U.S. housing construction. In T. Bollerslev, J. Russell, and M. Watson (Eds.), *Volatility and Time Series Econometrics: Essays in Honour of Robert F. Engle*. Oxford: Oxford University Press.

Taylor, J. B. (2007). Housing and monetary policy. *Proceedings*, 463–476. Federal Reserve Bank of Kansas City.

Taylor, J. B. (2009). The financial crisis and the policy responses: An empirical analysis of what went wrong. Working Papers 14631, NBER.

Taylor, J. B. (2011). Macroeconomic lessons from the great deviation. In D. Acemoglu and M. Woodford (Eds.), *NBER Macroconomics Annual 2010, Volume 25*. University of Chicago Press.

Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics 52*(2), 381–419.

Waggoner, D. F. and T. Zha (1999). Conditional forecasts in dynamic multivariate models. *Review of Economics and Statistics 81*(4), 639–651.

Watson, M. (2005). Comment on monetary policy in real time. In M. Gertler and K. Rogoff (Eds.), *NBER Macroeconomics Annual 2004*. MIT Press.

Tables

Table 1: Testing for the Number of Factors

q, r	λ_i^x	R	μ_i^x	IC_1
1	0.375	0.305	0.260	-0.237
2	0.134	0.069	0.114	-0.332
3	0.091	0.932	0.101	-0.436
4	0.066	0.030	0.067	-0.500
5	0.052	0.415	0.040	-0.519
6	0.040	0.684	0.035	-0.534
7	0.034	0.620	0.032	-0.547
8	0.028	0.589	0.023	-0.543
9	0.025	0.486	0.022	-0.539
10	0.021	0.591	0.019	-0.530

λ_i^x is the percentage of variance explained by i-th eigenvalue (in decreasing order) of the spectral density matrix of x. R is the p-value of the Onatski (2009) statistic for the null of $q-1$ common shocks against the alternative of q common shocks. μ_i^x is the percentage of variance explained by i-th eigenvalue (in decreasing order) of the variance covariance matrix of x. IC_1 is the criterion of Bai and Ng (2002).

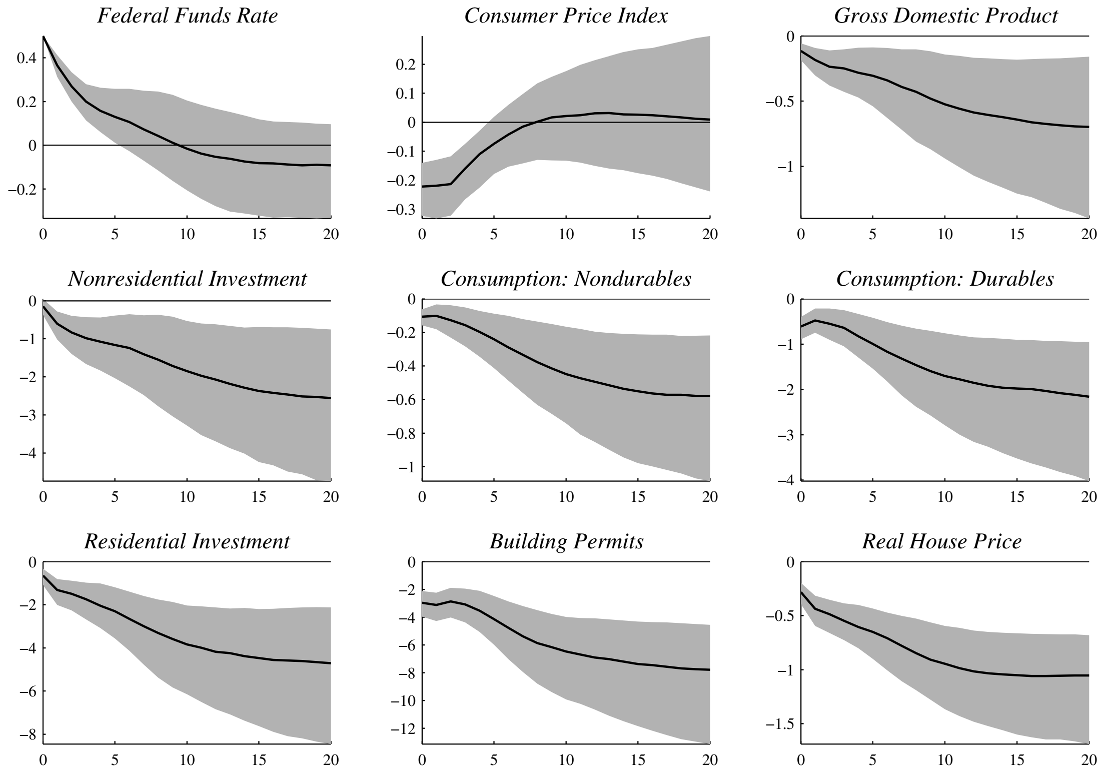
Table 2: Percentage of Variance Explained by the first q Common Shocks

q	1	2	3	4	5	6
Average	0.28	0.49	0.53	0.56	0.57	0.59
Federal Funds Rate	1.00	1.00	1.00	1.00	1.00	1.00
3-Month Treasury Bill	0.99	0.99	0.99	0.99	0.99	0.99
1-Year Treasury CM Rate	0.98	0.98	0.98	0.99	0.99	0.99
10-Year Treasury CM Rate	0.83	0.83	0.84	1.00	1.00	1.00
Consumer Price Index	0.20	0.39	0.52	0.68	0.49	0.51
'CPI: Commodities'	0.03	0.33	0.64	0.68	0.65	0.64
Industrial Production	0.30	0.86	0.85	0.86	0.88	0.90
Gross Domestic Product	0.24	0.67	0.70	0.71	0.80	0.74
Consumption: Non Durables	0.10	0.29	0.32	0.35	0.48	0.41
Consumption: Durables	0.05	0.23	0.28	0.31	0.30	0.35
Nonresidential Investment	0.32	0.65	0.64	0.65	0.65	0.65
Unemployment Rate	0.36	0.76	0.76	0.76	0.77	0.76
Duration of Unemployment	0.47	0.66	0.67	0.66	0.66	0.65
Residential Investment	0.28	0.58	0.57	0.59	0.67	0.69
Building Permits	0.17	0.46	0.44	0.52	0.49	0.53
Real House Price	0.08	0.13	0.14	0.12	0.19	0.16

This table shows the percentage of variance explained by the common component $\chi_t = \Lambda F_t$ where F_t is of dimension 7×1. The common component is estimated with Quasi Maximum Likelihood (Doz et al., 2011) by allowing for q common shocks.

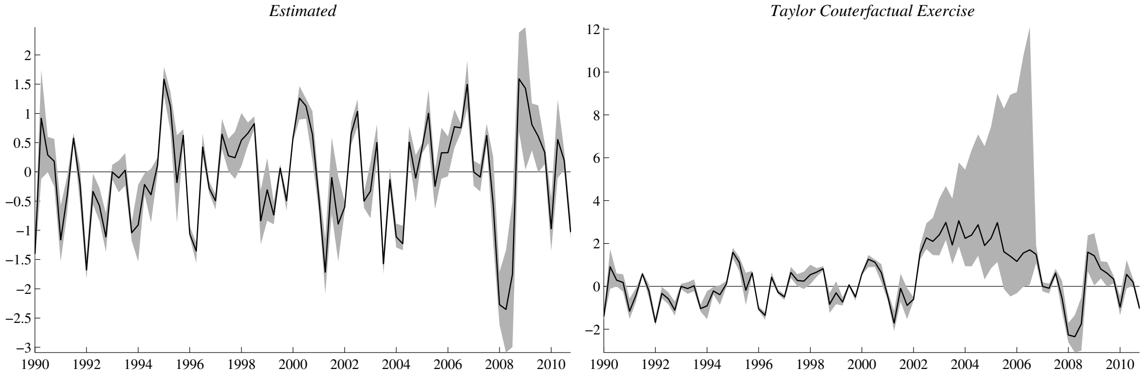
Graphs

Figure 1: Impulse Response Functions



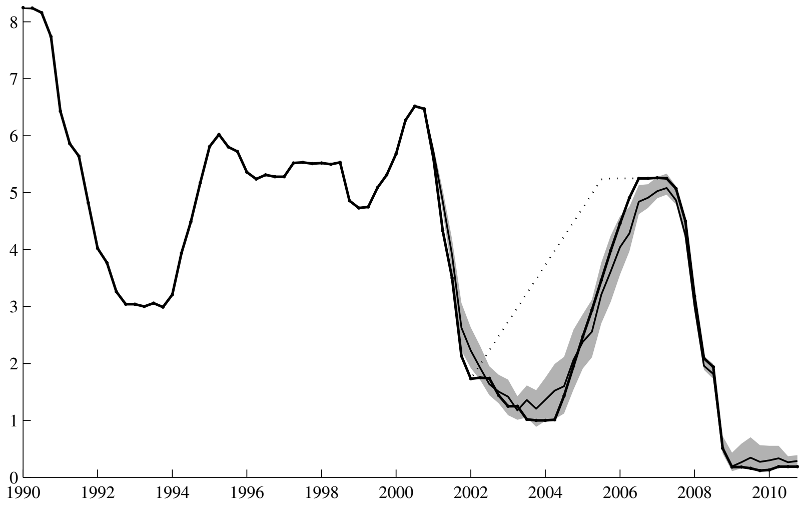
In each plot, the solid line and the shaded area represent, respectively, the median and the 68% confidence bands obtained with the bootstrap procedure described in footnote 4.

Figure 2: Monetary Policy Shocks



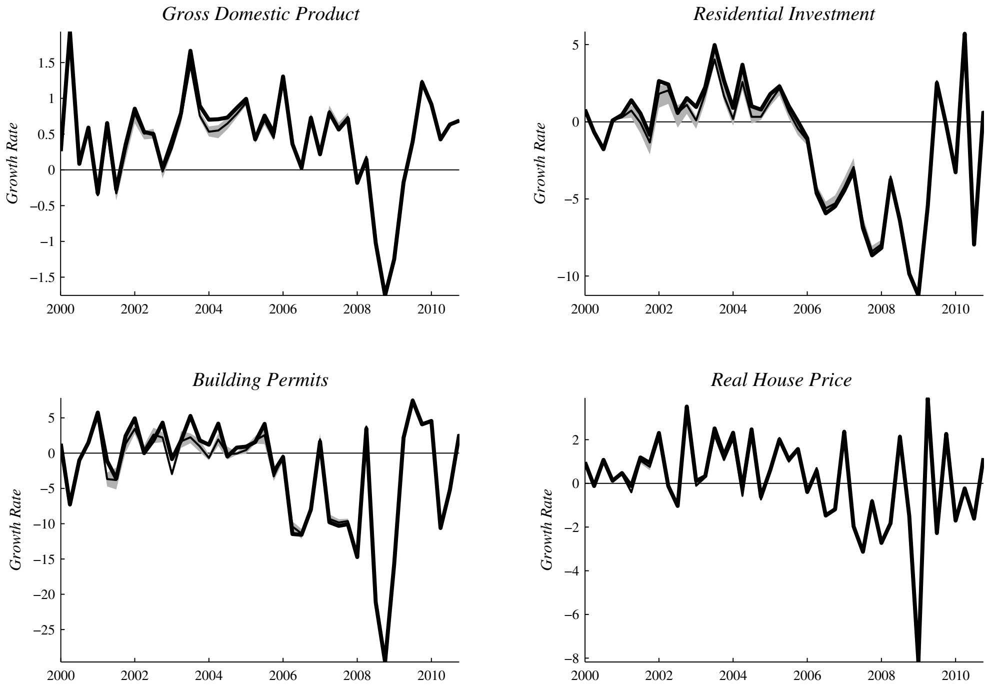
The left plot shows the estimated median shock (solid line) with 68% confidence bands (shaded area). The right plot shows the monetary policy shocks that would have been necessary to replicate the path of the federal funds rate suggested by Taylor (2007).

Figure 3: Federal Funds Rate



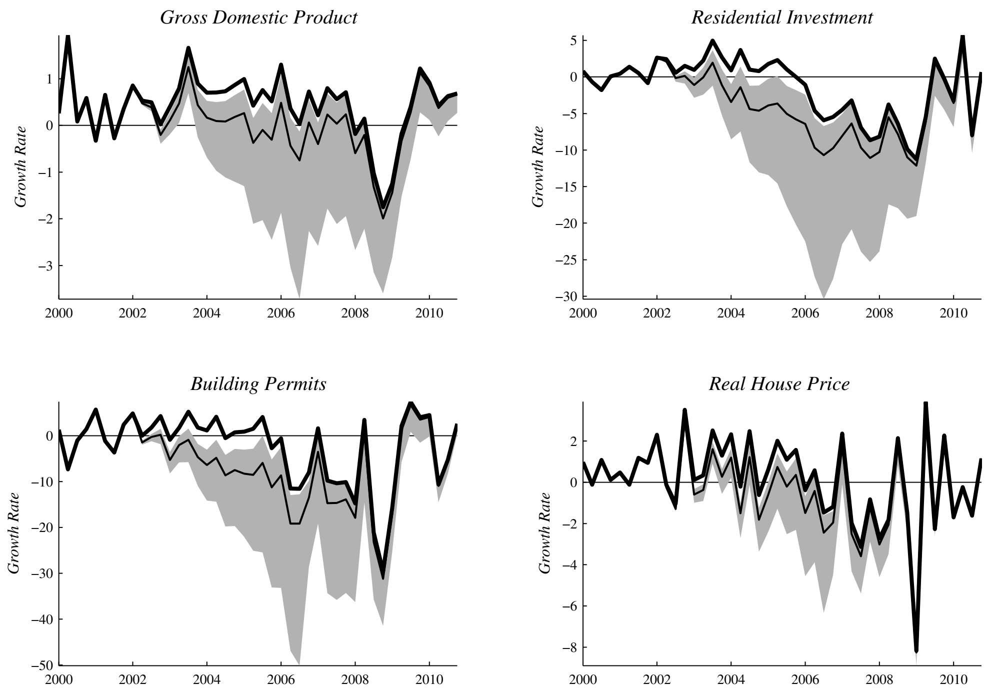
The thick solid line is the actual federal funds rate. The dotted line is the path of the federal funds rate suggested by Taylor (2007). The thin solid line is the median counterfactual interest rate with 68% confidence bands (shaded area) obtained by setting to zero all the estimated monetary policy shocks between 2002:2 and 2006:3, i.e. the median trajectory of the federal funds rate that would have happened if the Federal Reserve had followed the estimated monetary policy rule.

Figure 4: Counterfactuals Based on Structural Shocks
No Monetary Policy Shocks Exercise



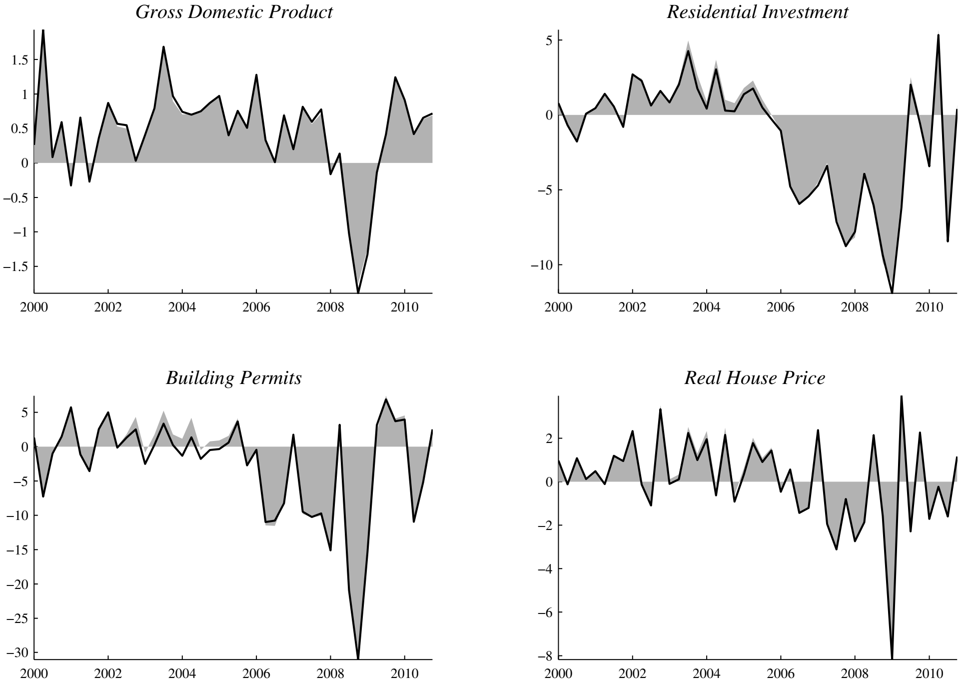
In each plot, the thick solid line represents the actual growth rate, while the thin solid line is the median counterfactual growth rate with 68% confidence bands (shaded area). The counterfactual is obtained by setting to zero all the estimated monetary policy shocks between 2002:2 and 2006:3, i.e. the median trajectory of the federal funds rate that would have happened if the Federal Reserve had followed the estimated monetary policy rule.

Figure 5: Counterfactuals Based on Structural Shocks
Taylor Conterfactual Exercise



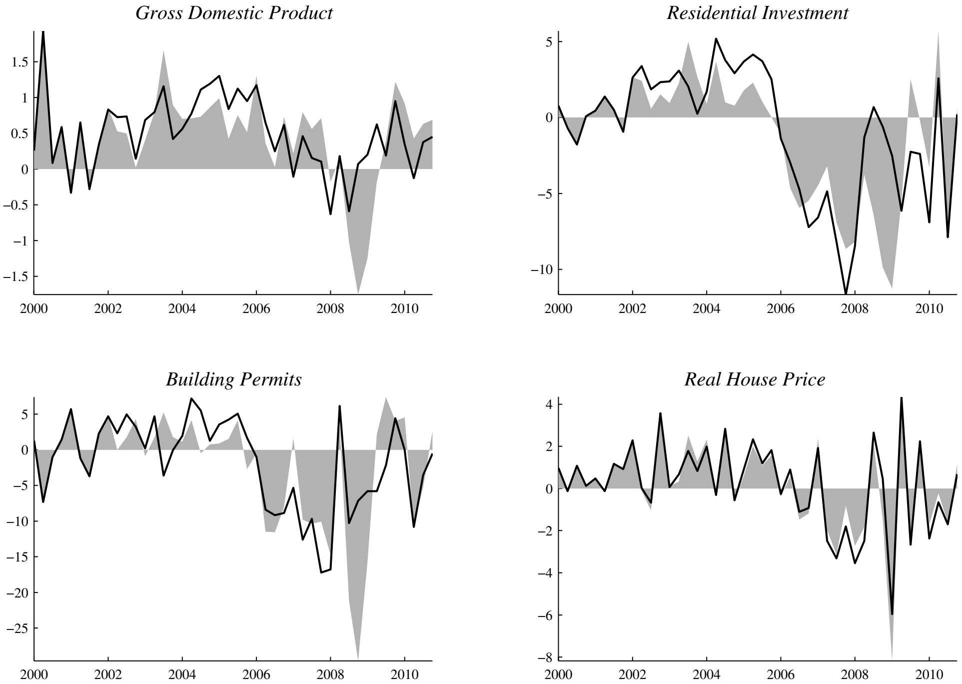
In each plot, the thick solid line represents the actual growth rate, while the thin solid line is the median counterfactual growth rate with 68% confidence bands (shaded area). The counterfactual is what would have occurred if the Federal Reserve had followed the path suggested by Taylor (2007).

Figure 6: Counterfactuals based on Conditional Forecasts
Taylor Conterfactual Exercise



Each plot shows the actual growth rate (shaded area) and the conditional forecast (solid line). The forecast is obtained conditional on the Federal Reserve following the path of the interest rate suggested by Taylor (2007).

Figure 7: Counterfactuals based on Conditional Forecasts
Business cycle fluctuations and the federal funds rate



Each plot shows the **actual** growth rate (shaded area) and the conditional forecast (solid line). The forecast is obtained conditional only on the actual federal funds rate.

Appendix A Data Description and Data Treatment

N°	Series ID	Definition	F	SA	Unit	T	C
1	INDPRO	Industrial Production Index	M	1	2002=100	2	1
2	IPBUSEQ	Industrial Production: Business Equipment	M	1	2002=100	2	1
3	IPDCONGD	Industrial Production: Durable Consumer Goods	M	1	2002=100	2	1
4	IPDMAT	Industrial Production: Durable Materials	M	1	2002=100	2	1
5	IPNCONGD	Industrial Production: Nondurable Consumer Goods	M	1	2002=100	2	1
6	IPNMAT	Industrial Production: nondurable Materials	M	1	2002=100	2	1
7	CPIAUCSL	Consumer Price Index for All Urban Consumers: All Items	M	1	1982-84=100	2	2
8	CPIENGSL	CPIAUCs: Energy	M	1	1982-84=100	2	2
9	CPILEGSL	CPIAUCs: All Items Less Energy	M	1	1982-84=100	2	2
10	CPILFESL	CPIAUCs: All Items Less Food & Energy	M	1	1982-84=100	2	2
11	CPIUFDSL	CPIAUCs: Food	M	1	1982-84=100	2	2
12	CPIULFSL	CPIAUCs: All Items Less Food	M	1	1982-84=100	2	2
13	CUSR0000SAC	CPI: Commodities	M	1	1982-84=100	2	2
14	PPICRM	Producer Price Index: Crude Materials for Further Processing	M	1	1982 = 100	2	3
15	PPIENG	Producer Price Index: Fuels & Related Products & Power	M	0	1982 = 100	2	3
16	PPIFGS	Producer Price Index: Finished Goods	M	1	1982 = 100	2	3
17	PPIIDC	Producer Price Index: Industrial Commodities	M	0	1982 = 100	2	3
18	PPICPE	Producer Price Index: Finished Goods: Capital Equipment	M	1	1982 = 100	2	3
19	PPIACO	Producer Price Index: All Commodities	M	0	1982 = 100	2	3
20	PPIITM	Producer Price Index: Supplies & Components	M	1	1982 = 100	2	3
21	AMBSL	St. Louis Adjusted Monetary Base	M	1	Bil. of $	2	4
22	ADJRESSL	St. Louis Adjusted Reserves	M	1	Bil. of $	2	4
23	CURRSL	Currency Component of M1	M	1	Bil. of $	2	4
24	M1SL	M1 Money Stock	M	1	Bil. of $	2	4
25	M2SL	M2 Money Stock	M	1	Bil. of $	2	4
26	BOGAMBSL	Board of Governors Monetary Base	M	1	Bil. of $	2	4
27	BOGNONBR	Non-Borrowed Reserves of Depository Institutions	M	1	Bil. of $	2	4
28	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks	M	1	Bil. of $	2	5
29	CONSUMER	Consumer (Individual) Loans at All Commercial Banks	M	1	Bil. of $	2	5
30	LOANINV	Total Loans and Investments at All Commercial Banks	M	1	Bil. of $	2	5
31	LOANS	Total Loans and Leases at Commercial Banks	M	1	Bil. of $	2	5
32	REALLN	Real Estate Loans at All Commercial Banks	M	1	Bil. of $	2	5
33	TOTALSL	Total Consumer Credit Outstanding	M	1	Bil. of $	2	5
34	GDPC1	Real Gross Domestic Product, 1 Decimal	Q	1	Bil. of Ch. 2000 $	2	6
35	FINSLC1	Real Final Sales of Domestic Product, 1 Decimal	Q	1	Bil. of Ch. 2005 $	2	6
36	GPDIC1	Real Gross Private Domestic Investment, 1 Decimal	Q	1	Bil. of Ch. 2005 $	2	6
37	SLCEC1	Real State & Local Cons. Exp. & Gross Investment, 1 Decimal	Q	1	Bil. of Ch. 2005 $	2	6
38	PRFIC1	Real Private Residential Fixed Investment, 1 Decimal	Q	1	Bil. of Ch. 2005 $	2	6
39	PNFIC1	Real Private Nonresidential Fixed Investment, 1 Decimal	Q	1	Bil. of Ch. 2005 $	2	6
40	IMPGSC1	Real Imports of Goods & Services, 1 Decimal	Q	1	Bil. of Ch. 2005 $	2	6
41	GCEC1	Real Government Cons. Exp. & Gross Investment, 1 Decimal	Q	1	Bil. of Ch. 2005 $	2	6
42	EXPGSC1	Real Exports of Goods & Services, 1 Decimal	Q	1	Bil. of Ch. 2005 $	2	6
43	CBIC1	Real Change in Private Inventories, 1 Decimal	Q	1	Bil. of Ch. 2005 $	1	6
44	PCNDGC96	Real Personal Consumption Expenditures: Nondurable Goods	Q	1	Bil. of Ch. 2005 $	2	6
45	PCESVC96	Real Personal Consumption Expenditures: Services	Q	1	Bil. of Ch. 2005 $	2	6
46	PCDGCC96	Real Personal Consumption Expenditures: Durable Goods	Q	1	Bil. of Ch. 2005 $	2	6
47	PCECC96	Real Personal Consumption Expenditures	Q	1	Bil. of Ch. 2005 $	2	6
48	DGIC96	Real National Defense Gross Investment	Q	1	Bil. of Ch. 2005 $	2	6
49	NDGIC96	Real Federal Nondefense Gross Investment	Q	1	Bil. of Ch. 2005 $	2	6
50	DPIC96	Real Disposable Personal Income	Q	1	Bil. of Ch. 2005 $	2	6
51	PCECTPI	Personal Consumption Expenditures: Chain-type Price Index	Q	1	Index 2005=100	2	5
52	GPDICTPI	Gross Private Domestic Investment: Chain-type Price Index	Q	1	Index 2005=100	2	5
53	GDPCTPI	Gross Domestic Product: Chain-type Price Index	Q	1	Index 2005=100	2	5
54	HOUSTMW	Housing Starts in Midwest Census Region	M	1	Thous. of Units	2	7
55	HOUSTNE	Housing Starts in Northeast Census Region	M	1	Thous. of Units	2	7
56	HOUSTS	Housing Starts in South Census Region	M	1	Thous. of Units	2	7
57	HOUSTW	Housing Starts in West Census Region	M	1	Thous. of Units	2	7
58	hp	Real House Price	Q	0	index	2	7
59	PERMIT	New Private Housing Units Authorized by Building Permit	M	1	Thous. of Units	2	7
60	ULCMFG	Manufacturing Sector: Unit Labor Cost	Q	1	1992 = 100	2	8
61	COMPRMS	Manufacturing Sector: Real Compensation Per Hour	Q	1	1992 = 100	2	8
62	COMPMS	Manufacturing Sector: Compensation Per Hour	Q	1	1992 = 100	2	8
63	HOAMS	Manufacturing Sector: Hours of All Persons	Q	1	1992 = 100	2	8
64	OPHMFG	Manufacturing Sector: Output Per Hour of All Persons	Q	1	1992 = 100	2	8
65	ULCBS	Business Sector: Unit Labor Cost	Q	1	1992 = 100	2	8
66	RCPHBS	Business Sector: Real Compensation Per Hour	Q	1	1992 = 100	2	8
67	HCOMPBS	Business Sector: Compensation Per Hour	Q	1	1992 = 100	2	8
68	HOABS	Business Sector: Hours of All Persons	Q	1	1992 = 100	2	8
69	OPHPBS	Business Sector: Output Per Hour of All Persons	Q	1	1992 = 100	2	8
70	OILPRICE	Spot Oil Price: West Texas Intermediate	M	0	$ per Barrel	2	8
71	MPRIME	Bank Prime Loan Rate	M	0	%	0	9
72	FEDFUNDS	Effective Federal Funds Rate	M	0	%	0	9
73	TB3MS	3-Month Treasury Bill: Secondary Market Rate	M	0	%	0	9
74	GS1	1-Year Treasury Constant Maturity Rate	M	0	%	0	9
75	GS3	3-Year Treasury Constant Maturity Rate	M	0	%	0	9
76	GS10	10-Year Treasury Constant Maturity Rate	M	0	%	0	9
77		GS1-FedFunds	M	0	%	0	9
78		GS10-FedFunds	M	0	%	0	9

79	EMRATIO	Civilian Employment-Population Ratio	M	1	%	1	10
80	CE16OV	Civilian Employment	M	1	Thous.	2	10
81	UNRATE	Civilian Unemployment Rate	M	1	%	1	10
82	UEMPLT5	Civilians Unemployed - Less Than 5 Weeks	M	1	Thous.	2	10
83	UEMP5TO14	Civilian Unemployed for 5-14 Weeks	M	1	Thous.	2	10
84	UEMP15T26	Civilians Unemployed for 15-26 Weeks	M	1	Thous.	2	10
85	UEMP27OV	Civilians Unemployed for 27 Weeks and Over	M	1	Thous.	2	10
86	UEMPMEAN	Average (Mean) Duration of Unemployment	M	1	Weeks	2	10
87	UNEMPLOY	Unemployed	M	1	Thous.	2	10
88	DMANEMP	All Employees: Durable Goods Manufacturing	M	1	Thous.	2	10
89	NDMANEMP	All Employees: Nondurable Goods Manufacturing	M	1	Thous.	2	10
90	SRVPRD	All Employees: Service-Providing Industries	M	1	Thous.	2	10
91	USCONS	All Employees: Construction	M	1	Thous.	2	10
92	USEHS	All Employees: Education & Health Services	M	1	Thous.	2	10
93	USFIRE	All Employees: Financial Activities	M	1	Thous.	2	10
94	USGOOD	All Employees: Goods-Producing Industries	M	1	Thous.	2	10
95	USGOVT	All Employees: Government	M	1	Thous.	2	10
96	USINFO	All Employees: Information Services	M	1	Thous.	2	10
97	USLAH	All Employees: Leisure & Hospitality	M	1	Thous.	2	10
98	USMINE	All Employees: Natural Resources & Mining	M	1	Thous.	2	10
99	USPBS	All Employees: Professional & Business Services	M	1	Thous.	2	10
100	USPRIV	All Employees: Total Private Industries	M	1	Thous.	2	10
101	USSERV	All Employees: Other Services	M	1	Thous.	2	10
102	USTPU	All Employees: Trade, Transportation & Utilities	M	1	Thous.	2	10
103	USWTRADE	All Employees: Wholesale Trade	M	1	Thous.	2	10
104	ORDERS	Business Surveys, ISM Manufacturing, New orders	M	1	index	1	11
105	PRODUCTION	Business Surveys, ISM Manufacturing, Production	M	1	index	1	11
106	EMPLOYMENT	Business Surveys, ISM Manufacturing, Employment	M	1	index	1	11
107	DELIVERIES	Business Surveys, ISM Manufacturing, Deliveries	M	1	index	1	11
108	INVENTORIES	Business Surveys, ISM Manufacturing, Inventories	M	1	index	1	11
109	GSPC	Standard & Poors, 500 Composite, Index, Price Return	M	0	index	2	12

NOTE: Outliers are detected as values differing from the median more than six times the interquantile difference. Outliers are replaced with the median of the five previous observations. All series are from the Fred II database of the Federal Reserve Bank of St. Louis with the exception of series 58, 77, 78 and of series 104-109. Series 58 is the Census Bureau House Price Index (*new one-family houses sold including value of lot*) deflated by the implicit price deflator for the nonfarm business sector (IPDNBS) taken from the Fred II database. Series 77 and 78 are own calculations. Series 104-108 are taken from ISM web site (http://www.ism.ws), while series 109 is from finance.yahoo.com.

Abbreviations

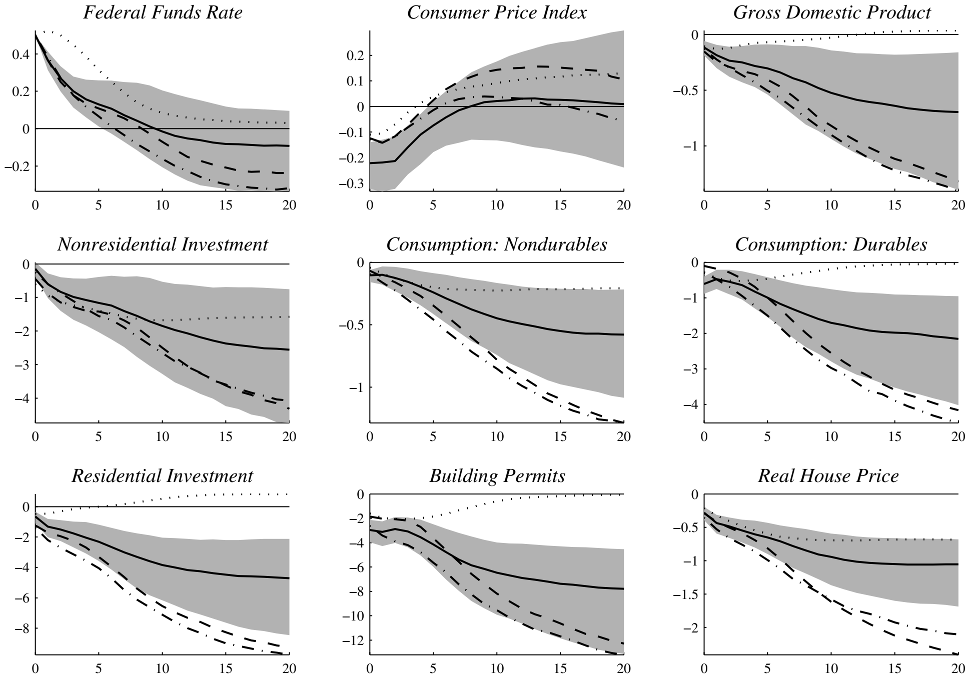
Categories	Frequency	Transformations	Seasonally Adjusted
1 = Industrial Production	Q = Quarterly	0 = none	0 = no
2 = Consumer Price Indexes	M = monthly*	1 = first difference	1 = yes
3 = Producer Price Indexes		2 = first difference of natural logarithm	
4 = Monetary Aggregates			
5 = Banking			
6 = GDP and Components			
7 = Housing Sector			
8 = Productivity & Cost			
9 = Interest Rates			
10 = Employment and Population			
11 = Survey			
12 = Financial Markets			

* All monthly series are transformed into quarterly observation by simple averages.

Appendix B Robustness Analysis

In this appendix we evaluate the robustness of our results with respect to the number of common shocks. Figure B1 shows impulses responses for $q = 3, 4, 5, 6$. The conclusion of the robustness analysis is that impulse responses are stable if $q > 3$.

Figure B1: Impulse Response Functions for Different Specification of the Number of Common Shocks



Straight Line is the median response for the benchmark model. Dotted line is the median response estimated with 3 common shocks. Dashed line is the median response estimated with 5 common shocks. Dash-Dotted line is the median response estimated with 6 common shocks. The Shaded area are the 68% confidence band for the benchmark model. In all models $r = 7$.