Monetary Policy and the Housing Market: A Structural Factor Analysis

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Matteo LUCIANI (*)

Abstract

This paper estimates a Structural Dynamic Factor Model on a panel of 102 US quarterly series. We model economic comovements by means of five underlying structural shocks (oil price, productivity, aggregate demand, monetary policy, and housing demand). The results of the benchmark model (impulse responses and variance decomposition) are in line with those predicted by economic theory and estimated in the empirical literature. We show that after the reforms to the housing finance sector starting in the early 1980s, housing demand shocks account for a slightly higher portion of model variability, while the role of monetary policy in determining residential investment fluctuations is slightly decreased. The model analyzes the sources of the fluctuations in the first decade of the 2000: we find that monetary policy shocks contributed to both the boom and bust in housing.

JEL Classification: C32, E32, E52, R2
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1 INTRODUCTION

After the beginning of 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 avoid major financial institutions (Fannie Mae, Freddie Mac, and Citibank among others) 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 policies needed to minimize the negative effects of the crisis and to help the economy regain a path of stable growth. At the same time, many tried to identify the causes of the crisis, pointing to the late 1990s financial deregulation, to FED policy after the events of 9/11, and to the real estate market bubble.

In order to understand the causes of this recession, it is necessary first to determine how many shocks drive the economy, that is, the type and number of forces that characterize business cycle fluctuations. Economic theory has in fact focused on a variety of shocks of different types but is not in agreement about which of them constitute significant sources of fluctuation. The recent crisis has diverted attention to the housing sector: does this sector simply reflect macroeconomic activity, or is it a source of business cycle fluctuations?

In this paper we estimate a Structural Dynamic Factor Model (SDFM) on a panel of US macroeconomic variables. The objective is twofold: from a methodological point of view, and following the seminal works of Stock and Watson (2005) and Forni et al. (2009), we show how SDFMs are a powerful tool for policy analysis; while from a policy analysis point of view, we use our model to get a better understanding of how many, and which, structural shocks drive US business cycle fluctuations.

Factor models are a recent econometric tool which has received increased attention since the beginning of this century due to their suitability for analyzing large databases. The interest in large databases comes from the consideration that a handful of variables may not be sufficient to recover the space spanned by the structural shocks. Moreover, the professional literature, such as economic reports from central banks or other economic institutions, typically provides analyses of the behavior of a large number of series. This suggests that policy makers consider all of them to contain significant information about the state of the economy. It is necessary, therefore, to take account of them in econometric analysis, lest we may miss some important aspect.

Factor models are also particularly appropriate for our purpose because, unlike other empirical models, they help to identify the sources of fluctuations by inferring the number of shocks directly from the data using various tests and information criteria, rather than choosing them on a priori grounds.

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 on several idiosyncratic shocks (generally of much less interest) resulting perhaps from measurement error or sectoral or regional dynamics, that influence one or a few variables. Therefore each variable in the dataset can be decomposed into a common component driven by the structural shocks, and an idiosyncratic
component, and by concentrating attention only on their co-movements (i.e. the common components), it is computationally feasible to analyze large databases.

Classical factor models are a common tool in many scientific fields but only achieved success in economic analysis in recent years. This is because they rely on the hypothesis that the idiosyncratic components are cross-sectionally uncorrelated, an assumption that clearly does not apply to economic data. However, recent research has demonstrated that consistent estimation of a factor model can be obtained using the method of static/generalized/dynamic principal components, even though the idiosyncratic components are "weakly" correlated in both dimensions (Bai and Ng, 2002; Bai, 2003; Forni et al., 2000, 2004, 2005; Forni and Lippi, 2001; Stock and Watson, 2002a). Thus estimating factor models on large datasets is not only computationally feasible, but also economically meaningful. These improvements make factor models extremely appealing to economists: they are used currently for forecasting (Stock and Watson, 2002b; Forni et al., 2003), constructing leading coincident indicators (Altissimo et al., 2010), structural analysis (Forni et al., 2009; Eickmeier, 2009), and policy analysis (Bernanke et al., 2005; Stock and Watson, 2005; Forni and Gambetti, 2010).

Our paper is related to the applied factor models literature, and particularly to Giannone et al. (2002, 2004), Forni and Gambetti (2010), and Forni et al. (2009) who use a pure structural factor approach to identify economic shocks, and to a lesser extent to Bernanke et al. (2005) and Stock and Watson (2005) who use the so-called Factor Augmented VAR (FAVAR) approach. Our contribution to this literature is based on the fact that, to the best of our knowledge, this is the first paper that uses factor models to fully identify macroeconomic shocks based on a classical identification scheme derived from an IS-LM model (an upgraded version of the one in Peersman, 2005). Full identification allows us to study the forces that characterize business cycle fluctuations. This paper also contributes from a policy analysis point of view as we analyze the role of structural shocks both over time, and in determining the US economy fluctuations in the new millennium.

Our analysis uses a panel of 102 quarterly series from 1963:1 to 2007:4 describing the US economy. We estimate that the business cycle is driven by five structural shocks which we identify as the oil price shock, the productivity shock, the aggregate demand shock, the monetary policy shock, and the housing demand shock. The impulse response functions estimated with the benchmark model are in line with those predicted by economic theory and most commonly estimated in the empirical literature. Estimation of the forecast error variance decomposition shows that in the short run inflation is driven almost entirely by oil shocks (82%), and that in the long run monetary policy shocks (19%) and aggregate demand shocks (19%) also contribute. GDP growth fluctuations are the result of both "supply" shocks (oil 6%, and productivity 26%), and "demand" shocks (aggregate demand 36%, monetary policy 23%, and housing demand 11%), while residential investment is driven mainly by "demand" shocks (aggregate demand 19%, monetary policy 24%, and housing demand 12%). The latter result suggests that the housing market is a source of business cycle fluctuations and does not just passively reflect macroeconomic dynamics.

We investigate the role of structural shocks during different periods in determining business cycle fluctuations. In line with the existing literature (Cardarelli et al., 2008; Iacoviello and Neri, 2010), we find that after the reforms in the housing finance sector that began in the early 1980s, housing demand shocks account for a slightly higher portion of model variability (11.6% of GDP,
15.2% of residential investments, and 24.5% of consumption of durable goods), thus confirming the increased importance of the housing market in determining business cycles fluctuations. We estimate also that the role of monetary policy in determining residential investment fluctuations has decreased slightly over time. This also could be attributable to the reform in the housing finance sector: after deposits lost their central role in the mortgage market, the ability of monetary policy to influence housing investment has decreased (Bernanke, 2007).

Finally, we use the model to analyze the sources of the fluctuations that have occurred since 2000. Similar to Iacoviello and Neri (2010), we find that monetary policy shocks contributed to both the boom and the bust in the housing sector. However, Leamer (2007) provides evidence that “eight of the ten [US] recessions were preceded by sustained and substantial problems in housing” (p. 164). Our results and those in Leamer (2007) taken together mean that we cannot exclude that monetary policy shocks played an important role in leading the way to the 2008 recession.

The rest of the paper is structured as follows: section 2 explains the econometric methodology, and section 3 presents the results of the estimation. Section 4 tests the robustness of our results with respect to several model specifications. Section 5 discusses the sub-sample analysis, and section 6 uses the model to analyze the fluctuations that have characterized the present millennium. Section 7 concludes.

2 THE MODEL

2.1 The Dynamic Factor Models

Let \( x_t \) be an \( N \times 1 \) vector of zero mean, finite second order moment, stationary variables, a “Dynamic Factor Model” is defined as:

\[
x_t = \lambda(L)f_t + \xi_t = \chi_t + \xi_t, \quad \text{for} \quad t = 1, \ldots, T,
\]

where \( f_t \) is a \( q \times 1 \) vector of common factors, with \( q \ll N, \lambda(L) = (\lambda_0 + \lambda_1 L + \cdots + \lambda_q L_q) \) is an \( N \times q \) matrix polynomial of dynamic factor loadings of finite order \( s \), and \( \xi_t \) are \( N \times 1 \) vectors containing respectively the common and the idiosyncratic component. The dynamic factors and the idiosyncratic components are assumed to be uncorrelated at all leads and lags \((E(f_t^i \xi_{is}) = 0, \forall t, i, s)\), while the idiosyncratic components are allowed to be both serially and cross-sectionally correlated albeit by a limited extent \((E(\xi_{it}^j \xi_{js}^j) = \kappa < \infty, \forall t, i, j, s)\). The dynamic factors \( f_t \) are assumed to evolve over time according to a \( VAR(p) \)

\[
\Psi(L)f_t = \eta_t
\]

where \( \Psi(L) \) is a matrix lag polynomial, and \( \eta_t \) is the \( q \times 1 \) vector of \( (iid) \) dynamic factors innovations or common shocks. Hence, by plugging (2) in (1) we can rewrite \( x_t \) as a function of the common shocks and the idiosyncratic components:

\( ^{2} \) The case where \( s \) is allowed to be infinite is referred to in the literature as the “Generalized Dynamic Factor Model” (Forni et al., 2000, 2004; Forni and Lippi, 2001).
\[ x_t = \lambda(L)D(L)\eta_k + \xi_t \] (3)

where \( D(L) = \Psi(L)^{-1} \).

Given a dynamic factor model such as (1), it is always possible to rewrite it in a static representation with \( r = q(s + 1) \) static factors:

\[ x_t = AF_t + \xi_t, \quad \text{for} \quad t = 1, \ldots, T, \] (4)

\[ A(L)F_t = u_t, \quad \text{with} \quad u_t = G\eta_t \] (5)

where \( F_t = [f_{t-1}' f'_{t-2} \ldots f'_{t-s}]' \) is an \( r \times 1 \) vector containing the static factors, \( A = [\lambda_0 \lambda_1 \ldots \lambda_s] \) 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 \( q \). Starting from the static factor representation (4) we can also express the \( x_t \) as a function of the common shocks and the idiosyncratic components: by rewriting \( F_t \) in his moving average representation

\[ F_t = C(L)\eta_t \] (6)

where \( C(L) = B(L)G \), and \( B(L) = A(L)^{-1} \) we have that:

\[ x_t = \Lambda C(L)\eta_t + \xi_t. \] (7)

### 2.2 Estimation

If assumptions A)-D) in Bai and Ng (2002) and Bai (2003) hold, and the assumptions of Lemma 1 in Bai and Ng (2007) hold, then: (i) the number of factors \( r \) can be estimated by means of the information criteria (IC or PC) proposed by Bai and Ng (2002) (Lemma 1 in Bai and Ng, 2007); and (ii) the space spanned by the static factors, and the common and idiosyncratic components can be consistently estimated using the method of principal components (Theorem 1 in Bai and Ng, 2002). Let \( X \) be the \( T \times N \) standardized data matrix, and \( \Sigma_X = (X'X) \) be the covariance matrix of the \( N \) variables, then by using the normalization \( \Lambda'\Lambda/N = I_r \) the matrix \( \Lambda \) can be estimated as: \( \hat{\Lambda} = V\sqrt{N} \) where \( V \) is the matrix containing the \( r \) eigenvectors associated with the largest eigenvalues of \( \Sigma_X \), and the static factors can be estimated as \( \hat{F}_t = FX\hat{\Lambda}/N \), where \( \hat{F}_t = [\hat{F}_t^1 \hat{F}_t^2 \ldots \hat{F}_t^r]' \).

Under the same assumptions, if the static factors are estimated with the method of principal components using the normalization \( \Lambda'\Lambda/N = I_r \), then: (i) the space spanned by the \( u_t \)'s can be consistently estimated by the residuals from a \( VAR(p) \) on the static factors \( \hat{F}_t^i \) (Lemma2 in Bai and Ng, 2007); and (ii) the number of dynamic factors \( q \) can be consistently estimated by the statistics \( D_1 \) and \( D_2 \) proposed by Bai and Ng (2007) (Proposition 2 in Bai and Ng, 2007). Other criteria to estimate the number of dynamic factors are suggested by Amengual and Watson (2007), Hallin and Liška (2007), and Onatski (2009).

Once \( u^i \) is estimated and \( q \) is determined, the common shocks can be retrieved as \( \hat{\eta}_t = M^{-1/2}\Gamma^i\hat{u}_t^i \), where \( M \) is a \( q \times q \) diagonal matrix containing the \( q \) largest eigenvalues of the variance-covariance matrix \( \Sigma_u \), while \( \Gamma^i \) is the \( r \times q \) matrix containing the associated eigenvectors, and therefore by construction \( \Sigma_\eta = I_q \).
2.3 The Structural Factor Model

The common shocks in equation (7) have no economic interpretation as they are simply uncorrelated white noise. However, Forni et al. (2009) show that the shocks $\eta_t$ span the same space as the structural macroeconomic shocks: structural shocks, and structural impulse response functions therefore can be retrieved by suitable rotations of the common shocks. This means that we need to find an orthonormal matrix that satisfies a set of economically meaningful just-identifying restrictions.

Following Forni et al. (2009) we assume that the $x_t$ are driven by $q$ structural shocks $\varepsilon_t$:

$$x_t = \Phi(L)\varepsilon_t + \xi_t$$

which implies, $\Phi(L) = \Lambda C(L)H$, and $\varepsilon_t = H'\eta_t$, with $H$ s.t. $HH' = I$. The rotation matrix $H$ can thus be estimated by imposing enough (economically meaningful) just-identifying restrictions on the $N \times q$ structural impulse response matrix $\Phi(L)$, and then solving the ensuing system of equations. As in Structural VAR (SVAR) analysis, identification can be achieved by imposing zero restrictions on the contemporaneous impact matrix $\Phi(0)$, on the long run impact matrix $\Phi(1)$, and by sign restrictions. However, different from SVAR analysis, the number of restrictions necessary to achieve identification depends on the number of shocks $q$ rather than the number of variables $N$. 3

3 THE EMPIRICAL ANALYSIS

3.1 Model Setup: Data and Number of Factors

The analysis is carried out on a panel of 102 quarterly series from 1963:1 to 2007:4 describing the US economy. The variables cover 12 different categories: Industrial Production, Consumer Price Index, Producer Price Index, Monetary Aggregates, Banking, GDP and Components, Housing Sector, Productivity and Cost, Interest Rates, Employment and Population, Business/Fiscal, and Financial Markets. All variables are first transformed to reach stationarity according to an ADF test where the number of lags is selected with the BIC and the maximum number of lags is set to 4; and then demeaned and standardized. The complete list of variables and transformations is reported in the Appendix.

In order to select the number of static factors we apply the information criteria in Bai and Ng (2002) and the refinements in Alessi et al. (2008): in both cases the number of maximum possible static factors is set equal to 20. The Bai and Ng (2002) $IC_1$ and $IC_3$ criteria suggest 9 and 8 factors respectively, while $IC_3$ fails to converge (table 1); Alessi et al.’s (2008) criteria suggest 8 factors (graph 1). Given that information criteria give clear indications, our final choice is to choose 8 static factors.

To select the number of dynamic factors we apply the test proposed by Onatski (2009), the

3 Recall that (i) any unitary matrix $H$ can be written as $\Pi_{\alpha}R_{\alpha\beta}$ where $R_{\alpha\beta}$ is an identity matrix with elements $R(i, j) = R(q, q) = \cos(\theta)$ and $R(i, q) = -R(q, j) = \sin(\theta)$, $0 \leq \theta \leq 2\pi$, i.e. the product of all possible bivariate rotation; and (ii) in any $q \times q$ unitary matrix there are $q(q - 1)/2$ restrictions.
Bai and Ng (2007) statistics, and the Amengual and Watson (2007) and Hallin and Liška (2007) criteria. The Onatski (2009) test clearly suggests five dynamic factors (table 2). The Bai and Ng (2007) $D_1$ and $D_2$ statistics suggest the presence of respectively 6 and 5 dynamic factors (table 3). The Amengual and Watson (2007) IC suggest between 5 and 8 dynamic factors, while PC suggests between 6 and 8 (table 4). Finally, Hallin and Liška (2007) log criteria suggest either 2, or 3 dynamic factors depending on the applied penalizing function (graph 2). Summing up: although the criteria support a number of dynamic factors ranging from 2 to 8, there is strong evidence supporting the choice of five dynamic factors, which is our final choice.

### 3.2 The Structural Model

Having fixed the dimension of the factor space we can identify and therefore interpret shocks from an economic point of view. As already pointed out in section 2.3, the task is to find an orthogonal rotation matrix $H$ such that $\varepsilon_t = H\eta_t$, where the $\eta_t$ are the dynamic factor innovations (or common shocks), and the $\varepsilon_t$ are the structural shocks. Given that we estimate that $\eta_t$ is a $5 \times 1$ vector we concentrate on the subsystem $X_t^q = \Phi(q)(L)\varepsilon_t$, where: (i) $X_t^q$ is a $5 \times 1$ vector containing the common component of: oil price ($\Delta p^{oil}$), real GDP ($\Delta Y$), CPI ($\Delta p^{cpi}$), FED Funds rate ($\Delta \varepsilon_{t}$), and real residential investment ($\Delta \varepsilon_{t}$), where $\Delta$ is the first difference operator; (ii) $\Phi(q)(L) = \sum_0^q \Phi_q^i L^i$ and the $\Phi_q^i$ are $5 \times 5$ matrices containing the structural impulse responses for $(\Delta p^{oil} \Delta Y \Delta p^{cpi} \Delta \varepsilon_{t} \Delta \varepsilon_{t})'$ to the five structural shocks $\varepsilon_t$; and, finally, (iii) $\varepsilon_t$ is a $5 \times 1$ vector containing the structural shocks.

We assume that the model is driven by the following structural shocks: the oil price shock ($\varepsilon_{oil}$), the productivity shock ($\varepsilon_{p}$), the aggregate demand shock ($\varepsilon_{ad}$), the monetary policy shock ($\varepsilon_{mp}$), and the housing demand shock ($\varepsilon_{hd}$). In order to identify these shocks we use a mix of short and long run restrictions. Our identification scheme is an upgraded version of the one in Peersman (2005), which in its turn is an upgraded version of the scheme derived by Gerlach and Smets (1995) and Monticelli and Tristani (1999) from a closed version of the IS-LM model. Identification relies on the following restrictions:

1. the oil shock can affect all variables without restrictions, while all other shocks have no contemporaneous effects on the oil price (4 restrictions);
2. we rely on a vertical Phillips curve, and therefore we allow only supply (i.e. oil and productivity) shocks to affect GDP in the long run (3 restrictions);
3. in order to distinguish between aggregate demand and monetary policy shocks, we assume no contemporaneous effect of the monetary policy shock on output (1 restriction);
4. in order to identify the housing demand shock, we assume that housing demand shocks have no contemporaneous effect on both output and prices (2 restrictions).

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*The $u_t, \varepsilon$ are obtained by estimating a VAR(1) for the 8 static factors, where the number of lags is selected with the BIC.*
Some Comments on the Identification Scheme

Restriction 1 is suggested by Peersman (2005) and Blanchard and Gali (2008): it relies on the assumption that although the US is the leading world economy, the oil price is determined in the world market and therefore US shocks are able to influence oil market only after these shocks have spread to the whole economy. This assumption is criticized by Lippi and Nobili (2009), who in their empirical analysis show that the oil price is influenced by US business cycle fluctuations. Moreover, this restriction is criticized because it makes it impossible to disentangle whether the shock stems from the demand or the supply side of the crude oil market. In fact, Lippi and Nobili (2009) and Kilian (2009) show how oil supply and oil demand shocks have different effects on the US economy. However, we follow Blanchard and Gali (2008) who points out that “what matters […] to any given country is not the level of global oil production, but the price at which firms and households can purchase oil”, and how “if the price of oil rises as a result of, say, higher Chinese demand, this is just like an exogenous oil supply shock for the remaining countries”.

Restrictions 4 is suggested by Cardarelli et al. (2008). In addition to these two restrictions, Cardarelli et al. (2008) also apply sign restrictions to distinguish between housing demand and housing supply shocks. In our scheme, we can differentiate between housing demand and housing supply shocks by imposing long run neutrality (restriction 2) of housing demand shocks on GDP. This long run restrictions is both theoretically coherent with the overall identification scheme, and supported by the empirical literature since Cardarelli et al. (2008) and Iacoviello and Neri (2010) find that while housing supply shocks have long run (albeit small) effects on GDP, housing demand shocks are neutral in the long run.

Finally, restrictions 2 and 3 are widely used in VAR literature (see among others, Blanchard and Quah 1989, and Gali 1992 for restriction 2, and Bernanke and Blinder 1992, for restriction 3).

3.3 Impulse Responses

Figure 3 shows the responses of oil price, GDP, CPI, FED Funds Rate, Residential Investment, and of the real house price to the five identified structural shocks together with 68% confidence band. Overall, the impulse responses follow the expected pattern, with the exception that the responses of the oil price are puzzling sometimes. However, given that the oil price behavior is not the focus of this paper, we believe that this does not invalidate our model.

Before commenting on the impulse responses, a clarification on the confidence bands is necessary. Confidence intervals are obtained using a bootstrap procedure that works as follows: let $\tilde{x}_t^d$ be the data generated by the d-th draw, then $\tilde{x}_t^d = \tilde{x}_t^d + \tilde{\xi}_t^d$, where (i) $\tilde{x}_t^d$ is obtained through a normal bootstrap procedure applied to the estimated structural shocks, $\tilde{x}_t^d = \Phi(L)\tilde{\xi}_t^d$; and (ii) $\tilde{\xi}_t^d$ is obtained through a block-bootstrap procedure on the estimated idiosyncratic component ($\tilde{\xi}_t^d$), where the length of the block is set to 20 quarters, sufficiently long.
to retain the cyclical information in the series.\(^6\)

Figure 3 shows the impulse responses together with 68% confidence band obtained using the procedure described above with 1000 draws. Unfortunately, confidence bands are often wide and are not centered around the point estimates. The fact that point estimates sometimes lie outside the bands depends on the bias induced by the estimation of the VAR on the static factors. Wide confidence bands might depend instead on the data treatment. For example, if some series are not “fully stationary”, confidence bands tend to be wide. In our dataset this might be the case for interest rates, prices, and monetary aggregates. Not surprisingly, Bernanke et al. (2005) and Forni and Gambetti (2010) who apply the same data transformations as in the current paper have wide confidence band, which also are a frequent problem when applying long run restrictions (Monticelli and Tristani, 1999; Peersman, 2005).\(^7\) Hence, our conclusion is that problems raised by wide confidence bands do not constitute a major weakness in the present case.

**Oil Shock**

The effects of a positive oil shock is the same as can be expected from an exogenous increase in production costs. The oil price increases substantially reaching a peak after five quarters before decreasing smoothly to a new equilibrium level where the oil price is 11% higher than the baseline. GDP falls down permanently (-0.6%), with substantial decrease in the first 10 quarters. Inflation increases substantially in the first three quarters and then decreases smoothly to zero, steadying finally at a permanent 1% increase in price levels. In response to inflation, the interest rate increases and then returns slowly to its steady state equilibrium. Finally, similar to GDP, residential investment falls for the first five quarters and then stabilizes.

**Productivity Shock**

As predicted by economic theory, a positive productivity shock produces a permanent increase in GDP (0.6%) and residential investment (2%), and a permanent 0.5% decrease in price levels. The interest rate first decreases following disinflation, and then slowly returns to the baseline.

**Aggregate Demand Shock**

Following a positive aggregate demand shock, GDP increases for the first two quarters reaching a peak of 0.2% above the baseline, and then decreases to the baseline. Inflation increases, reaching a peak after one quarter (0.14%) and then slowly decreases to zero (with a permanent increase of 1.1% in price levels). The interest rate following inflation increases and after two quarters starts to decrease to the baseline. Finally residential investment rises above equilibrium (1.4%) for the first quarter and steadies at an equilibrium level lower than the baseline.

\(^6\) Other possibilities would be to follow Bernanke et al. (2005) who suggest applying a bootstrap after bootstrap (Kilian, 1998) algorithm on the us, or Forni et al. (2009) who suggest a block bootstrap algorithm on the xs. However, while the confidence bands obtained from this second alternative are definitely not centered around the point estimates, we a priori exclude the alternative suggested by Bernanke et al. (2005) because it ignores the uncertainty introduced by the presence of the idiosyncratic component.

\(^7\) Faust and Leeper (1997) show how given that the matrix of long run multipliers is estimated imprecisely unless restrictive restrictions are imposed, the inference under long run restriction schemes is likely to be unreliable.
**Monetary Policy Shock**

After a positive (tightening) monetary policy shock the FED funds rate rises 24 basis points and then decreases to below its baseline level. This pattern for the FED funds rate, where the decrease to below the baseline level is faster than is usually estimated in the literature (e.g. Stock and Watson, 2005; Forni and Gambetti, 2010) is slightly puzzling. However, Galí (1992) estimates a similar pattern for the FED funds rate in response to a money supply shock.

In response to the interest rate increase, GDP falls to a low after four quarters before returning to the baseline, while the price level permanently decreases (-9%) by starting to fall substantially only after two quarters. Finally, monetary policy seems to affect the housing market. Residential investment falls substantially for the first two quarters (-3%) and then begins to increase to a post shock level that is lower than the baseline. In the first four quarters, house prices decrease before increasing slowly to a new equilibrium level that is 0.15% lower than the baseline.

**Housing Demand Shock**

As would be expected, the housing demand shock mimics the effect of an aggregate demand shock. GDP increases for the first three quarters reaching a peak 0.34% higher than the baseline, before slowly returning to the baseline: Prices increase permanently (0.8%), while the FED funds rate increases to reach a maximum of 33 basis points after three quarters, and then slowly decreases to the baseline. Finally, residential investment increases for the first three quarters, reaching a peak at 2% higher than the baseline level, and then slowly returns to the baseline. Also as expected from an housing demand shock, real house prices increase for the first three quarters (up to +0.2%) and then slowly return to the baseline.

### 3.4 Variance Decomposition

Table 5 shows the contribution of each structural shock to the variance of the forecast error for the common components of the oil price, GDP, CPI, FED Funds Rate, Residential Investment, and real house price. The common component of the oil price is substantially driven by oil price shocks which account for almost 90% of total variance. GDP growth is driven mainly by productivity and aggregate demand shocks, which together account for almost 67% of the common component variation after five years, with a non negligible contribution of both monetary policy (14%) and housing demand (12%) shocks. CPI inflation is mainly driven by oil shocks which, in the short run, account for more than 90% of common component variation, and in the long run account for a smaller portion of the variation (50%). In the long run, monetary policy shocks (13%) and aggregate demand shocks (21%) are also sources of price variation. The FED funds rate common component is driven in the short run mainly by aggregate demand shocks (37%), monetary policy shocks (47%), and productivity shocks (15%), while the five year variation depends mainly on monetary policy shocks (32%), and aggregate demand shocks (34%). The common component of residential investments growth is driven mainly by aggregate

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8 It should be noted also, that in line with other empirical analyses, figure 4 shows how (i) the impact of a monetary policy shock is quicker and stronger on residential investment than on consumption expenditure (Calza et al., 2009); and (ii) the impact of a monetary policy shock on the housing market is similar across US regions (Vargas-Silva, 2008a,b).
demand shocks (37%), and monetary policy shocks (35%), while housing demand shocks accounts for only 18% of total variation. In contrast, the common component of the real house price is driven by monetary (57%), productivity (22%), and housing demand (11%) shocks.

Overall these results are reasonable and do not give rise to puzzles. Coherent with our assumptions, the oil price is driven almost entirely by oil price shocks (i.e. the oil market). GDP growth, and inflation fluctuations in the long run are both due to a mixture of real (oil price and productivity) and nominal (aggregate demand, housing demand, and monetary policy) shocks. Interestingly, short run inflation is driven mainly by oil price shocks. While most shocks first spread through the entire economy before influencing inflation, increases in the oil price due to an oil shock spread almost immediately to gasoline prices, a relevant component of CPI inflation.

It should be noted that, the contribution of housing demand shocks is important since it accounts for 10.5% of GDP growth, 7.7% of CPI inflation, 12% of residential investment, 2.4% of real house prices, and 25% of consumption expenditure. This suggest that housing demand shocks are a relevant source of business cycle fluctuations.

The housing market, on the other hand, is influenced strongly by monetary policy: we estimate that monetary policy shocks account for 24% of residential investment growth variance (35% of common components), a figure that is only slightly higher than the figures estimated for the US by Jarociński and Smets (2008) (14% by estimating a BVAR from 1987 to 2007) and by Iacoviello and Neri (2010) (15%-20% by estimating a DSGE model from 1965-2006). We discuss the above in more detail in section 5.2.

4 ROBUSTNESS ANALYSIS

In this section we evaluate the robustness of our results with respect to three aspects of our model specification, namely number of static factors, number of common shocks, and identification hypotheses.

The information criteria in section 3.1 suggest the presence of eight static factors. However, there is also support for the presence of nine static factors. Therefore here we investigate the sensitivity of our results with respect to the number of static factors. Figure 5 and figure 6 respectively compare the impulse responses and variance decompositions obtained from estimating the model with eight and nine static factors. They show that the results obtained with the benchmark model are robust to both numbers of factors: impulse responses are qualitatively similar, and variance decompositions show only minor differences.

In section 3.1 we estimated the presence of five dynamic factors, i.e. five sources of fluctuations (structural shocks). To test the robustness of the specification, we investigate the properties of the model if less than five dynamic factors are considered. Figure 7 plots impulse responses, and figure 8 plots the five years forecasts error variance decomposition, for the benchmark model, for the model with four structural shocks, and for the model with just three structural shocks. Regarding IRF, the results for $q = 5$ and $q = 4$ are very similar; if we

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9 For an exhaustive review of the effects of monetary policy on the housing market see Mishkin (2007).

10 The model with four structural shocks is estimated simply by eliminating the housing demand shock and by using the same identification scheme used by Peersman (2005). The model with three structural shocks is estimated by using a classical IS-LM identification scheme as in Gerlach and Smets (1995) and Monticelli and Tristani (1999).
estimate the model with just three dynamic factors (i.e. excluding the oil shocks) the reaction to a monetary shock is puzzling in that it contrasts with the predictions of the theoretical model (IS-LM) supporting the identification scheme. Regarding FEVD, the results from the model with $q = 3$ are plausible, and if we compare the model with $q = 5$ and $q = 4$ the different role of the oil shock is obvious; in particular in the model with four dynamic factors fully 90% of GDP, and only 10% of CPI, variation is determined by the oil shock, while monetary policy shocks account for only 4.6% of the FED funds rate, which does not seem credible.

Figure 9 shows the sensitivity of our results to the identification scheme. We consider two alternatives: first, we drop the hypothesis of no contemporaneous effect of housing demand shocks on GDP (Cardarelli et al., 2008) in favor of the restriction suggested by Jarociński and Smets (2008) according to which, on impact, the only aggregate demand component that is influenced by the housing demand shock is residential investment, and therefore the effect of the shock on the level of output and the level of residential investment is roughly the same. Second, we drop the hypothesis of no contemporaneous effect of monetary policy shock on GDP in favor of the hypothesis of sticky prices according to which CPI reacts to a monetary policy shock only after one quarter. Figure 9 shows that the results are robust to both identification schemes: qualitatively the IRF are very similar, while quantitatively there are two slight differences. First, when implementing the restriction suggested by Jarociński and Smets (2008), the magnitude of the response to a monetary policy shock is smaller than the benchmark model, while the response to a housing demand shock is greater. Second, under the hypothesis of sticky prices, the magnitude of the response to a monetary policy shock of both output and prices is greater than the magnitude of the response for the benchmark specification.

5 SUB-SAMPLE ANALYSIS

Next, we investigate the possibility that the US economy experienced structural changes. We perform structural break analysis to identify if/when changes occurred. Having identified possible structural breaks, we perform a structural estimation on different sub-samples to evaluate the consequences of these structural breaks.

5.1 Testing for Structural Breaks

Stock and Watson (2002a) (thm. 3) demonstrate that the space spanned by the static factors can be estimated consistently if there is limited time variation in the factor loadings. Consistent estimation of the factor space means that testing for breaks in the $\lambda_{i,t}$ can be treated in almost the same way as a classical structural breaks testing problem for the linear regression model $x_i = \lambda_i F_{i,t} + \xi_i$, where $F_{i,t}$ are the factor estimated over the whole sample. Hence, Stock and Watson (2008) suggest testing for structural breaks by applying N Chow tests with the Newey and West (1987) HAC covariance estimator. However, as confirmed by the simulation exercise in Breitung and Eickmeier (2009), in the presence of autocorrelation OLS estimates are inefficient and this test may perform poorly in small samples. Consequently, Breitung and Eickmeier (2009) suggest testing for structural breaks by applying an LM test on a GLS
transformation of the model, and demonstrate that (thm. 2) under the null of a structural break at \( t = t^* \) the LM statistic for the i-th variable \( (s_i) \) is distributed as a \( \chi^2(r) \) and therefore \( LM = \sum_{t=1}^N s_i \sim \chi^2(Nr) \).

Results of the Breitung and Eickmeier (2009) LM test indicate two possible break points (figure 11): one in the first half of the 1980s, and one in 2000. Some of the variables indicate the presence of a third break point in the mid 1970s (figure 12). Regarding the break point at the beginning of the 2000s, there are some caveats since there is a degrees of freedom problem when computing the test at the end of the sample: eight static factors means we have to estimate eight parameters, thus testing for structural breaks at \( t = 2000:1 \) means estimating a regression with 32 observations, or 24 degrees of freedom.

The possibility of a break point in the mid 1970s was largely expected: the oil shocks in 1974 and 1979 are events likely to change the structure of the model. Similarly, a break point in the first half of the 1980s is not surprising: 1984 is considered to be the start of the so called “great moderation”, i.e. the decline in output growth and inflation variability (for an exhaustive discussion see Galí and Gambetti, 2009). In addition, the institutional changes in housing finance during the 1980s, such as abrogation of the so-called Reg Q (a deposit rate ceiling) and the state laws capping the mortgage rate, likely also consistently influenced the US economy. Moreover, the loan crisis in the late 1980s changed the housing finance sector substantially, causing it progressively to switch from a system based on bank deposits to a system based on the mortgage market: the percentage of mortgages that were securitized increased from 10% in the 1980s to more than 50% in 2006 (Bernanke, 2007). In contrast then, why a break around 2000? A first answer might be that it is due to the simple degrees of freedom problem already highlighted. However, it might also be due to the intensification of globalization, the exponential growth of financial markets, or the advent of the “new economy”.

5.2 Structural Analysis

Having established the presence of structural breaks, we now proceed to subsample analysis. This involves the following steps: (i) in each subsample we run an OLS estimation of \( x_i = \beta\notin + \xi_i \), for \( i = 1, \ldots, N \), to obtain the new factor loadings; then (ii) we estimate a new rotation matrix \( H \), and compute impulse responses and variance decompositions.

We consider two subsamples each ending in 2007:4 but with different start dates. In line with the results of the Breitung and Eickmeier (2009) LM test, we estimate the model on a first subsample starting in the mid 1970s, and on a second subsample starting in the first half of the 1980s. The first subsample starts in 1974:1, and coincides with the first oil shock which determined an 85% increase in the oil price; the second sub-sample starts at 1982:4 when the Federal Reserve changed its policy rule and switched from targeting Nonborrowed Reserve to targeting the FED funds rate (Clarida et al., 2000).

Figure 13 shows the impulse responses of the model considering the whole sample, and

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11 Suppose that the idiosyncratic components evolve over time according to an autoregressive process of order \( p \), \( \xi_t = \rho_1 \xi_{t-1} + \cdots + \rho_p \xi_{t-p} + \nu_t \), with \( \nu_t \sim iid(\sigma^2) \), and \( \rho_i(L) = (1 - \rho_1 - \cdots - \rho_p) \). The GLS transformed model is \( \rho_i(L) x_t = \lambda(L) \xi_t + \nu_t \).

12 We do not consider a break around 2000 because the degrees of freedom problem would make our subsample estimates extremely unreliable.
the two subsamples. Overall, impulse response functions are qualitatively and quantitatively similar, confirmed by the forecast error variance decomposition (figure 14). However, there are two important exceptions. First, compared to the estimation for the whole sample, in the second subsample housing demand shocks account for a higher percentage of the variance in the key macroeconomic variables: GDP (11.6 vs. 10.5), Residential Investment (15.2 vs. 12.3) house prices (6.5 vs. 2.4) and consumption expenditure (27.8 vs. 24.5), and especially expenditure on durable goods (24.5 vs. 19.8). Evidence of the increased importance of the housing demand shock in business cycle fluctuation is in line with the results in Cardarelli et al. (2008) which show that: (i) in countries with advanced housing finance systems, housing shocks account for larger variability of output and consumption; and (ii) over time housing demand shocks increasingly contribute to consumption volatility. Similar to Cardarelli et al. (2008), we interpret our result as a consequence of the financial liberalization that occurred in the housing finance sector. The institutional changes (deregulation) in the housing finance sector changed the mechanism of transmission of housing demand shocks. These reforms, by easing access to mortgages, increased the share of the population that could afford to buy a house. Moreover, and perhaps more importantly, these reforms increased the role of residential property as loan collateral (Iacoviello and Neri, 2010) thus increasing the spillovers from the housing market to the whole economy.

The second exception is related to monetary policy shocks. In the second subsample, monetary policy shocks have a smaller effect on residential investment compared to the effect for the whole sample (19.2% vs. 23.9, in line with the results in the literature, Jarociński and Smets, 2008; Iacoviello and Neri, 2010). This indicates that the contribution of monetary policy to residential investment volatility has decrease over time: as pointed out by Bernanke (2007), in a housing finance sector that relies less and less on deposits, and with no ceilings operating on deposit rates (Reg Q), the role of monetary policy in determining residential investment fluctuations decreases.

6 STRUCTURAL SHOCKS AND BUSINESS CYCLE FLUCTUATIONS IN THE 2000S

Here we identify the sources of fluctuations in the current millennium. We present the historical contribution of each shock computed using the specification with a structural break at 1982:3.

Figure 15 shows the historical decomposition of both GDP and residential investment growth. GDP growth has been strongly influenced by all five structural shocks. The contribution of oil shocks was negative from 2002:3 onwards. Productivity shocks contributed in both directions with four relevant troughs: 2000:1, 2000:3, 2003:4, and 2006:4. Monetary policy shocks on the other hand, generally contributed positively except in 2000:2 to 2001:2, 2002:1 to 2002:4, and 2006:4 onwards.

An important contribution to GDP growth fluctuations in this millennium has come from aggregate demand shocks, the main cause of the 2001 downturn. Starting in 2000:4 to 2001:4 the contribution of aggregate demand shocks to GDP growth is highly negative due to the negative wealth effect following the burst of the dot com bubble and the terrorist attack of 9/11
(in this period the S&P index lost almost 24% of its value). From 2002 onwards, probably because of the increased military spending due to the wars in Afghanistan and Iraq, in 16 out of 24 quarters the contribution of aggregate demand shocks to GDP growth was positive.

It should be noted also that the contribution of housing demand shocks was mostly positive from 2002 onwards probably due to the diffusion of sub-prime mortgages\textsuperscript{13} and mortgage equity withdrawals (MEW).\textsuperscript{14} In section 5.2 we argue that the increased role of housing demand shocks in business cycle fluctuations is caused by the liberalizations in the housing finance sector during the 1980s, which decreased the fraction of credit constrained people, and increased the role of residential property as loan collateral. Sub-prime mortgages and MEW exemplify this argument: sub-prime mortgages allowed a larger portion of the population (non-prime borrowers) to access credit and buy houses.\textsuperscript{15} At the same time, increasing house prices allowed households to increase their expenditure through borrowing using house as collateral (MEW).

Similarly, in 2002 to 2006, growth in residential investment was the result of the positive contribution of aggregate demand, monetary policy, and housing demand shocks. The effect of these three shocks was sufficiently strong to counteract the negative contribution (from 2002:2 onwards) of oil price shocks. Of particular interest is the contribution of monetary policy shocks: from 2002:4 to 2006:1 monetary policy shocks mostly contributed positively to residential investment growth, but from 2006:2 onwards their contribution was highly negative. Both these result are important. The first shows how the FED’s loose monetary policy (2002-2004) contributed to the housing boom, the second shows the importance of the FED’s role in ending the housing boom (Iacoviello and Neri, 2010). However, Leamer (2007) emphasizes that, before a recession, residential investments are the first GDP component to soften, and provides evidence that “eight of the ten [US] recessions were preceded by sustained and substantial problems in housing, and there was a more minor problem in housing prior to the 2001 recession. The one clear exception was the 1953 recession, which commenced without problems from housing” (p. 164). Our results taken together with those in Leamer (2007) show that we cannot exclude that monetary policy shocks played an important role in leading the way to the 2008 recession.

6.1 Some Comments on Historical Decomposition

Figure 15 shows that monetary policy shocks contributed substantially to the recent housing boom and the subsequent housing bust: Why is that?

The answer is closely related to the characteristics of sub-prime mortgages, most of which were adjustable rate mortgage (ARM), which provides a fixed rate for the first two or three years, and then a reset to a floating rate for the remaining years of the loan. Jaffee (2008) shows that sub-prime lending experienced an expansion starting in 2002, when the interest rate was at a

\textsuperscript{13} The proportion of sub-prime mortgage on the whole stock of new mortgage grew from 8 to 22% in 2003-2005 (Green and Wachter, 2007).

\textsuperscript{14} Although MEW has long been a source of funding for households, this source have been exploited in major way only from 2002 (Klyuev and Mills, 2007).

\textsuperscript{15} Green and Wachter (2007) report that in 1997-2005, while the number of households grew by 9%, the number of mortgage owing households increased by 20%.
historically low value. “The mistake the industry apparently made was offering a loss-leader price in the early years of a loan in order to get borrowers into the market, in hopes that they would make up the difference in later years” (Green and Wachter, 2007, p. 54). Most sub-prime borrowers then experienced their first interest rate reset when the interest rate was substantially higher: between 2004:3 and 2006:2 the Federal Reserve raised interest rates to fight the risk of inflation. The unintended consequences were that, after interest rate resetting, many non-prime borrowers could no longer afford their mortgage loan repayments. Bernanke (2007) reports that in June 2006 the proportions of ARMs with serious delinquencies doubled over mid-2005. Moreover, once problems began to emerge in sub-prime mortgage, the percentage of total mortgages that were sub-prime dropped substantially (see Jaffee, 2008); the collapse of sub-prime origination caused the collapse in housing demand and consequently the downturn in residential investment.

The contemporaneous default by many borrowers, and the decrease in house prices that followed this collapse of residential investment, implied losses for the banks which were unable to recover the entire values of their loans. Unfortunately, as pointed out by Green and Wachter (2007) “[banks] were not capitalized enough to make good on any promises in the event of large-scale default” (p. 56). Therefore, all mortgage-backed securities became toxic assets, generating huge losses for all investors (whether financial institutions or households). The problem then spread through the financial market to the world economy, resulting in the 2008 recession.

7 CONCLUSIONS

In this paper we estimated a Structural Dynamic Factor Model on a panel of 102 US quarterly series from 1963 to 2007 describing the US economy. We model economic comovements by means of five underlying structural shocks (oil price, productivity, aggregate demand, monetary policy, and housing demand). The impulse response functions estimated with the benchmark model are in line with those predicted by economic theory, and estimated in the empirical literature. Variance decompositions show that the housing market is a source of business cycle fluctuations and does not passively reflect macroeconomic dynamics.

We investigated the role of structural shocks over time and found that after the reforms to the housing finance sector that began in the early 1980s, housing demand shocks account for a slightly higher portion of model variability and the role of monetary policy in determining residential investment fluctuations slightly decreased.

We applied our model to analyze the sources of fluctuations in the 2000s and found that monetary policy shocks contributed to the housing boom and the housing bust. However, given that residential investment is the first GDP component to soften prior to a recession (Leamer, 2007), we cannot exclude that monetary policy shocks were significant in causing the 2008 recession.
REFERENCES


Lippi F, Nobili A. 2009. Oil and the macroeconomy: a quantitative structural analysis.


### A DATA DESCRIPTION AND DATA TREATMENT

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<th>Unit of Measure</th>
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*Note: The table continues with similar entries for various economic indicators.*
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**Abbreviations**

- **Series 99, 102:** Series 99 is the U.S. Census Bureau House Price Index (HPI) and Series 102 is the S&P/Case-Shiller Home Price Index (S&P/CASE). These series use different methodologies, with the HPI focusing on new homes and the S&P/CASE on existing homes.

- **Transformations:**
  - Q = Quarterly
  - M = Monthly
  - 1 = first difference
  - E = values at the end of the quarter
  - S = values at the beginning of the quarter
  - A = Average of the quarter

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### Table 1: Determining the Number of Static Factors

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<td>-0.751</td>
<td>0.62</td>
<td>0.69</td>
<td>0.95</td>
<td>0.92</td>
<td>0.96</td>
<td>0.74</td>
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<td>-0.494</td>
<td>-0.755</td>
<td>0.62</td>
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<td>0.96</td>
<td>0.92</td>
<td>0.96</td>
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<tr>
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<td>-0.39</td>
<td>-0.778</td>
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<td>0.96</td>
<td>0.92</td>
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<td>-0.758</td>
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<td>0.69</td>
<td>0.96</td>
<td>0.92</td>
<td>0.96</td>
<td>0.77</td>
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<td>17</td>
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<td>-0.328</td>
<td>-0.797</td>
<td>0.60</td>
<td>0.69</td>
<td>0.96</td>
<td>0.92</td>
<td>0.96</td>
<td>0.77</td>
<td>0.58</td>
</tr>
<tr>
<td>18</td>
<td>-0.466</td>
<td>-0.34</td>
<td>-0.806</td>
<td>0.60</td>
<td>0.70</td>
<td>0.97</td>
<td>0.92</td>
<td>0.96</td>
<td>0.77</td>
<td>0.64</td>
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<tr>
<td>19</td>
<td>-0.466</td>
<td>-0.324</td>
<td>-0.815</td>
<td>0.60</td>
<td>0.70</td>
<td>0.97</td>
<td>0.92</td>
<td>0.96</td>
<td>0.79</td>
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</tr>
<tr>
<td>20</td>
<td>-0.442</td>
<td>-0.307</td>
<td>-0.823</td>
<td>0.60</td>
<td>0.70</td>
<td>0.97</td>
<td>0.92</td>
<td>0.96</td>
<td>0.79</td>
<td>0.65</td>
</tr>
</tbody>
</table>

Note: Columns IC1, IC2, and IC3 are the Bai and Ng (2002) criteria where the bold entries are the maximum for each criterion. Column 5 shows the average variance explained by the first r factors. Columns 6 to 11 show the share of the variance explained by the first r factors for: consumption, oil price, GDP, CPI, PSB funds ratio, residential investment, real house price, consumption, durable consumption.

### Table 2: Determining the Number of Dynamic Factors

#### Onodera (2009)

<table>
<thead>
<tr>
<th>F2 vs. F1</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.002</td>
<td>0.064</td>
<td>0.005</td>
<td>0.006</td>
<td>0.008</td>
<td>0.01</td>
<td>0.011</td>
<td>0.012</td>
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<tr>
<td>1</td>
<td>0.189</td>
<td>0.025</td>
<td>0.034</td>
<td>0.043</td>
<td>0.052</td>
<td>0.066</td>
<td>0.068</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.014</td>
<td>0.025</td>
<td>0.034</td>
<td>0.043</td>
<td>0.052</td>
<td>0.066</td>
<td>0.069</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.909</td>
<td>0.029</td>
<td>0.010</td>
<td>0.050</td>
<td>0.069</td>
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<td></td>
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<tr>
<td>4</td>
<td>0.161</td>
<td>0.029</td>
<td>0.040</td>
<td>0.050</td>
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<td></td>
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<tr>
<td>6</td>
<td>0.541</td>
<td>0.468</td>
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<tr>
<td>7</td>
<td>0.253</td>
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<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Note: This table shows p-values of the null of p dynamic factors against the alternative of p dynamic factors. The Dynamic Factor Transformation of the data is composed for w_j = x_j/[^T], with r ∈ {1, ..., 22}, thus it includes waves between 2 and 12 years.
### Table 3: Determining the Number of Dynamic Factors:  
*Bai and Ng (2007)*

<table>
<thead>
<tr>
<th>q</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>c_i</td>
<td>1.8692</td>
<td>1.5414</td>
<td>1.2937</td>
<td>1.0996</td>
<td>0.9556</td>
<td>0.7766</td>
<td>0.5868</td>
<td>0.1512</td>
</tr>
<tr>
<td>D_1</td>
<td>0.4813</td>
<td>0.3871</td>
<td>0.3247</td>
<td>0.3109</td>
<td>0.2425</td>
<td><strong>0.1208</strong></td>
<td>0.0472</td>
<td></td>
</tr>
<tr>
<td>D_2</td>
<td>0.8120</td>
<td>0.6350</td>
<td>0.5270</td>
<td>0.4151</td>
<td><strong>0.2750</strong></td>
<td>0.1297</td>
<td>0.0472</td>
<td></td>
</tr>
</tbody>
</table>

1) Both criteria are computed by using the correlation matrix of the s_t's, δ = 0.1, and m = 1.25 for D_1, while m = 1.25 for D_2, as suggested by Bai and Ng (2007).

2) The first row shows the eigenvalues of the correlation matrix in decreasing order.

---

### Table 4: Determining the Number of Dynamic Factors:  
*Amenegud and Watson (2007)*

<table>
<thead>
<tr>
<th>q</th>
<th>IC</th>
<th>PC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y_A</td>
<td>1</td>
<td>-0.5348</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-0.5977</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>-0.6074</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>-0.6151</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>-0.6237</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td><strong>-0.6307</strong></td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>-0.6296</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>-0.6261</td>
</tr>
</tbody>
</table>

| Y_B | 1 | -0.5904 | -0.5334 |
| | 2 | -0.6483 | -0.6668 |
| | 3 | -0.6621 | -0.7190 |
| | 4 | -0.6738 | -0.7497 |
| | 5 | -0.6830 | -0.7789 |
| | 6 | -0.6943 | -0.8083 |
| | 7 | **-0.6950** | -0.8280 |
| | 8 | -0.6914 | -0.8433 |

**Note:** The values in bold indicate the selected number of factors.
### Table 5: Forecast Error Variance Decomposition

<table>
<thead>
<tr>
<th>(0)</th>
<th>$\varepsilon^{om}$</th>
<th>$\varepsilon^{fr}$</th>
<th>$\varepsilon^{ad}$</th>
<th>$\varepsilon^{mp}$</th>
<th>$\varepsilon^{re}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>100.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
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</tr>
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<td>4.4879</td>
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<tr>
<td>$\Delta y^{pl}$</td>
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<tr>
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<tr>
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<tr>
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</table>

Note: Results refer to common components.
C  GRAPHS

**Figure 1:** Determining the Number of Static Factors  
*Alessi et al. (2007)*

![Graphs showing the number of selected factors by each criterion as the value of the penalty function changes. Dotted lines indicate the variance of the number of factors selected in each subsample (see Alessi et al., 2007)](image1)

**Figure 2:** Determining the Number of Dynamic Factors  
*Hallin and Liika (2007)*

![Graphs showing the number of selected factors by each criterion as the value of the penalty function changes. Dotted lines indicate the variance of the number of factors selected in each subsample (see Hallin and Liika, 2007)](image2)
Figure 3: Impulse Response Functions

Thick straight lines are the Impulse Responses, thin straight lines are the 95% bootstrap confidence band, while dashed line are the median of the bootstrap distribution. All responses are cumulated but those of the FED Funds rate.
Figure 4: Impulse Response to a Contractionary Monetary Policy Shock

Residential Investment and Consumption Expenditures

Housing Starts

Figure 5: Impulse Response Functions
For Different Number of Static Factors

Solid thick lines are IRF obtained with 5 static factors, while dotted lines are IRF obtained with 9 static factors. In the model with 9 static factors, the number of lags included in the VAR is 3. All Responses are cumulated but those of the FED Funds rate.
Figure 6: 5 Years Forecast Error Variance Decomposition
For Different Number of Static Factors

Black bars are FEVD with 8 static factors, while white bars are FEVD with 9 static factors. Rows list refer to common components.

Figure 7: Impulse Response Functions
For Different Number of Common Shocks

Solid lines are IRF with q = 5, dotted lines are IRF with q = 4, and dashed lines are IRF with q = 3. IRF with q = 4 and q = 3 are obtained by setting r = 0 and p = 1. All Responses are cumulated but those of the FED Funds rate.
Figure 8: 5 Years Forecast Error Variance Decomposition
For Different Number of Common Shocks

Black bars are FVEV with $q = 5$, gray bars are FVEV with $q = 4$, and white bars are FVEV with $q = 3$. FVEV with $q = 4$ and $q = 3$ are obtained by setting $r = 9$ and $y = 1$. Asterisks refer to common components.

Figure 9: Impulse Response Functions
For Different Identification Schemes

Solid lines are the benchmark model. Dashed lines are obtained by implementing the Jurečková and Lintr (2001) hypothesis on the housing demand shock. Dotted lines are obtained by employing the sticky prices hypothesis. Oil and supply shocks are not shown because identification of such shocks is not affected by the modification in the identification scheme. All responses are cumulated but those of the FED Puzzle rate.
Figure 10: 5 Years Forecast Error Variance Decomposition
For Different Identification Schemes

- **Oil Price**
  - AD Shock
  - MD Shock
  - ED Shock

- **HIBOR Rate**
  - AD Shock
  - MD Shock
  - ED Shock

- **Residential Investment**
  - AD Shock
  - MD Shock
  - ED Shock

- **Base Rates**
  - AD Shock
  - MD Shock
  - ED Shock

Stock bars are the benchmark model. Gray bars are obtained by implementing the Johanniskal and Scone (2008) hypothesis on the monetary demand shock. White bars are obtained by implementing the sticky prices hypothesis. Oil and supply shock are not shown because identification of such shocks is not affected by those modification in the identification scheme. Lines refer to common components

Figure 11: Breitung and Einsele (2009) Structural Break Test

- L.M Test Statistic
- L.M Relative Frequencies of Rejection
- Residual Sum of Squares

The 1%, 5%, and 10% critical values for the statistic are respectively 904.5, 874.25, and 839.9. Eq = No Break.
The Relative Frequency of Rejection is the share of variables that at each date reject the null.

The Residual Sum of Squares is the average of RSSs obtained from the auxiliary regression necessary to compute the statistic in. Here, the smaller the sum of squared residual, the higher the probability of being in presence of a structural break.
Figure 12: Breitung and Eickmeier (2009) Structural Break Test
p-values for selected variables

Globed lines are pr-values, while dotted lines indicate 99% and 95%. H0: No Break.
Figure 13: Impulse Response Functions
Estimation on Different Sub-Samples

Solid thick lines is the benchmark model (whole sample), dashed thick lines are obtained over the subsample starting at 1994:1, and dotted thick lines are obtained over the subsample starting at 1992:1. All responses are correlated less those of the FRED Fund rate.
Figure 14: 5 Years Forecast Error Variance Decomposition
Estimation on Different Sub-Samples

[Bar graphs showing decomposition of forecast error variance for different variables (Oil Price, CPI, FE bond yield, residential investment, home prices, personal consumption expenditures)]

Black bars are the benchmark model (whole sample), dark grey bars are obtained over the subsample starting at 1974Q1, and white bars are obtained over the subsample starting at 1982Q4. Results refer to the variables.
Figure 15: Historical Decomposition

Each blue line represents the contribution of a structural shock to either GDP or residential investment growth rate. If the line is above the zero-level blue line, the contribution of the shock is positive, while if the blue line is below the zero line, the contribution of the shock is negative.

The shaded areas are respectively the GDP and residential investment standardised growth rates. The baseline of the shaded area is set so that it corresponds to zero in the non-transformed areas, meaning that if the area is below the baseline the growth rate of the variable is negative.