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Scuola di Dottorato in Economia

Working papers

No. 7 (January/26/2010)

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MONETARY POLICY, THE HOUSING MARKET, AND THE 2008 RECESSION: A STRUCTURAL FACTOR ANALYSIS

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Abstract. This paper estimates a Structural Dynamic Factor Model on a panel of 102 US quarterly series. We model economic comovements by means of 5 underlying structural shocks (oil price, productivity, aggregate demand, monetary policy, and housing demand). The results of the benchmark model (impulse responses and variance decompositions) are in line with those predicted by economic theory and usually estimated by the empirical literature. We show that while over the whole sample the contribution of the housing demand shock is negligible, after the early eighties' liberalizations in housing finance, the housing demand shock has become a substantial source of business cycle fluctuations. The model is then used to analyze the causes of the 2008 recession: results indicate that we cannot exclude that monetary policy played a non negligible role in leading the way for the downturn in residential investment and the ensuing recession.
JEL Classification: C32, E32, E52, R2
Keywords: Structural Factor Model, Business Cycle, Monetary Policy, Housing

1. introduction

Since the beginning of 2006 residential investment in the US has collapsed and so have house prices. Between September and October 2008, as banks started showing huge losses due to the "sub-prime mortgage bubble", a furious storm hit the stock market. The bank crisis has been so profound that public intervention has been necessary to avoid the default of major financial institutions (like Fannie Mae, Freddie Mac, and Citibank among others). From the financial market, the contagion propagated to the real economy and to the rest of the world, resulting in a severe recession of global proportions.

Policy analysts and economists are debating which policies are needed in order to minimize the negative effects of the crisis, and help the economy to re-enter a path of stable growth. At the same time, many among them are trying to identify the causes of the crisis, pointing to the late nineties' financial deregulation, to FED policy after 9/11, and to the real estate market bubble.

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 suitable for policy analysis; while from a policy analysis point of view, we use our model to shed light on the causes of the current recession.

* Address: University of Rome "La Sapienza", Department of Economics, Circonvallazione Tiburtina 4, 00185 Roma. E-mail: *matteoluciani@yahoo.it*. An earlier version of this paper was circulated under the title "A Structural Dynamic Factor Model for the US Economy". I am particularly in debt with Marco Lippi for useful suggestions and comments. I have also benefited from discussions with seminar participants at the Bank of Italy, the University of Modena, the 2^{nd} Italian Doctoral Conference, the DIW Berlin Macroeconometric Workshop, the Piero Moncasca Money-Macro Workshop, and in particular with Gianni Amisano, Mario Forni, Massimo Franchi, Stefano Neri, and Francesco Nucci. Of course, any error is my responsibility.

In order to understand what the causes of this recession are, it is, obviously, first necessary to determine how many shocks drive the economy, that is how many forces characterize business cycle fluctuations. Economic theory has in fact focused on a variety of shocks of different types but it has not agreed yet on which of these are significant sources of fluctuations. In this regard, the recent crisis has focused attention on the housing sector: does the housing sector simply reflect macroeconomic activity, or is it a source of business cycle fluctuations?

Factor models are a recently developed econometric tool that has received increasing attention in the last ten years because they are suitable for the analysis of large databases. The interest in large databases comes from the consideration that a handful of variables may not be sufficient to span the space of structural shocks. Moreover, typical professional literature, such as economic reports from central banks or other economic institutions, contains analyses of the behavior of a large number of series. This suggests that all these series are considered by policymakers as containing significant information about the state of the economy. It is therefore necessary to take them into account in econometric analysis, lest we may miss a not irrelevant part of the picture.

Factor models are also particularly appropriate for our purpose because, differently from other empirical models, they help identify the sources of the fluctuations by inferring the number of shocks directly from the data through different statistics and selection criteria, rather than choosing them on *apriori* grounds.

The main idea behind factor models is that fluctuations in the economy depends from a few structural shocks affecting all variables, and from many idiosyncratic shocks (generally not of interest) resulting for example from measurement error, or from sectoral or regional dynamics, that influence one or few variables. Therefore each variable in the dataset can be decomposed into a common component that is driven by the structural shocks, and an idiosyncratic component. Hence, by concentrating attention on the co-movements (*i.e.* the common components) only, it is computationally feasible to analyze large databases.

Classical factor models are indeed a common tool for many sciences but did not achieve success in economic analysis until recently. This is so because they rely on the hypothesis that the idiosyncratic components are cross-sectionally uncorrelated, an hypothesis that clearly does not hold with economic data. However, recent research has demonstrated that consistent estimation of a factor model can be obtained with the method of static/generalized/dynamic principal components, even though the idiosyncratic component 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 2002b). Thus estimating factor models on large datasets has become not only computationally feasible, but also economically meaningful. These improvements make factor models extremely appealing for economists: nowadays they are used in forecasting (Stock and Watson 2002a, and Forni et al. 2003), construction of leading coincident indicators (Altissimo et al. 2010), structural analysis (Forni et al. 2009, and Eickmeier 2009), and policy analysis (Bernanke et al. 2005, Stock and Watson 2005, and Forni and Gambetti 2010).

Our paper is related to the applied factor models literature, in particular with Giannone et al. (2002, 2004), Forni and Gambetti (2010), and Forni et al. (2009) that use a purely structural factor approach to identify economic shocks, and to a smaller extent to Bernanke et al. (2005) and Stock and Watson (2005) that, however, use the so-called Factor Augmented VAR (FAVAR) approach. We contribute to this literature because we perform full identification of economic shocks, and by doing so we are able to understand what forces characterize business cycle fluctuations, and to what extent. We also contribute from a policy analysis point of view as we analyze both the role of structural shocks over time (the housing sector in particular), and, especially, their role in determining the 2008 recession.

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 5 structural shocks that 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 those usually estimated by empirical literature. Estimation of the forecast error variance decomposition points out that GDP growth is mainly driven by productivity shocks (26%), aggregate demand shocks (35%), and monetary policy shocks (23%), while inflation is driven in the short run almost entirely by oil shocks (82%), and in the long run by monetary policy shocks (19%) and aggregate demand shocks (19%). It is noteworthy that, the contribution of housing demand shocks is almost negligible: they account for only 0.9% of residential investments, and 0.8% of GDP growth volatility. This result suggests that the housing market just passively reflect macroeconomic dynamics.

We then investigate the effect of financial liberalization. In line with the existing literature (Cardarelli et al. 2008 and Iacoviello and Neri 2010), we find that after the reforms in the housing finance sector started in the early eighties, housing demand shocks account for a relevant portion of model variability (26% of GDP, and 25% of residential investments), thus pointing out the importance of the housing market in determining business cycles fluctuations. This result confirms the importance of the housing market as a source of business cycles fluctuations thus turning the conclusion reached through the estimation over the whole sample upside down.

To conclude, we use our model to analyze the sources that lie behind the fluctuations in the new millennium. As in Iacoviello and Neri (2010), we find that monetary policy shocks are the main responsible for the downturn of residential investment that started in early 2006. This is indeed an important result: in fact, if we put together our results and the evidence provided by Leamer (2007), according to which “eight of the ten [US] recessions were preceded by sustained and substantial problems in housing” (p. 164), we then cannot exclude that monetary policy shocks played a non negligible role in leading the way for the 2008 recession.

The rest of the paper is structured as follows: section 2 explains the econometric methodology, and section 3 presents the result of the estimation. Section 4 tests the robustness of the model to different specifications, while section 5 discusses sub-sample analysis. In section 6 we use our model to analyze the fluctuations that characterized the new millennium and the causes of the 2008 recession; finally, 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:

$$x_t = \lambda(L) f_t + \xi_t = \chi_t + \xi_t, \quad \text{for} \quad t = 1, \ldots, T, \tag{2.1}$$

where f_t is a $q \times 1$ vector of common factors, with $q \ll N$, $\lambda(L) = (\lambda_0 + \lambda_1 L + \ldots + \lambda_s L^s)$ is an $N \times q$ matrix polynomial of dynamic factor loadings of finite order s,[1] and χ_t and ξ_t are $N \times 1$ vectors containing respectively the common and the idiosyncratic component. The

[1]In the case where s is allowed to be infinite the literature referred to this model as the “Generalized Dynamic Factor Model” (Forni et al. 2000, 2004, Forni and Lippi 2001).

dynamic factors and the idiosyncratic components are assumed to be uncorrelated at all leads and lags ($E(f_t, \xi_{is}) = 0$, $\forall\ t, i, s$), while the idiosyncratic components are allowed to be both serially and cross-sectionally correlated albeit by a limited amount ($E(\xi_{it}, \xi_{js}) = \kappa < \infty$, $\forall$ t, i, j, s). The dynamic factors f_t are assumed to evolve over time according to a VAR(p)

$$\Psi(L) f_t = \eta_t \tag{2.2}$$

where $\Psi(L)$ is a matrix lag polynomial, and η_t is the $q \times 1$ vector of (iid) dynamic factors innovations or common shocks. Hence, by plugging (2.2) in (2.1) we can rewrite x_t as a function of the common shocks and the idiosyncratic components:

$$x_t = \lambda(L) D(L) \eta_t + \xi_t \tag{2.3}$$

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

Given a dynamic factor model such as (2.1), it is always possible to rewrite it in a static representation with $r = q(s + 1)$ static factors:

$$x_t = \Lambda F_t + \xi_t, \quad \text{for} \quad t = 1, \ldots, T, \tag{2.4}$$

$$A(L) F_t = u_t, \quad \text{with} \quad u_t = G\eta_t \tag{2.5}$$

where $F_t = [f'_{t-1}\ f'_{t-2}\ \ldots\ f'_{t-s}]'$ is an $r \times 1$ vector containing the static factors, $\Lambda = [\lambda_0\ \lambda_1\ \ldots\ \lambda_s]$ 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 (2.4) we can as well express the xs as a function of the common shocks and the idiosyncratic components: by rewriting F_t in his moving average representation

$$F_t = C(L) \eta_t \tag{2.6}$$

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

$$x_t = \Lambda C(L) \eta_t + \xi_t. \tag{2.7}$$

2.2. **Estimation.** If assumptions A)-D) in Bai and Ng (2002) and Bai (2003), and the assumption 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 component (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 Λ can be estimated as: $\hat{\Lambda} = V\sqrt{N}$ where V is the matrix containing the r eigenvectors associated with the largest eigenvalues of Σ_X, and the static factors can be estimated as $\hat{F} = X\hat{\Lambda}/N$, where $\hat{F} =[\ \hat{F}_1\ \hat{F}_2\ \ldots\ \hat{F}_T]'$.

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_ts can be consistently estimated by the residuals from a VAR(p) on the static factors $\hat{F}_t$ (lemma 2 in Bai and Ng 2007), and (ii) the number of dynamic factors q can be consistently estimated by the statistics $\mathcal{D}_1$ and $\mathcal{D}_2$ proposed by Bai and Ng (2007) (Proposition 2 in Bai and Ng 2007). Alternatively, other criteria to estimate the number of dynamic factors have been proposed by Amengual and Watson (2007), by Hallin and Liŝka (2007), and by Onatski (2009).

Once u_t is estimated and q is determined, the common shocks can be retrieved as $\hat{\eta}_t = M^{-1/2}\Gamma'\hat{u}_t$, where M is a $q \times q$ diagonal matrix containing the q largest eigenvalues of the variance-covariance matrix Σ_u, while Γ is the $r \times q$ matrix containing the associated eigenvectors, and therefore $\hat{\Sigma}_\eta = I_q$ by construction.

2.3. **The Structural Factor Model.** The common shocks in equation (2.7) have no economic interpretation as they are simply uncorrelated white noises. However, Forni et al. (2009) shows that the shocks η_t span the same space of the structural macroeconomic shocks: structural shocks, and structural impulse response functions, can therefore be retrieve by a suitable rotation of the common shocks; that means we need to find an orthonormal matrix that satisfy a set of economically meaningful just-identifying restrictions.

Following Forni et al. (2009) we assume that the xs are driven by q structural shocks ε, that is:

$$x_t = \Phi(L)\varepsilon_t + \xi_t \tag{2.8}$$

that 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 by solving the ensuing system of equations. As in Structural VAR analysis, identification can be achieved by imposing zero restrictions on the contemporaneous impact matrix $\Phi(0)$, on the long run impact impact matrix $\Phi(1)$, and by sign restrictions. However, differently 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.[2]

3. THE EMPIRICAL ANALYSIS

3.1. **The Data.** The analysis has been carried out on a panel of 130 quarterly series from 1963:1 to 2007:4 (N= 130, T= 180) 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 have been first transformed to reach stationarity according to an ADF test where the number of lags has been selected with the BIC and the maximum number of lag has been set to 4; and then demeaned and standardized (see the appendix for the complete list of variables and transformations). The results of the ADF test are pretty clear for all variables but for prices and interests rates (figure 1). This is indeed a long debate in economics: as it has been pointed out by Galí (1992) we have to have that the interest rate and inflation are integrated of the same order, otherwise we would have that the real rate is not a stationary process, something that is incompatible with a steady state equilibrium. Similarly, prices and monetary aggregates have to be integrated of the same order because a non stationary growth rate of real balances "is difficult to reconcile with reasonable specifications of money demand" (Galí 1992 p. 717). Our tests do not clarify whether the interests rates are $I(1)$ or $I(0)$, and whether prices are integrated of order one or two, while all monetary aggregates are tested to be $I(1)$. Following the literature (Peersman 2005, and Gerlach and Smets 1995) we consider the interests rate $I(0)$ and prices $I(1)$.

[2]Recall that (i) any unitary matrix H can be written as $\prod_{l,q} R_{l,q}$ where $R_{l,q}$ is an identity matrix with elements $R(l,l) = R(q,q) = \cos(\theta_j)$ and $R(l,q) = -R(q,l) = \sin(\theta_j)$, $0 \leq \theta_j \leq 2\pi$, that is the product of all possible bivariate rotation; and (ii) in any $q \times q$ unitary matrix there are $q(q-1)/2$ possible bivariate rotations. Therefore, in order to achieve identification we need $q(q-1)/2$ restrictions.

Boivin and Ng (2006), by starting from the consideration that in factor models analysis the selection of variables is a subjective choice of the researcher, investigate whether it is always worth adding series to the database or not and find that, when adding extra variables imply adding cross-section correlation between idiosyncratic components, estimation and forecast performances of the model are poorer than without adding these variables. In fact, as we have seen in the previous section, the space spanned by the static factors can be consistently estimated if the idiosyncratic errors are weakly correlated in both dimensions (assumption C in Bai and Ng 2002). However, quite surprisingly this hypothesis is not tested when empirical analysis is performed. It follows that, perhaps due to excess correlation between idiosyncratic components, the information criteria cited in the previous section often perform poorly.

In our analysis, we follow the intuition of Boivin and Ng (2006), and select the variables by applying a heuristic procedure consisting in the following steps: 1) select the number of static factors; 2) for each variable compute: (*i*) the two highest cross-correlation coefficients in absolute value, (*ii*) the average (of the absolute value) cross-correlation coefficients, (*iii*) the first order autocorrelation coefficients, and (*iv*) the percentage of variance explained by the common components; 3) by looking at these statistics, try to understand whether a series adds information or noise.

By applying this procedure we end up with a database of 102 variables. Table 3 shows how the cross-correlation has diminished consistently given that the share of variables with the highest cross-correlation coefficient higher than .7 drops from 48% to 15%. A different possibility would have been to follow Stock and Watson (2008) and estimating the factors by excluding those series that by construction are the sum of other series contained in the database such as GDP, CPI, etc. By applying the Stock and Watson (2008) criteria we would end up with a much smaller database (87 variables) that, on the other hand, would be characterized by an amount of cross correlation less relevant (table 3).

3.2. **The Number of Factors.** In order to select the number of static factors we have applied the IC criteria of Bai and Ng (2002) and the refinements of 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_2 criteria suggest respectively 9 and 8 factors, while the IC_3 fails to converge (table 4); the Alessi et al. (2008) criteria, instead, suggest 5 factors (graph 2). Given that we want a model that is able to capture most of the variability in GDP, we can immediately rule out the hypothesis of 5 static factors: it explains only 65% of GDP variance while with 8 or 9 factors we explain 90% of variation. Between 8 and 9 factors we are indifferent: there is no particular reason to add an extra factor when 8 factors are considered. Therefore, our final choice will be to pick a more parsimonious specification for the model with 8 factors.

To select the number of dynamic factors we apply the Bai and Ng (2007) statistics, the Amengual and Watson (2007) and Hallin and Liŝka (2007) criteria, and the test proposed by (Onatski 2009).[3] The Bai and Ng (2007) $\mathcal{D}_1$ and $\mathcal{D}_2$ criteria suggest the presence of respectively 6 or 5 dynamic factors (table 5); the IC criterion applied using the Amengual and Watson (2007) methodology suggests between 5 and 8 dynamic factors, while the PC suggests between 6 and 8 (table 6); finally, Hallin and Liŝka (2007) log criteria suggest either 2, or 3 dynamic factors depending on the applied penalizing function (graph 3), while the

[3]The u_ts are obtained by estimating a VAR(1) for the 8 static factors. Regarding the number of lags to include in the VAR, the BIC suggests 1 lag, the HQ criteria suggests 2, while the AIC does not converge. We chose $p = 1$ because by looking at the autocorrelation and partial autocorrelation function of the factors it does not seems necessary to include 2 lags.

test proposed by Onatski (2009) (table 7) suggests $q = 6$. Table 8 shows the average forecast error variance decomposition explained by each dynamic factor at different horizons, where the averages are taken over the common components of each variable. As we can see while the first three dynamic factors explain only 60% of total variation, the first five account for 80%, with the sixth dynamic factors accounting for 8%. Summing up: the criteria are pretty flat between 5-8 dynamic factors, while the average forecast error variance decomposition suggests a parsimonious choice of 5 or 6 factors. Given this little uncertainty, we choose 5 dynamic factors because it is a specification easier to reconcile with theoretical macroeconomic models to which we need to refer in the choice of the identifying restrictions necessary to obtain a structural model.

3.3. **The Structural Model.** Once we have established the dimension of the factor space we can identify and therefore interpret shocks from an economic point of view. As said already in section 2.3, the task here is to find an orthogonal rotation matrix H such that $\varepsilon_t = H'\eta_t$, where the ηs are the dynamic factor innovations (or common shocks), and the εs are the structural shocks. Given that we have established that η_t is a 5×1 vector we concentrate on the subsystem $\chi_t^q = \Phi_{(q\times q)}(L)\varepsilon_t$, where: (i) χ_t^q is a 5×1 vector containing the common component of: oil price (Δoil), real GDP (Δy), CPI (Δp), FED Funds rate (i), and real residential investment (ΔI^h), where Δ is the first difference operator; (ii) $\Phi_{(q\times q)}(L) = \sum_0^\infty \Phi_i^q L^i$ and the Φ_i^q are 5×5 matrices containing the structural impulse responses for $[\Delta oil\ \Delta y\ \Delta p\ i\ \Delta y]'$ to the five structural shocks ε_t; and, finally, (iii) ε_t is a 5×1 vector containing the structural shocks.

We assume that the model is driven by the following structural shocks: the oil price shock (ε^{oil}), the productivity shock (ε^{p}), the aggregate demand shock (ε^{ad}), the monetary policy shock (ε^{mp}), and the housing demand shock (ε^{hd}). We think of the oil price shock as an event that has occurred in the oil market and that cannot be explained by our model; productivity shocks are, for example, those coming from the result of R&D activity, from the implementation in the production process of more productive capital goods, or from organizational changes; monetary policy shocks are movements in the interest rate essentially determined by the Federal Reserve that cannot be explained by the model (for an exhaustive discussion on monetary policy shocks see Christiano et al. 1999); housing demand shocks are trivially interpreted as movements in the demand for houses that cannot be explained by the determinants of housing demand, as might be deriving, for example, from shifts in consumer preferences, or from financial innovations that allow a larger share of population to be eligible for a mortgage. Finally, aggregate demand shocks are a broader concept: we can think of them as shocks to consumption, investment, or public expenditure, that is as shocks to the components of aggregate demand, which cannot be explained by the model.

In order to compute H we use a mix of short and long run restrictions. Our identification scheme is an upgraded version of the one used by Peersman (2005), that 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 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 the contemporaneous impact of the housing demand shock is the same for residential investment and for output (1 restriction);
(5) finally, in order to close the model, we assume that the housing demand shock has no contemporaneous effect on CPI (1 restriction).

3.3.1. *Some Comments on the Identification Scheme.* Restriction (1) is suggested by Peersman (2005) and by Blanchard and Galí (2010): it relies on the assumption that although the US are the leading world economy, the oil price is determined on a world market and therefore US shocks are able to influence oil market only after these shocks have spread over the whole economy. This assumption has been criticized by Lippi and Nobili (2009) that in their empirical analysis show that the oil price is influenced by US business cycle fluctuations. Moreover, this restriction has also been criticized because it does not allow disentangling whether the shock stems from the demand side 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 Galí (2010) that points out how "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" (p. 15).

Restrictions (4) and (5) are suggested by Jarociñski and Smets (2008): the idea is that housing demand shocks affect contemporaneously only residential investments and no other component of GDP. Hence the impact of housing demand shocks on prices can be negligible. In addition to these two restrictions Jarociñski and Smets (2008), use also sign restrictions to distinguish between housing demand and housing supply shocks. Similarly, Cardarelli et al. (2008) identify housing shocks by imposing zero contemporaneous restrictions on GDP, the GDP deflator, and the policy interest rates, and by using sign restrictions they disentangle between housing demand and housing supply shocks. In our scheme, we identify housing shocks by means of restriction (4) and (5) and we are able to disentangle between housing demand and housing supply shocks by imposing a 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 as both Cardarelli et al. (2008) and Iacoviello and Neri (2010) find that while housing supply shocks have long run effects on GDP (albeit small), 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 Galí 1992 for restriction (2), and Bernanke and Blinder 1992, for restriction (3)).

3.4. **Impulse Responses.** Figure 4 and 5 show the response of oil price, GDP, CPI, FED Funds Rate, Residential Investment, and of the real house price to the five identified structural shocks respectively with and without confidence band. Overall, the impulse responses follow the expected pattern, with the main exception to this proposition being the response of the oil price. However, given that the behavior of oil price is not the focus of this paper, we do not consider the sometimes non intuitive responses of oil prices to the shocks as invalidating our model.

Before commenting the impulse responses, a clarification on confidence bands is necessary. Confidence intervals are obtained with a bootstrap procedure that works as follows: let $\tilde{x}_t^d$ be the data generated by the d-th draw, then $\tilde{x}_t^d = \tilde{\chi}_t^d + \tilde{\xi}_t^d$, where (i) $\tilde{\chi}_t^d$ is obtained through a normal bootstrap procedure applied on the estimated structural shocks, $\tilde{\chi}_t^d = \hat{\Phi}(L)\hat{\varepsilon}_t^d$; and (ii) $\tilde{\xi}_t^d$ is obtained through a block-bootstrap procedure on the estimated idiosyncratic component $(\hat{\xi}_t)$, where the length of the block was set to 20 quarters, large enough to retain the cyclical information in the series.[4]

Figure 4 shows impulse responses together with 68% confidence band obtained through the procedure just described 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 from the bias induced by the estimation of the VAR on the static factors. Wide confidence bands, instead, might depend on the data treatment. Namely, when some series are not "fully stationary", confidence bands tend to be wide. As we have discuss in section 3.1, in our dataset this is the case of the interest rates, prices, and monetary aggregates. Not surprisingly, wide confidence band can be found both in Bernanke et al. (2005) and in Forni and Gambetti (2010) that apply the same data transformations that we have used. In addition, wide confidence bands are a problem that often arise when using long run restrictions (Monticelli and Tristani 1999 and Peersman 2005).[5] Hence, we conclude that these problems with confidence bands do not represent a major weakness of the analysis.

3.4.1. *Oil Shock.* The effects of a positive oil shock is the same as it would be expected from an exogenous increase in the production costs: the oil price increases substantially reaching a peak after 5 quarters and then smoothly decreases to a new equilibrium level (0.887); GDP falls down permanently (-0.7430), with a substantial decrease in the first 12 quarters; inflation increase substantially in the first three quarters and then smoothly returns to zero, with the final result of a permanent increase in the price level (1.3187); in response to inflation, the interest rate increases for the first three quarters and then returns slowly to its steady state equilibrium; finally, similarly to GDP, residential investment falls for the first four quarters and then stabilizes.

3.4.2. *Productivity Shock.* As predicted by economic theory, a positive productivity shock produces a permanent increase in GDP (0.8307) and residential investment (0.4499), while it produces a permanent decrease in prices (-0.5797). Finally, the interest rate decreases following the *disinflation* and then slowly returns to the base line.

3.4.3. *Aggregate Demand Shock.* After a positive aggregate demand shock, GDP increases for the first three quarters and then starts decreasing to return to the baseline; inflation increases reaching a peak after one quarter and then slowly decreases eventually reaching zero (with a permanent increase of prices of 1.417); the interest rate following inflation increases and after two quarters starts returning to the baseline; finally residential investments rise above their

[4]A different possibility would have been to follow Bernanke et al. (2005) who suggest to apply a bootstrap after bootstrap (Kilian 1998) algorithm on the us, or Forni et al. (2009) who suggest to apply a block bootstrap algorithm on the xs. However, while confidence bands obtained with the latter method were heavily not centered around the point estimates, we *apriori* excluded the method suggested by Bernanke et al. (2005) because it ignores the uncertainty brought about the presence of the idiosyncratic components.

[5]Faust and Leeper (1997) show how given that the matrix of long run multiplier is estimated imprecisely unless restrictive restrictions are imposed, the inference under long run restriction schemes is likely to be unreliable.

equilibrium level for the first quarter and then reach an equilibrium level lower than the level pre-shock (-0.4021).

The reaction of residential investment is somewhat puzzling: we see that an aggregate demand shock has transitory effects on GDP due to the restriction imposed, while it has permanent effects on residential investment, *i.e.* a component of GDP that we would expect to be affected only temporary by that shock. Of course, we cannot expect that the model estimate a zero long run response for all GDP components unless we explicitly impose such restriction. Therefore, given that we have imposed the restriction that aggregate demand shocks are neutral in the long run with respect to GDP only, we do not consider the response of GDP components as a sign of rejection of our identification scheme. The problem would arise if the model estimates a positive/negative long run effect of an aggregate demand shock for all components, something that would not make sense. At least we need to have that on some components the long run effect is positive and on some other is negative. Luckily, table 9 shows that this is the situation and therefore we can consider the reaction of residential investment easily understood.

3.4.4. *Monetary Policy Shock.* After a positive (tighten) monetary policy shock GDP falls down reaching a peak after 3 quarters and then returning to the baseline, while prices permanently decrease (-1.5587) by starting to fall substantially only after three quarters. The FED funds rate rises at time zero and then decreases under its baseline level reaching a minimum after four quarters and then returning to the baseline. The response of the interest rates to the monetary policy shock might be puzzling as it falls below the baseline level faster than is usually estimated by the literature (Stock and Watson (2005) and Forni and Gambetti (2010) for example). However, a similar path has been estimated by Galí (1992) as the effect of a money supply shock.

Finally, monetary policy seems to affect the housing market. Residential investment falls substantially for the first two quarters and then starts increasing by reaching a post shock level lower than the pre shock one (-0.1857).[6] Moreover, in accordance to other empirical analysis, figure 6 shows how (*i*) the impact on residential investment is quicker and stronger 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, 2008b)

3.4.5. *Housing Demand Shock.* Not surprisingly, the housing demand shock mimics the effect of an aggregate demand shock: GDP increases (for the first six quarters by a small amount) and slowly returns to the baseline; prices permanently increase, but quite interestingly they are a little bit slower than output in reacting to the shock and start rising only after nine quarters; the interest rate after decreasing at time zero goes up reaching a maximum after one quarter and slowly approaches its baseline.

Finally, residential investment stay above their baseline level for the first 5 quarters and then reach a permanent level below the baseline (-0.0228),[7] while, coherently with what expected

[6]As we have argued for the aggregate demand shock, the fact that residential investment are affected in the long run by monetary policy is a little bit puzzling. However as we have explained in section 3.4.3, this is a consequence of the long run restriction on GDP, that is it is a mathematical fact with no economic interpretation.

[7]Once again, in order to explain why housing demand shocks have long run effects on residential investments, we resort to the same argument we have used in section 3.4.3: it is a consequence of the long run restriction on GDP, that is it is a mathematical fact with no economic interpretation.

from an housing demand shock, real house prices increase for the first 6 quarters and then stabilize to a post shock level higher than the pre-shock one (0.0666).

3.5. **Variance Decomposition.** Table 10 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 the real house price. The common component of oil price is substantially driven by oil price shocks that account for almost 90% of total variation. GDP growth is mainly driven by productivity and aggregate demand shocks that combined account for almost 70% of its common component variation after 5 years, with a non negligible contribution of monetary policy shocks (25%). CPI inflation is mainly driven by oil shocks that in the short run account for more than 90% of common component variation at the time of the shock, while after five years they account for 50%; monetary policy shocks (21%) and aggregate demand shocks (21%) are other relevant sources of prices' variation at the 5 years horizon. The FED funds rate common component is mainly driven in the short run by aggregate demand shocks (41%), monetary policy shocks (37%), and productivity shocks (15%), while the 5 years variation depends mainly on monetary policy shocks (49%), and aggregate demand shocks (34%) only. The common component of residential investments growth is mainly driven by aggregate demand shocks (27%), and monetary policy shocks (52%), while quite surprisingly housing demand shocks accounts only for 1.3% of total variation. Quite similarly, the common component of the real house price is driven by monetary shocks (65%), and productivity shocks (21%).

Overall the results are reasonable and do not give rise to puzzles. Coherently with our assumptions the oil price is driven almost entirely by oil price shocks (*i.e.* the oil market). GDP growth fluctuations are equally due to a mixture of real (oil price and productivity) and nominal (AD and monetary policy) shocks. Similarly, inflation in the long run depends on all shocks, whereas in the short run it is almost totally driven by oil price shocks. In fact, all shocks need first to propagate over the whole economy, and then are able to influence inflation. Differently, increases in oil price spread to gasoline prices, a relevant component of CPI inflation, almost without frictions.

It is noteworthy that, the contribution of housing demand shocks is almost negligible thus suggesting that the housing market just passively reflect macroeconomic dynamics. In fact, housing demand shocks account only for 0.9% of residential investments, and 0.8% of GDP growth volatility.

The housing market, instead, is strongly influenced by monetary policy: we estimate that monetary policy shocks account for 35.7% of residential investment (52% of the common components), a figure higher than those estimated for the US by Jarociñski and Smets (2008) (14% by estimating a BVAR from 1987 to 2007) and by Iacoviello and Neri (2010) (between 15 and 20% by estimating a DSGE model from 1965-2006).[8] In section 5.2 we will discuss extensively this result and those presented in the previous paragraph, particularly so because when estimating the model in subsample these results change substantially.

4. ROBUSTNESS ANALYSIS

In this section we evaluate the robustness of our results with respect to the model specification.

[8]For an exhaustive review of the effects of monetary policy on the housing market see Mishkin 2007.

In section 3.2 we were indifferent between including 8 or 9 static factors in the model. Similarly, in footnote 3 we were indifferent between including 1 or 2 lags in the VAR model that characterize the law of motion of the static factors. Given this uncertainty, in this section we compute IRF and FEVD for two different specifications. In the first specification we allow for a different law of motion of the static factors ($ra_1 = \{r = 8,\ p = 2,\ q = 5\}$), while in the second specification we allow for a different number of static factors $ra_2 = \{r = 9,\ p = 1,\ q = 5\}$. Although overall the impulse responses obtained with ra_1 and ra_2 looks very similar to those obtained with our benchmark specification ($ra_0 = \{r = 8,\ p = 1,\ q = 5\}$), some differences can be noticed (figure 7). First, when allowing for two lags in the VAR for the static factors (ra_1), two puzzles come out: (*i*) after a positive productivity shock prices decrease and then slowly tend to return to their baseline level; and, (*ii*) after a positive housing demand shock prices decrease. However, given that these two shocks account for such a small percentage of the variance of prices inflation (respectively 3.5% and 0.5%, figure 8), we do not consider these two puzzles as invalidating the robustness of our estimates. Second, when the model is estimated with 9 static factors (ra_2), the responses to a housing demand shock are larger in magnitude than those estimated with 8 static factors. In fact, in ra_2 the portion of variance explained by the housing demand shock is larger than in the other specifications (figure 8), and therefore the magnitude of the impulse responses is larger. However, once again given that the difference between the portion of variance explained with ra_2 (9.9%) and with ra_0 (1.2%) is not that large we do not consider this result as invalidating the robustness of our estimates.

In section 3.2 we have estimated the presence of at least five dynamic factors, *i.e.* of at least 5 sources of fluctuations (structural shocks). To test the robustness of this specification, we investigate the properties of the model if less than five dynamic factors are considered. This will in turn also help to better understand the role of shocks. Thus we estimate a model with four structural shocks by eliminating the housing demand shock and by using the same identification scheme used by Peersman (2005), and we estimate a model with three structural shocks by estimating an IS-LM model as in Gerlach and Smets (1995) and Monticelli and Tristani (1999). Figure 9 plots impulse responses and figure 10 plots the five years forecasts error variance decomposition for different q.[9] Regarding IRF, the results for $q = 5$ or $q = 4$ are almost identical, while when estimating the model with just three dynamic factors (*i.e.* by excluding the oil shocks) the reaction to a monetary shock is puzzling given that it is in contrast with the prediction of the theoretical model (IS-LM) supporting the identification scheme. Regarding FEVD, the model with $q = 3$ gives plausible results, while comparing 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: these figures seem quite incredible.

Summing up, the model seems robust with respect to the number of static factors and the number of lags used in the VAR on the static factors, while when considering a smaller number of dynamic factors, as often is suggested by economic theory and *apriori* imposed in many econometric models, either IRF ($q = 3$) or FEVD ($q = 4$) are inconsistent with economic theory.

[9]IRF and FEVD are obtained by setting $r = 9$ and $p = 1$ in the specifications with three and four dynamic factors, while when $q = 5$ we used our benchmark specification with $r = 8$, and $p = 1$. We ha choose this combination of r and p because it is the one that gives the best results in terms of the specification with three or four dynamic factors.

5. SUB-SAMPLE ANALYSIS

In this section we investigate the possibility that the US economy has experienced structural changes. We first perform structural break analysis to identify if/when changes have occurred. Once we have identified possible structural breaks, we can perform the structural estimation in different sub-samples thus evaluating the consequences of these structural breaks.

5.1. **Testing for Structural Breaks.** Stock and Watson (2002b) (thm. 3) demonstrates that the space spanned by the static factors can be consistently estimated if there is *limited* time variation in the factor loadings. Once the factor space is consistently estimated, a test for breaks in the λ_is can be treated almost as a classical structural breaks testing problem on the linear regression model $x_i = \lambda_i' \hat{F}_t + \xi_i$, where $\hat{F}_t$ are the factor estimated over the whole sample. Thus, 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 of Breitung and Eickmeier (2009), in presence of autocorrelation the OLS estimates are inefficient and the 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,[10] and demonstrate that (thm. 2) the LM statistic for the i-th variable (s_i) for testing for a structural break at $t = t^*$ is distributed as a $\chi^2(r)$ and therefore $LM = \sum_{i=1}^{N} s_i \sim \chi^2(Nr)$.

Figures 11 and 12 show the Breitung and Eickmeier (2009) LM test performed at different horizons. Results indicate clearly two possible break points: one in the first half of the eighties, and one at the start of the new millennium. Moreover, some variables indicate the presence of a third break point in the mid seventies. We must however express a note of caution regarding the break point around the 2000 as there is a degrees of freedom problem when computing the test at the end of the sample: with 8 static factors we have 8 parameter to estimate, thus testing for structural breaks at $t = 2000{:}1$ means estimating a regression with 32 observations, that is 24 degrees of freedom.

The possibility of a break point in the mid seventies was largely expected: the two oil shocks of 1974 and 1979 are events likely to change the structure of the model. Similarly a break point in the first half of the eighties is not surprising: 1984 is considered the starting date of the so called “great moderation”, that is the decline in output growth and inflation variability (for an exhaustive discussion see Galí and Gambetti 2009). In addition, institutional changes which occurred in housing finance during the ’80s, such as the abrogation of the so-called Reg Q (a deposit rate ceiling) and of the state laws capping the mortgage rate, are likely to have influenced consistently the model as well. Moreover, the loan crisis of the late 80s changed substantially the housing finance sector, which progressively switched 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 80s to more than 50% in 2006 (Bernanke 2007). In contrast, why a break around 2000? A first answer could be: it is a simple degrees of freedom problem as we have already pointed out. Another possible answer is the intensification of globalization, or the exponential growth of financial markets, or the advent of the “new economy”.

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[10]Let us suppose that the idiosyncratic components evolve over time according to an autoregressive process of order p, $\xi_{it} = \rho_{i,1}\xi_{it-1} + \ldots + \rho_{i,p}\xi_{it-p} + v_{it}$, with $v_{it} \sim iid(\sigma_i^2)$, and $\rho_i(L) = (1 - \rho_{i,1} - \ldots - \rho_{i,p})$. The GLS transformed model is $\rho_i(L)x_{it} = \lambda_i'\rho_i(L)F_t + \rho_i(L)\xi_{it}$.

5.2. **Structural Analysis.** Having established the presence of structural breaks, we can now proceed with subsample analysis. In order to do so, the following steps are necessary: (i) in each subsample, run an OLS estimation of $x_i = \lambda_i' \hat{F}_t + \xi_i$, for $i = 1, \dots, N$, thus obtaining the new factor loadings; and (ii) estimate a new rotation matrix H.[11]

We consider two subsamples with each subsample ending in 2007:4 but starting at different dates. According to the evidence provided by the Breitung and Eickmeier (2009) LM test we estimate the model on a first subsample starting on the mid seventies, and on a second subsample starting in the first half of the eighties, while we do not to consider a break around 2000 because, due to the degrees of freedom problem, our subsample estimates would be extremely unreliable. The first subsample starts in 1974:1, that is in coincidence with the first oil shock which determined an 85% increase in the oil price; while the second sub-sample starts at 1982:4, that is when the Federal Reserves 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 when considering the whole sample and the two subsamples that we have just defined. Overall, the IRF over the three subsamples are qualitatively identical and quantitatively similar with the main exception being the impact of housing demand shocks in the third subsample. This result is confirmed by the forecast error variance decomposition of the common components (figure 14). In the third subsample housing demand shocks account for a larger share of business cycle fluctuations: 26% of GDP growth variation (29% of common component), and for 25% of residential investments growth variation (32% of the common component).

Evidence of the increased importance of the housing demand shock in business cycle fluctuation is perfectly in line with the findings of Cardarelli et al. (2008). Cardarelli et al. (2008) find 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 have increasingly contributed to consumption volatility. Similarly to Cardarelli et al. (2008), we interpret our result as a consequence of the financial liberalization occurred in the housing finance sector. The institutional changes (deregulation) in the housing finance sector have changed the transmission mechanism of housing demand shocks. These reforms, by easing the access to mortgages, increased the share of population that can afford to buy a house: from 1961 to 1991 residential investment grew at an average rate of 1.75% per year, while from 1992 to 2005 it grew at an average annual rate of 5.67%. Moreover, and perhaps more importantly, these reforms increased the role of housing as a collateral for loans (Iacoviello and Neri 2010) thus increasing the spillovers from the housing market to the whole economy.

Finally, it is worth noting that, in the third subsample, monetary policy shocks account for 30% (35% of the common component) of residential investment fluctuations (figure 13), a figure closer to, but still a bit higher than, that estimated by the literature (Jarociñski and Smets 2008 and Iacoviello and Neri 2010). However, if we further restrict our sample to match those of Jarociñski and Smets (2008), we obtain that monetary policy shocks account for 22% of residential investment volatility, a number in line with the aforementioned studies. Beyond the specific percentage of variance that monetary policy shocks account for, the important result here is 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

[11]Step 2 is necessary because the impulse responses are a function of the factor loadings ($\Phi(L) = \Lambda C(L)H$, see also equation (2.8)). Hence, once new loadings are estimated, the rotation matrix estimated over the whole sample does no more satisfy the restrictions imposed.

decreasingly relies on deposits, and with no ceilings operating on deposit rate (Reg Q), the role of monetary policy in determining residential investment fluctuations decreases.

6. STRUCTURAL SHOCKS AND THE 2008 RECESSION

In this section we identify the sources that lie behind the fluctuations in this new millennium. In order to perform this task we present the historical contribution of each shock computed by using the specification with a structural break at 1982:3.

Figure 15 shows the historical decomposition of GDP and residential investment growth. GDP growth has been strongly influenced by all five structural shocks: the contribution of oil shocks is negative from 2002:3 onwards; productivity shocks contribute in both directions with four relevant negative peaks: 2000:1, 2000:3, 2003:4, and 2006:4; while monetary policy contributes positively overall except from 2001:2 to 2002:4, and from 2006:2 onwards.

Particularly relevant is the contribution of aggregate demand shocks which are the main cause of the 2001 downturn: starting from 2000:4 to 2001:4 the contribution of aggregate demand shocks to GDP growth has been highly negative due to the negative wealth effect ensuing the dot com bubble burst and the terrorist attack of 9/11 (in this period the S&P lost almost 24% of its value, figure 1). From 2002 onwards, instead, probably because of the increase in military spending due to the war in Afghanistan and Iraq, on 16 of 24 quarters the contribution of aggregate demand shock to GDP growth has been positive.

It should be noted that, the contribution of housing demand shocks has been mostly positive from 2002 onwards due to the diffusion of sub-prime mortgages[12] and mortgage equity withdrawals (MEW).[13] In section 5.2 we have argued that the increased role of housing demand shocks in business cycle fluctuations is caused by liberalizations that occurred in the housing finance sector during the eighties: these reforms have increase both the share of population potentially able to buy a house, and the role of housing as collateral for loans. This is also the case of sub-prime mortgages and MEW: in fact, sub-prime mortgages allowed a larger portion of population (non-prime borrowers) to access credit and afford a house;[14] while, thanks to increasing house prices, households have been able of increasing their expenditure by borrowing using their house as a collateral (MEW).

Similar observations can be done by looking at residential investments: housing demand shocks (from 2001:1 to 2005:4), and monetary policy shocks (2002:3 - 2006:1) are the principal engine for residential investment growth. A minor contribution comes from both productivity and aggregate demand shocks, while from 2001:3 onwards oil shocks contribute negatively. Moreover, as in Iacoviello and Neri (2010) we find that monetary policy shocks are the main cause of the downturn of residential investment starting in 2006:2. This is indeed an important result. In fact, Leamer (2007) emphasizes that residential investments are the first GDP component to soften before a recession 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).

[12]The proportion of sub-prime mortgage on the whole stock of new mortgage grew from 8 to 22% from 2003 to 2005, Green and Wachter 2007

[13]Although mortgage equity withdrawal is a source of funding available to households since long ago, households substantially resorted at MEW only from 2002 (Klyuev and Mills 2007).

[14]Green and Wachter (2007) report that from 1997 to 2005 while the number of households grew of 9%, the number of those with a mortgage increased of 20%.

In conclusion, if we put together our results and those provided by Leamer (2007), we cannot exclude that monetary policy shocks played a non negligible role in leading the way for the 2008 recession.

6.1. **Some Comments on Historical Decomposition.** Figure 15 shows how the beginning of the downturn in residential investments originated from the negative contribution of monetary policy shocks: Why is that?

Our answer is closely related with the characteristics of sub-prime mortgages. Most of the sub-prime mortgages were of the adjustable rate mortgage (ARM) kind, that provides a fixed rate for the first two or three years, and then a reset to a floating rate for the remaining years. Many of these mortgages were issued between 2002 and 2004, that is when the interest rate was at historical low values (figure 1).[15] Therefore, most of sub-prime borrowers experienced their first interest rate reset when the interest rate had increased substantially. In fact, from 2004:3 to 2006:2 the Federal Reserve raised interest rates to fight the risk of inflation. The unfortunate consequence was that, after the interest rate reset, many non prime borrowers could no longer afford to pay the installments of their loans: Bernanke (2007) reports that in June 2006 the proportions of ARMs with serious delinquencies was doubled over mid-2005. Green and Wachter (2007) perfectly synthesized the events: "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" (p. 54). Moreover, once problems in sub-prime mortgage arose, the percentage of total mortgages that were sub-prime mortgages 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 of so many borrowers, and the decrease in house prices that followed the collapse of residential investment, implied losses for the banks that could no longer 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 to all investors (whether they were financial institutions or households). From here, the problem has spread through the financial market to the world economy, precipitating in the 2008 recession.

7. CONCLUSIONS

In this paper we estimate a Structural Dynamic Factor Model (SDFM) on a panel of 102 US quarterly series from 1963 to 2007 describing the US economy. We model economic comovements by means of 5 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 with those usually estimated by the empirical literature. Variance decompositions show how the contribution of housing demand shocks is almost negligible thus suggesting that the housing market just passively reflects macroeconomic dynamics.

We investigate the effect of financial liberalization and find that after reform in the housing finance sector started in the early eighties, housing demand shocks account for a relevant

[15]"Of course, the Fed was pursuing an anti-deflation program in 2002 – 2004. But, [...] the inevitable effect of the low rates has been an acceleration of the home building clock, transferring building backward in time from 2006 – 2008 to 2003 – 2005" (Leamer 2007 p. 154).

portion of model variability (26% of GDP, and 25% of residential investments), thus pointing to the importance of the housing market in determining business cycles fluctuations.

The model is then used to analyze the sources that lie behind the fluctuations in this new millennium. We find that monetary policy shocks are the main cause of the downturn of residential investment that started in early 2006. Hence, given that that residential investment is the first GDP component to soften before a recession (Leamer 2007), we cannot exclude that monetary policy shocks played a non negligible role in leading the way for the 2008 recession.

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Appendix A. Data Description and Data Treatment

N°	Series ID	Definition	Orig. Freq.	Seas. Adj.	Unit	Trans	Cat
1	INDPRO	Industrial Production Index	ME	yes	2002=100	Δ log	1
2	IPBUSEQ	Industrial Production: Business Equipment	ME	yes	2002=100	Δ log	1
3	IPCONGD	Industrial Production: Consumer Goods	ME	yes	2002=100	Δ log	1
4	IPDCONGD	Industrial Production: Durable Consumer Goods	ME	yes	2002=100	Δ log	1
5	IPDMAT	Industrial Production: Durable Materials	ME	yes	2002=100	Δ log	1
6	IPFINAL	Industrial Production: Final Products (Market Group)	ME	yes	2002=100	Δ log	1
7	IPMAT	Industrial Production: Materials	ME	yes	2002=100	Δ log	1
8	IPNCONGD	Industrial Production: Nondurable Consumer Goods	ME	yes	2002=100	Δ log	1
9	IPNMAT	Industrial Production: nondurable Materials	ME	yes	2002=100	Δ log	1
10	CPIAUCSL	Consumer Price Index for All Urban Consumers: All Items	ME	yes	1982-84=100	Δ log	2
11	CPIENGSL	CPIAUCs: Energy	ME	yes	1982-84=100	Δ log	2
12	CPILEGSL	CPIAUCs: All Items Less Energy	ME	yes	1982-84=100	Δ log	2
13	CPILFESL	CPIAUCs: All Items Less Food & Energy	ME	yes	1982-84=100	Δ log	2
14	CPIUFDSL	CPIAUCs: Food	ME	yes	1982-84=100	Δ log	2
15	CPIULFSL	CPIAUCs: All Items Less Food	ME	yes	1982-84=100	Δ log	2
16	PPICRM	Producer Price Index: Crude Materials for Further Processing	ME	yes	1982 = 100	Δ log	3
17	PPIENG	PPI: Fuels & Related Products & Power	ME	no	1982 = 100	Δ log	3
18	PPIFCG	PPI: Finished Consumer Goods	ME	yes	1982 = 100	Δ log	3
19	PPIFGS	PPI: Finished Goods	ME	yes	1982 = 100	Δ log	3
20	PPIIDC	PPI: Industrial Commodities	ME	no	1982 = 100	Δ log	3
21	PPICPE	PPI: Finished Goods: Capital Equipment	ME	yes	1982 = 100	Δ log	3
22	PPIACO	PPI: All Commodities	ME	no	1982 = 100	Δ log	3
23	PPIITM	PPI: Supplies & Components	ME	yes	1982 = 100	Δ log	3
24	AMBSL	St. Louis Adjusted Monetary Base	ME	yes	billions of $	Δ log	4
25	ADJRESSL	St. Louis Adjusted Reserves	ME	yes	billions of $	Δ log	4
26	CURRSL	Currency Component of M1	ME	yes	billions of $	Δ log	4
27	M1SL	M1 Money Stock	ME	yes	billions of $	Δ log	4
28	M2SL	M2 Money Stock	ME	yes	billions of $	Δ log	4
29	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks	ME	yes	Bil. of $	Δ log	5
30	CONSUMER	Consumer (Individual) Loans at All Commercial Banks	ME	yes	Bil. of $	Δ log	5
31	LOANINV	Total Loans and Investments at All Commercial Banks	ME	yes	Bil. of $	Δ log	5
32	LOANS	Total Loans and Leases at Commercial Banks	ME	yes	Bil. of $	Δ log	5
33	OTHSEC	Other Securities at All Commercial Banks	ME	yes	Bil. of $	Δ log	5
34	REALLN	Real Estate Loans at All Commercial Banks	ME	yes	Bil. of $	Δ log	5
35	TOTALSL	Total Consumer Credit Outstanding	ME	yes	Bil. of $	Δ log	5
36	GDPC1	Real Gross Domestic Product, 1 Decimal	Q	yes	Bil. of Ch. 2000 $	Δ log	6
37	FINSLC1	Real Final Sales of Domestic Product, 1 Decimal	Q	yes	Bil. of Ch. 2000 $	Δ log	6
38	GPDIC1	Real Gross Private Domestic Investment, 1 Decimal	Q	yes	Bil. of Ch. 2000 $	Δ log	6
39	SLCEC1	Real State & Local Cons. Exp. & Gross Investment, 1 Dec.	Q	yes	Bil. of Ch. 2000 $	Δ log	6
40	PRFIC1	Real Private Residential Fixed Investment, 1 Decimal	Q	yes	Bil. of Ch. 2000 $	Δ log	6
41	PNFIC1	Real Private Nonresidential Fixed Investment, 1 Decimal	Q	yes	Bil. of Ch. 2000 $	Δ log	6
42	NRIPDC1	Real Nonresidential Investment: Equipment & Software, 1 Dec.	Q	yes	Bil. of Ch. 2000 $	Δ log	6
43	IMPGSC1	Real Imports of Goods & Services, 1 Decimal	Q	yes	Bil. of Ch. 2000 $	Δ log	6
44	FGCEC	Real Federal Cons. Exp. & Gross Investment, 1 Decimal	Q	yes	Bil. of Ch. 2000 $	Δ log	6
45	GCEC1	Real Government Cons. Exp. & Gross Investment, 1 Dec.	Q	yes	Bil. of Ch. 2000 $	Δ log	6
46	FPIC1	Real Private Fixed Investment, 1 Decimal	Q	yes	Bil. of Ch. 2000 $	Δ log	6
47	EXPGSC1	Real Exports of Goods & Services, 1 Decimal	Q	yes	Bil. of Ch. 2000 $	Δ log	6
48	CBIC1	Real Change in Private Inventories, 1 Decimal	Q	yes	Bil. of Ch. 2000 $	Δ	6
49	PCNDGC96	Real Personal Consumption Expenditures: Nondurable Goods	Q	yes	Bil. of Ch. 2000 $	Δ log	6
50	SLINVC96	Real State & Local Government: Gross Investment	Q	yes	Bil. of Ch. 2000 $	Δ log	6
51	PCESVC96	Real Personal Consumption Expenditures: Services	Q	yes	Bil. of Ch. 2000 $	Δ log	6
52	PCDGCC96	Real Personal Consumption Expenditures: Durable Goods	Q	yes	Bil. of Ch. 2000 $	Δ log	6

53	PCECC96	Real Personal Consumption Expenditures	Q	yes	Bil. of Ch. 2000 $	Δ log	6
54	DGIC96	Real National Defense Gross Investment	Q	yes	Bil. of Ch. 2000 $	Δ log	6
55	NDGIC96	Real Federal Nondefense Gross Investment	Q	yes	Bil. of Ch. 2000 $	Δ log	6
56	DPIC96	Real Disposable Personal Income	Q	yes	Bil. of Ch. 2000 $	Δ log	6
57	PCECTPI	Personal Consumption Expenditures: Chain-type Price Index	Q	yes	Index 2000=100	Δ log	6
58	GPDICTPI	Gross Private Domestic Investment: Chain-type Price Index	Q	yes	Index 2000=100	Δ log	6
59	GDPDEF	Gross Domestic Product: Implicit Price Deflator	Q	yes	Index 2000=100	Δ log	6
60	GDPCTPI	Gross Domestic Product: Chain-type Price Index	Q	yes	Index 2000=100	Δ log	6
61	GNPDEF	Gross National Product: Implicit Price Deflator	Q	yes	Index 2000=100	Δ log	6
62	GNPCTPI	Gross National Product: Chain-type Price Index	Q	yes	Index 2000=100	Δ log	6
63	HOUSTMW	Housing Starts in Midwest Census Region	MS	yes	Thous. of Units	Δ log	7
64	HOUSTNE	Housing Starts in Northeast Census Region	MS	yes	Thous. of Units	Δ log	7
65	HOUSTS	Housing Starts in South Census Region	MS	yes	Thous. of Units	Δ log	7
66	HOUSTW	Housing Starts in West Census Region	MS	yes	Thous. of Units	Δ log	7
67	PERMIT	New Private Housing Units Authorized by Building Permit	MS	yes	Thous. of Units	Δ log	7
68	hp	Real House Price	Q	no	index	Δ log	7
69	ULCNFB	Nonfarm Business Sector: Unit Labor Cost	Q	yes	1992 = 100	Δ log	8
70	COMPRNFB	Nonfarm Business Sector: Real Compensation Per Hour	Q	yes	1992 = 100	Δ log	8
71	COMPNFB	Nonfarm Business Sector: Compensation Per Hour	Q	yes	1992 = 100	Δ log	8
72	HOANBS	Nonfarm Business Sector: Hours of All Persons	Q	yes	1992 = 100	Δ log	8
73	OPHNFB	Nonfarm Business Sector: Output Per Hour of All Persons	Q	yes	1992 = 100	Δ log	8
74	ULCMFG	Manufacturing Sector: Unit Labor Cost	Q	yes	1992 = 100	Δ log	8
75	COMPRMS	Manufacturing Sector: Real Compensation Per Hour	Q	yes	1992 = 100	Δ log	8
76	COMPMS	Manufacturing Sector: Compensation Per Hour	Q	yes	1992 = 100	Δ log	8
77	HOAMS	Manufacturing Sector: Hours of All Persons	Q	yes	1992 = 100	Δ log	8
78	OPHMFG	Manufacturing Sector: Output Per Hour of All Persons	Q	yes	1992 = 100	Δ log	8
79	ULCBS	Business Sector: Unit Labor Cost	Q	yes	1992 = 100	Δ log	8
80	RCPHBS	Business Sector: Real Compensation Per Hour	Q	yes	1992 = 100	Δ log	8
81	HCOMPBS	Business Sector: Compensation Per Hour	Q	yes	1992 = 100	Δ log	8
82	HOABS	Business Sector: Hours of All Persons	Q	yes	1992 = 100	Δ log	8
83	OPHPBS	Business Sector: Output Per Hour of All Persons	Q	yes	1992 = 100	Δ log	8
84	MPRIME	Bank Prime Loan Rate	MA	no	%	none	9
85	FEDFUNDS	Effective Federal Funds Rate	MA	no	%	none	9
86	AAA	Moody's Seasoned Aaa Corporate Bond Yield	MA	no	%	none	9
87	BAA	Moody's Seasoned Baa Corporate Bond Yield	MA	no	%	none	9
88	TB3MS	3-Month Treasury Bill: Secondary Market Rate	MA	no	%	none	9
89	TB6MS	6-Month Treasury Bill: Secondary Market Rate	MA	no	%	none	9
90	GS1	1-Year Treasury Constant Maturity Rate	MA	no	%	none	9
91	GS3	3-Year Treasury Constant Maturity Rate	MA	no	%	none	9
92	GS5	5-Year Treasury Constant Maturity Rate	MA	no	%	none	9
93	GS10	10-Year Treasury Constant Maturity Rate	MA	no	%	none	9
94	CIVPART	Civilian Participation Rate	MA	no	%	Δ	10
95	EMRATIO	Civilian Employment-Population Ratio	MA	no	%	Δ	10
96	CLF16OV	Civilian Labor Force	ME	no	Thous.	Δ log	10
97	CE16OV	Civilian Employment	ME	no	Thous.	Δ log	10
98	UNRATE	Civilian Unemployment Rate	MA	no	%	Δ	10
99	UEMPLT5	Civilians Unemployed - Less Than 5 Weeks	ME	no	Thous.	Δ log	10
100	UEMP5TO14	Civilian Unemployed for 5-14 Weeks	ME	no	Thous.	Δ log	10
101	UEMP15T26	Civilians Unemployed for 15-26 Weeks	ME	no	Thous.	Δ log	10
102	UEMP27OV	Civilians Unemployed for 27 Weeks and Over	ME	no	Thous.	Δ log	10
103	UEMPMEAN	Average (Mean) Duration of Unemployment	MA	no	Weeks	Δ log	10
104	UNEMPLOY	Unemployed	ME	no	Thous.	Δ log	10
105	PAYEMS	Total Nonfarm Payrolls: All Employees	ME	no	Thous.	Δ log	10
106	MANEMP	Employees on Nonfarm Payrolls: Manufacturing	ME	no	Thous.	Δ log	10
107	DMANEMP	All Employees: Durable Goods Manufacturing	ME	no	Thous.	Δ log	10
108	NDMANEMP	All Employees: Nondurable Goods Manufacturing	ME	no	Thous.	Δ log	10
109	SRVPRD	All Employees: Service-Providing Industries	ME	no	Thous.	Δ log	10
110	USCONS	All Employees: Construction	ME	no	Thous.	Δ log	10
111	USEHS	All Employees: Education & Health Services	ME	no	Thous.	Δ log	10
112	USFIRE	All Employees: Financial Activities	ME	no	Thous.	Δ log	10
113	USGOOD	All Employees: Goods-Producing Industries	ME	no	Thous.	Δ log	10
114	USGOVT	All Employees: Government	ME	no	Thous.	Δ log	10
115	USINFO	All Employees: Information Services	ME	no	Thous.	Δ log	10
116	USLAH	All Employees: Leisure & Hospitality	ME	no	Thous.	Δ log	10
117	USMINE	All Employees: Natural Resources & Mining	ME	no	Thous.	Δ log	10
118	USPBS	All Employees: Professional & Business Services	ME	no	Thous.	Δ log	10
119	USPRIV	All Employees: Total Private Industries	ME	no	Thous.	Δ log	10
120	USSERV	All Employees: Other Services	ME	no	Thous.	Δ log	10
121	USTPU	All Employees: Trade, Transportation & Utilities	ME	no	Thous.	Δ log	10

122 USTRADE	All Employees: Retail Trade	ME	no	Thous.	Δ log	10
123 USWTRADE	All Employees: Wholesale Trade	ME	no	Thous.	Δ log	10
124 OILPRICE	Spot Oil Price: West Texas Intermediate	MA	no	$ per Barrel	Δ log	11
125 NAPM	ISM Manufacturing: PMI Composite Index	MA	yes	index	Δ	11
126 usa04025	Business Surveys, ISM Manufacturing, Employment	MA	yes	index	Δ	11
127 usa04010	Business Surveys, ISM Manufacturing, New orders	MA	yes	index	Δ	11
128 usa04005	Business Surveys, ISM Manufacturing, Production	MA	yes	index	Δ	11
129 usa15525	Dow Jones, Averages, Industrial Index, Price Return	MA	no	index	Δ log	12
130 usa15505	Standard & Poors, 500 Composite, Index, Price Return	MA	no	index	Δ log	12

NOTE: All series are from the Fred II database of the Federal Reserve Bank of St. Louis with the exception of series 68 and of series 125-129. Series 68 is the Census Bureau House Price Index (*new one-family houses sold including value of lot*) that has been deflated with the implicit price deflator for the nonfarm business sector (IPDNBS) taken from the Fred II database. Series 126-130 are taken from Ecowin.

Abbreviations

Categories	Original Frequency	Transformation
1 = Industrial Production	Q = Quarterly	Δ = first difference
2 = Consumer Price Indexes	M = monthly	log = natural logarithm
3 = Producer Price Indexes	E = value at the end of quarter	
4 = Monetary Aggregates	S = Sum over the quarter	
5 = Banking	A = Average of the quarter	
6 = GDP and Components		
7 = Housing Sector		
8 = Productivity & Cost		
9 = Interest Rates		
10 = Employment and Population		
11 = Business/Fiscal		
12 = Financial Markets		

Appendix B. Variables Selection

N°	Series ID	R^2	j_1	j_2	τ_1	τ_2	$\bar{\tau}$	ρ	ML
1	INDPRO	0.89	7	6	0.77	0.65	0.14	0.03	x
2	IPBUSEQ	0.73	1	6	0.54	0.53	0.11	0.17	x
3	IPCONGD	0.67	6	8	0.83	0.72	0.12	0.22	o
4	IPDCONGD	0.63	3	6	0.60	0.49	0.09	0.24	x
5	IPDMAT	0.79	7	1	0.65	0.48	0.11	0.03	x
6	IPFINAL	0.75	3	1	0.83	0.65	0.12	0.08	o
7	IPMAT	0.80	1	5	0.77	0.65	0.10	0.01	o
8	IPNCONGD	0.36	3	6	0.72	0.60	0.10	0.24	x
9	IPNMAT	0.66	7	1	0.45	0.38	0.10	0.02	x
10	CPIAUCSL	0.89	15	13	0.73	0.56	0.11	0.00	x
11	CPIENGSL	0.71	15	10	0.54	0.40	0.10	0.23	x
12	CPILEGSL	0.84	13	10	0.66	0.55	0.12	0.07	x
13	CPILFESL	0.80	15	12	0.70	0.66	0.12	0.13	x
14	CPIUFDSL	0.45	20	15	0.52	0.46	0.09	0.08	x
15	CPIULFSL	0.81	10	13	0.73	0.70	0.11	0.11	x
16	PPICRM	0.63	22	57	0.48	0.33	0.10	0.06	x
17	PPIENG	0.81	20	14	0.55	0.37	0.11	0.01	x
18	PPIFCG	0.83	19	14	0.95	0.45	0.10	0.14	o
19	PPIFGS	0.86	18	14	0.95	0.39	0.10	0.15	x
20	PPIIDC	0.87	17	14	0.55	0.52	0.10	0.05	x
21	PPICPE	0.76	23	20	0.38	0.33	0.10	0.37	x
22	PPIACO	0.89	16	15	0.48	0.43	0.11	0.05	x
23	PPIITM	0.82	20	10	0.49	0.42	0.10	0.28	x
24	AMBSL	0.46	25	26	0.77	0.62	0.14	0.01	x
25	ADJRESSL	0.35	24	57	0.77	0.49	0.13	0.27	x
26	CURRSL	0.39	24	75	0.62	0.32	0.09	0.38	x
27	M1SL	0.54	25	24	0.37	0.36	0.10	0.35	x
28	M2SL	0.54	118	86	0.26	0.25	0.08	0.37	x
29	BUSLOANS	0.45	32	31	0.67	0.47	0.10	0.46	x
30	CONSUMER	0.52	35	118	0.51	0.36	0.09	0.45	x
31	LOANINV	0.44	32	29	0.77	0.47	0.12	0.12	x
32	LOANS	0.63	31	29	0.77	0.67	0.14	0.19	x
33	OTHSEC	0.09	31	29	0.46	0.22	0.07	0.17	o
34	REALLN	0.47	32	46	0.37	0.31	0.11	0.35	x
35	TOTALSL	0.57	30	108	0.51	0.26	0.09	0.50	x
36	GDPC1	0.85	38	83	0.75	0.64	0.15	0.21	x
37	FINSLC1	0.83	48	38	0.63	0.55	0.12	0.09	x
38	GPDIC1	0.58	36	48	0.75	0.74	0.15	0.18	x
39	SLCEC1	0.51	50	83	0.82	0.45	0.10	0.08	x
40	PRFIC1	0.64	46	104	0.54	0.31	0.10	0.07	x
41	PNFIC1	0.64	42	46	0.81	0.73	0.12	0.13	x
42	NRIPDC1	0.60	41	46	0.81	0.62	0.11	0.06	o
43	IMPGSC1	0.25	47	81	0.53	0.31	0.08	0.28	x
44	FGCEC1	0.39	45	54	0.86	0.41	0.11	0.05	o
45	GCEC1	0.60	44	79	0.86	0.58	0.12	0.03	x
46	FPIC1	0.73	41	42	0.73	0.62	0.12	0.17	o
47	EXPGSC1	0.09	43	54	0.53	0.22	0.07	0.40	x
48	CBIC1	0.37	38	37	0.74	0.63	0.13	0.23	x
49	PCNDGC96	0.42	53	5	0.50	0.25	0.08	0.09	x
50	SLINVC96	0.40	39	83	0.82	0.47	0.11	0.09	o
51	PCESVC96	0.48	52	109	0.31	0.24	0.08	0.02	x
52	PCDGCC96	0.54	53	37	0.68	0.38	0.11	0.27	x
53	PCECC96	0.76	52	49	0.68	0.50	0.11	0.05	x
54	DGIC96	0.23	44	45	0.41	0.35	0.10	0.23	x
55	NDGIC96	0.21	52	53	0.23	0.21	0.07	0.06	x
56	DPIC96	0.34	41	25	0.20	0.20	0.07	0.33	x
57	PCECTPI	0.90	60	62	0.50	0.50	0.13	0.14	x
58	GPDICTPI	0.75	62	60	0.41	0.40	0.11	0.22	x
59	GDPDEF	0.89	61	60	1.00	0.94	0.14	0.00	o
60	GDPCTPI	0.90	62	61	1.00	0.94	0.15	0.10	x
61	GNPDEF	0.89	59	62	1.00	0.94	0.14	0.00	o
62	GNPCTPI	0.90	60	61	1.00	0.94	0.15	0.10	o
63	HOUSTMW	0.31	65	83	0.31	0.27	0.09	0.34	x
64	HOUSTNE	0.18	22	65	0.22	0.20	0.08	0.44	x
65	HOUSTS	0.42	63	110	0.31	0.31	0.08	0.05	x
66	HOUSTW	0.64	67	114	0.74	0.33	0.11	0.64	x
67	PERMIT	0.67	66	69	0.74	0.44	0.12	0.62	x
68	hp	0.15	58	93	0.36	0.22	0.08	0.23	x
69	ULCNFB	0.83	71	72	0.97	0.86	0.16	0.52	o
70	COMPRNFB	0.86	71	72	0.83	0.79	0.15	0.48	o
71	COMPNFB	0.86	69	72	0.97	0.91	0.17	0.47	o

72	HOANBS	0.86	71	69	0.91	0.86	0.15	0.51	o
73	OPHNFB	0.75	83	36	0.78	0.56	0.13	0.18	o
74	ULCMFG	0.62	78	76	0.66	0.55	0.13	0.06	x
75	COMPRMS	0.52	76	74	0.93	0.52	0.14	0.01	x
76	COMPMS	0.63	75	74	0.93	0.55	0.14	0.02	x
77	HOAMS	0.83	36	106	0.48	0.43	0.14	0.05	x
78	OPHMFG	0.32	74	77	0.66	0.35	0.10	0.15	x
79	ULCBS	0.83	45	81	0.58	0.57	0.13	0.03	x
80	RCPHBS	0.63	81	79	0.85	0.48	0.16	0.04	x
81	HCOMPBS	0.72	80	79	0.85	0.57	0.15	0.11	x
82	HOABS	0.81	36	83	0.48	0.32	0.11	0.23	x
83	OPHPBS	0.76	73	36	0.78	0.64	0.13	0.22	x
84	MPRIME	0.67	85	93	0.68	0.54	0.10	0.19	x
85	FEDFUNDS	0.71	88	84	0.70	0.68	0.11	0.05	x
86	AAA	0.78	87	93	0.77	0.74	0.12	0.00	o
87	BAA	0.77	86	93	0.77	0.58	0.11	0.11	o
88	TB3MS	0.76	89	90	0.92	0.74	0.12	0.03	x
89	TB6MS	0.84	88	90	0.92	0.90	0.14	0.08	o
90	GS1	0.89	89	88	0.90	0.74	0.16	0.08	x
91	GS3	0.90	92	93	0.93	0.72	0.16	0.02	x
92	GS5	0.87	91	93	0.93	0.88	0.15	0.01	o
93	GS10	0.82	92	86	0.88	0.74	0.13	0.00	x
94	CIVPART	0.19	95	96	0.83	0.63	0.09	0.10	o
95	EMRATIO	0.72	94	97	0.83	0.61	0.09	0.04	x
96	CLF16OV	0.27	97	94	0.88	0.63	0.09	0.28	o
97	CE16OV	0.65	96	95	0.88	0.61	0.09	0.28	x
98	UNRATE	0.85	104	94	0.50	0.33	0.10	0.02	x
99	UEMPLT5	0.27	104	96	0.53	0.32	0.08	0.22	x
100	UEMP5TO14	0.49	104	98	0.49	0.27	0.07	0.33	x
101	UEMP15T26	0.48	80	81	0.33	0.32	0.10	0.27	x
102	UEMP27OV	0.58	104	103	0.51	0.47	0.09	0.34	x
103	UEMPMEAN	0.66	102	119	0.47	0.25	0.09	0.04	x
104	UNEMPLOY	0.72	99	102	0.53	0.51	0.09	0.16	x
105	PAYEMS	0.95	119	109	0.82	0.66	0.13	0.22	o
106	MANEMP	0.90	107	113	0.91	0.70	0.15	0.30	o
107	DMANEMP	0.89	106	113	0.91	0.60	0.13	0.24	x
108	NDMANEMP	0.77	106	113	0.62	0.50	0.12	0.25	x
109	SRVPRD	0.88	105	121	0.66	0.53	0.14	0.36	x
110	USCONS	0.68	107	106	0.45	0.41	0.11	0.17	x
111	USEHS	0.46	120	48	0.43	0.26	0.09	0.20	x
112	USFIRE	0.53	67	110	0.35	0.34	0.09	0.59	x
113	USGOOD	0.93	106	119	0.70	0.61	0.13	0.29	x
114	USGOVT	0.48	109	105	0.50	0.42	0.09	0.26	x
115	USINFO	0.54	72	119	0.35	0.30	0.08	0.17	x
116	USLAH	0.49	109	70	0.34	0.24	0.07	0.04	x
117	USMINE	0.24	113	1	0.42	0.32	0.09	0.18	x
118	USPBS	0.62	109	130	0.48	0.38	0.10	0.53	x
119	USPRIV	0.96	105	113	0.82	0.61	0.14	0.12	x
120	USSERV	0.66	111	43	0.43	0.23	0.10	0.34	x
121	USTPU	0.85	122	109	0.81	0.53	0.10	0.12	x
122	USTRADE	0.71	121	109	0.81	0.38	0.10	0.02	o
123	USWTRADE	0.78	121	85	0.36	0.23	0.07	0.40	x
124	OILPRICE	0.60	60	62	0.38	0.38	0.09	0.01	x
125	NAPM	0.81	128	127	0.77	0.75	0.12	0.07	o
126	usa04025	0.73	125	128	0.63	0.41	0.10	0.20	x
127	usa04010	0.71	125	128	0.75	0.71	0.12	0.15	x
128	usa04005	0.72	125	127	0.77	0.71	0.11	0.15	x
129	usa15525	0.27	130	118	0.93	0.34	0.10	0.10	o
130	usa15505	0.25	129	118	0.93	0.38	0.10	0.16	x

$\|\tau_1\|$ is the highest cross-correlation coefficient of variable i and $\|\tau_2\|$ is the second highest coefficient. j_1 indicates the variable with which variable i has the highest correlated, and j_2 refers to the second variable. $\bar{\tau}$ is the average cross correlation of variable i with all other variables. ρ is the first order autocorrelation coefficient. Finally in the column "ML" , "x" stands for not eliminated, while "o" indicates that the variable have been eliminated.

Table 3. *Variables Selection*

	Highest Cross-Correlation			Autocorrelation of order 1		
	All	ML	SW	All	ML	SW
N	130	102	87	130	102	87
$\|\tau\| > .5$	73.8462	56.8627	32.1839	5.3846	3.9216	2.2989
$\|\tau\| > .6$	60.7692	38.2353	22.9885	1.5385	0	1.1494
$\|\tau\| > .7$	48.4615	14.7059	20.6897	0	0	0
$\|\tau\| > .8$	30.7692	6.8627	11.4943	0	0	0
$\|\tau\| > .9$	14.6154	0	2.2989	0	0	0
$N^{-1}\sum_{i=1}^{N}\tau$	0.1110	0.1102	0.1041	0.1826	0.1897	0.1913

Note: Column All indicates result on the entire database, column ML indicates results after the procedure is applied, and finally column SW indicates results if we would have applied the Stock and Watson (2008) procedure

Appendix C. Tables

Table 4. *Determining the Number of Static Factors: Bai and Ng (2002) Criteria*

Factors	M.R^2	A.R^2	AR(1)	IC1	IC2	IC3	% GDP
1	0.2319	0.2319	0.7239	-0.2052	-0.1983	-0.2241	0.6243
2	0.1557	0.3876	0.8241	-0.3675	-0.3536	-0.4053	0.6244
3	0.0653	0.4529	0.5623	-0.416	-0.3951	-0.4727	0.6416
4	0.0549	0.5078	0.4117	-0.4575	-0.4297	-0.5331	0.6421
5	0.0438	0.5516	0.393	-0.4864	-0.4517	-0.5809	0.6489
6	0.0327	0.5843	0.0726	-0.498	-0.4564	-0.6114	0.7049
7	0.0291	0.6134	0.1968	-0.5064	-0.4578	-0.6386	0.7504
8	0.0278	0.6413	0.0533	-0.5168	**-0.4613**	-0.668	0.9096
9	0.0234	0.6646	0.171	**-0.5199**	-0.4575	-0.69	0.9155
10	0.0205	0.6851	-0.0539	-0.5188	-0.4494	-0.7077	0.9201
11	0.0183	0.7034	0.0605	-0.5145	-0.4381	-0.7223	0.9203
12	0.017	0.7204	0.0903	-0.5092	-0.4259	-0.7359	0.9347
13	0.0163	0.7367	0.0482	-0.5051	-0.4149	-0.7508	0.9505
14	0.0153	0.752	-0.0106	-0.5007	-0.4035	-0.7652	0.9574
15	0.014	0.766	-0.1636	-0.4945	-0.3904	-0.7779	0.9614
16	0.0126	0.7786	0.0276	-0.4854	-0.3743	-0.7878	0.9617
17	0.0118	0.7903	0.2317	-0.4757	-0.3577	-0.797	0.9623
18	0.0112	0.8015	0.1432	-0.4662	-0.3413	-0.8064	0.9652
19	0.0105	0.812	0.055	-0.4562	-0.3244	-0.8153	0.9677
20	0.0098	0.8217	-0.0152	-0.4453	-0.3065	**-0.8233**	0.9679

Note: The first column is the additional percentage of total variance explained by the r-th factor, while column two is the cumulative share of total variance explained by the first r factors. The third column is the first order autocorrelation coefficient for each factor. Columns IC1, IC2, and IC3 are the Bai and Ng (2002) criteria where bold entries are the minimum for each criteria. Finally, in the last column is shown the cumulative share of GDP variance explained by the first r factors

Table 5. *Determining the Number of Dynamic Factors: Bai and Ng (2007)*

q	$\mathcal{D}_1$	$\mathcal{D}_2$	c_i
1	0.4813	0.8120	1.8692
2	0.3871	0.6539	1.5414
3	0.3247	0.5270	1.2397
4	0.3109	0.4151	1.0396
5	0.2425	**0.2750**	0.9956
6	**0.1208**	0.1297	0.7766
7	0.0472	0.0472	0.3868
8			0.1512

1) Both criteria have been computed using the correlation matrix of the u_ts. $\delta = 0.1$, and $m = 1.25$ for $\mathcal{D}_{1k}$, while $m = 2.25$ for $\mathcal{D}_{2k}$ as suggested by Bai and Ng (2007).
2) In the third column are the eigenvalues of Σ_u in decreasing order.
3) $q : \mathcal{D}_i < M$, $i = 1, 2$, where $M = 0.1573$ for D_1, and $M = 0.2831$ for $\mathcal{D}_2$.

Table 6. *Determining the Number of Dynamic Factors: Amengual and Watson (2007)*

	q	IC			PC		
Y_A	1	-0.5448	-0.5378	-0.5638	0.5644	0.5666	0.5583
	2	-0.5977	-0.5837	-0.6357	0.5248	0.5292	0.5126
	3	-0.6074	-0.5864	-0.6644	0.5108	0.5175	0.4926
	4	-0.6151	-0.5872	-0.6911	0.5001	0.5091	0.4759
	5	-0.6237	**-0.5888**	-0.7187	0.4913	0.5025	0.4610
	6	**-0.6307**	-0.5888	-0.7447	0.4851	**0.4985**	0.4487
	7	-0.6296	-0.5806	-0.7625	**0.4835**	0.4992	0.4410
	8	-0.6261	-0.5703	**-0.7781**	0.4840	0.5019	**0.4355**
Y_B	1	-0.5904	-0.5834	-0.6094	0.5388	0.5409	0.5331
	2	-0.6488	-0.6348	-0.6868	0.4981	0.5023	0.4867
	3	-0.6621	-0.6411	-0.7190	0.4830	0.4893	0.4660
	4	-0.6738	-0.6458	-0.7497	0.4712	0.4795	0.4484
	5	-0.6839	-0.6490	-0.7789	0.4621	0.4726	0.4337
	6	-0.6943	**-0.6524**	-0.8083	0.4550	0.4676	0.4209
	7	**-0.6950**	-0.6461	-0.8280	**0.4529**	**0.4676**	0.4131
	8	-0.6914	-0.6355	**-0.8433**	0.4535	0.4702	**0.4080**

Table 7. *Determining the Number of Dynamic Factors: Onatski (2009)*

		q_1 6	7	8
	5	0.0240	0.0430	0.0590
q_0	6	x	0.9540	0.5670
	7	x	x	0.3190

This table shows p-values for the test proposed by Onatski (2009) for H_0: $q = q_0$ vs. H_1: $q_0 < q < q_1 + 1$. The Descrete Fourier Transformation of the data is computed for $\omega_j = 2\pi s_j/T$, with $s_j \in [1, ..., 40]$.

Table 8. *Forecast Error Variance Decompositions Averaged over All Common Components*

years	η_1	η_2	η_3	η_4	η_5	η_6	η_7	η_8
0	34.8221	16.8902	9.2014	10.5179	8.7499	8.6235	6.7059	4.4891
1	37.3378	18.3853	7.8992	6.9641	11.6248	9.1880	4.3630	4.2378
2	37.6053	18.2070	7.7210	6.6806	11.7840	9.3346	4.3818	4.2857
5	38.1111	17.7038	7.5572	6.5057	11.8659	9.5157	4.4992	4.2414

Table 9. *Long Run Effects of Shocks on GDP and Components*

Variable	ε^{oil}	ε^{p}	ε^{ad}	ε^{mp}	ε^{hd}
Gross Domestic Product	-0.753	0.837	0	0	0
Final Sales of Domestic Product	-0.846	0.941	-0.245	-0.180	-0.324
Gross Private Domestic Investment	-0.419	0.355	0.192	0.010	0.303
SLCEC1*	-0.646	0.799	-0.381	0.197	-0.129
Private Residential Fixed Investment	-0.445	0.451	-0.405	-0.181	-0.023
Private Nonresidential Fixed Investment	-0.628	0.465	0.162	-0.292	-0.046
Imports of Goods & Services	-0.541	0.196	-0.001	-0.052	0.159
GCEC1**	-0.242	0.706	-0.064	-0.066	-0.045
Exports of Goods & Services	-0.170	0.124	-0.017	-0.040	0.012
Change in Private Inventories	-0.003	0.048	0.208	0.268	0.491
Personal Consumption Expenditures	-0.935	0.704	-0.283	0.017	-0.351
PCE: Nondurable Goods	-0.847	0.567	-0.411	0.259	-0.145
PCE: Services	-0.727	0.480	-0.271	-0.209	-0.186
PCE: Durable Goods	-0.614	0.544	-0.090	-0.023	-0.366
National Defense Gross Investment	0.260	0.235	0.397	-0.317	-0.035
Federal Nondefense Gross Investment	0.024	0.295	-0.008	-0.022	0.161
Disposable Personal Income	-0.658	0.184	0.039	-0.090	-0.060

Note: all variables are in real terms.
* State & Local Consumption Expenditures & Gross Investment.
** Government Consumption Expenditures & Gross Investment.

Table 10. *Forecast Error Variance Decomposition*

	years	ε^{oil}	ε^{p}	ε^{ad}	ε^{mp}	ε^{hd}
Δoil	0	100.0000	0.0000	0.0000	0.0000	0.0000
	1	89.4659	4.4537	4.9258	0.6789	0.4757
	2	89.3256	4.4903	4.9312	0.7773	0.4756
	5	88.9885	4.5299	5.0588	0.9488	0.4740
Δy	0	0.7794	43.0728	55.2036	0.0000	0.9442
	1	6.8264	29.3638	39.2306	23.6651	0.9141
	2	7.1411	28.8214	39.2068	23.9397	0.8911
	5	7.1078	28.3127	38.9465	24.7517	0.8813
Δp	0	91.0457	2.5243	6.2213	0.2088	0.0000
	1	62.8039	8.8163	20.3447	7.8296	0.2054
	2	54.3131	7.7443	21.3258	16.3961	0.2207
	5	50.4155	7.2068	21.3613	20.7751	0.2413
i	0	0.3263	14.8617	41.3630	37.3852	6.0638
	1	12.5941	11.6471	41.1401	34.0135	0.6052
	2	11.0847	8.9034	36.3677	43.1823	0.4619
	5	9.7234	7.1242	33.6059	49.1179	0.4286
ΔI^h	0	0.4573	11.5445	24.8517	61.6646	1.4818
	1	10.0877	10.3502	27.4585	50.8099	1.2937
	2	9.7565	10.0244	27.0147	51.9453	1.2591
	5	9.7212	9.9914	26.9463	52.0828	1.2583
Δp^h	0	5.1980	22.6587	0.0050	68.7723	3.3660
	1	6.0334	22.9067	1.1924	66.7309	3.1366
	2	6.6836	22.7209	2.3599	65.2048	3.0308
	5	6.8521	21.6773	3.8925	64.7062	2.8720

Results refer to common components.

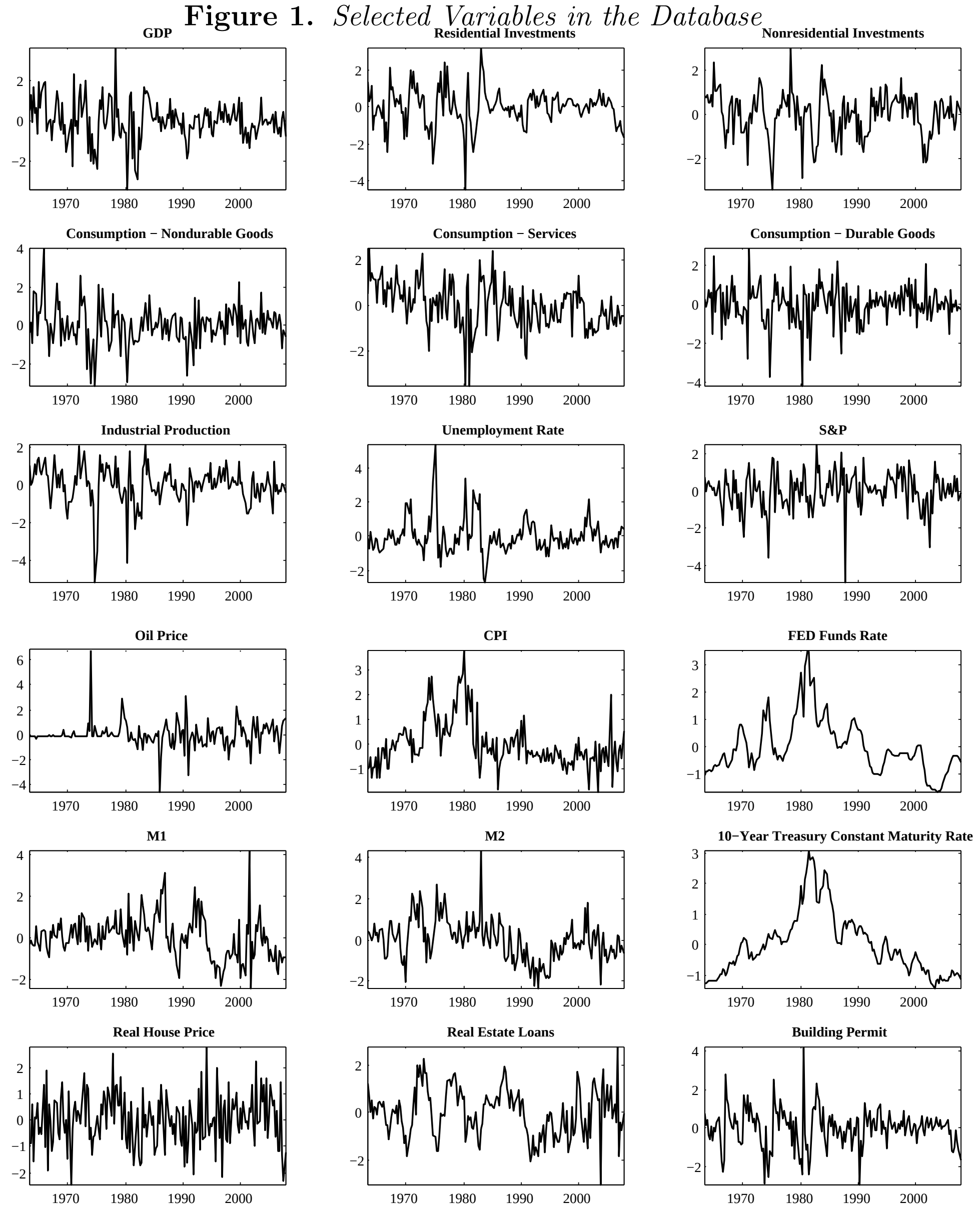
Table 11. *5 years FEVD for GDP and Components*

Variable	ε^{oil}	ε^{p}	ε^{ad}	ε^{mp}	ε^{hd}
Gross Domestic Product	7.1078	28.313	38.946	24.752	0.88134
Final Sales of Domestic Product	9.1708	29.152	23.651	27.351	10.675
Gross Private Domestic Investment	4.5948	7.8359	42.562	24.811	20.197
SLCEC1⋆	14.022	66.341	2.3604	9.8741	7.4028
Private Residential Fixed Investment	9.7212	9.9914	26.946	52.083	1.2583
Private Nonresidential Fixed Investment	8.9506	4.5969	45.693	39.803	0.95618
Imports of Goods & Services	11.433	4.2338	40.517	34.104	9.7115
GCEC1⋆⋆	1.7237	85.063	0.9973	11.012	1.2042
Exports of Goods & Services	17.262	6.5681	35.302	39.916	0.952
Change in Private Inventories	1.3162	4.7804	16.791	22.513	54.599
Personal Consumption Expenditures	17.972	12.801	34.291	22.737	12.199
PCE: Nondurable Goods	28.004	13.239	31.524	24.09	3.1429
PCE: Services	17.805	6.689	22.237	41.782	11.487
PCE: Durable Goods	12.831	17.048	37.04	16.916	16.165
National Defense Gross Investment	9.0153	66.17	7.7847	16.144	0.88545
Federal Nondefense Gross Investment	0.92343	62.573	1.9311	11.987	22.586
Disposable Personal Income	33.506	4.2972	46.384	15.066	0.74772

Note: all variables are in real terms. Results refer to common components.
⋆ State & Local Consumption Expenditures & Gross Investment.
⋆⋆ Government Consumption Expenditures & Gross Investment.

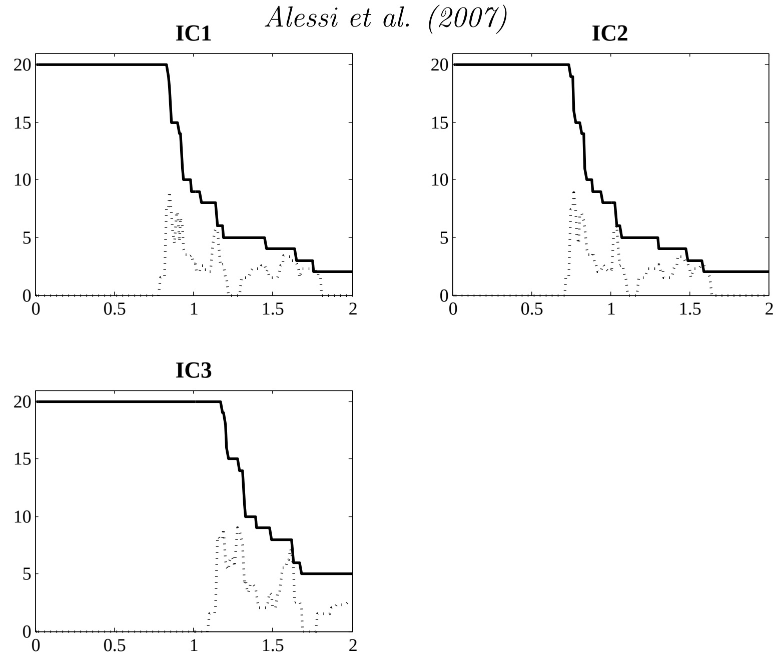
Appendix D. Graphs

Figure 1. *Selected Variables in the Database*



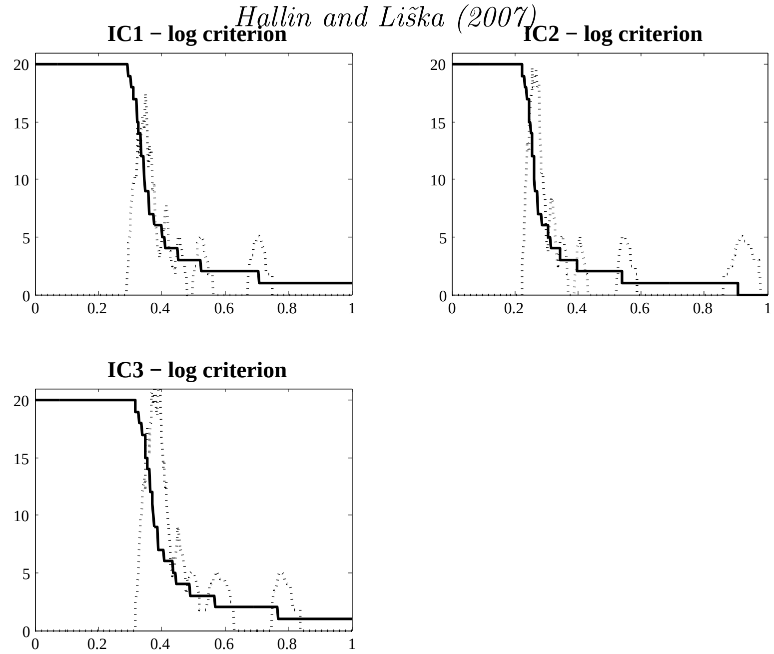
All series have been differenced, demeaned and standardized but the FED Funds, and the 10y bond Rate that are in levels

Figure 2. *Determining the Number of Static Factors*
Alessi et al. (2007)



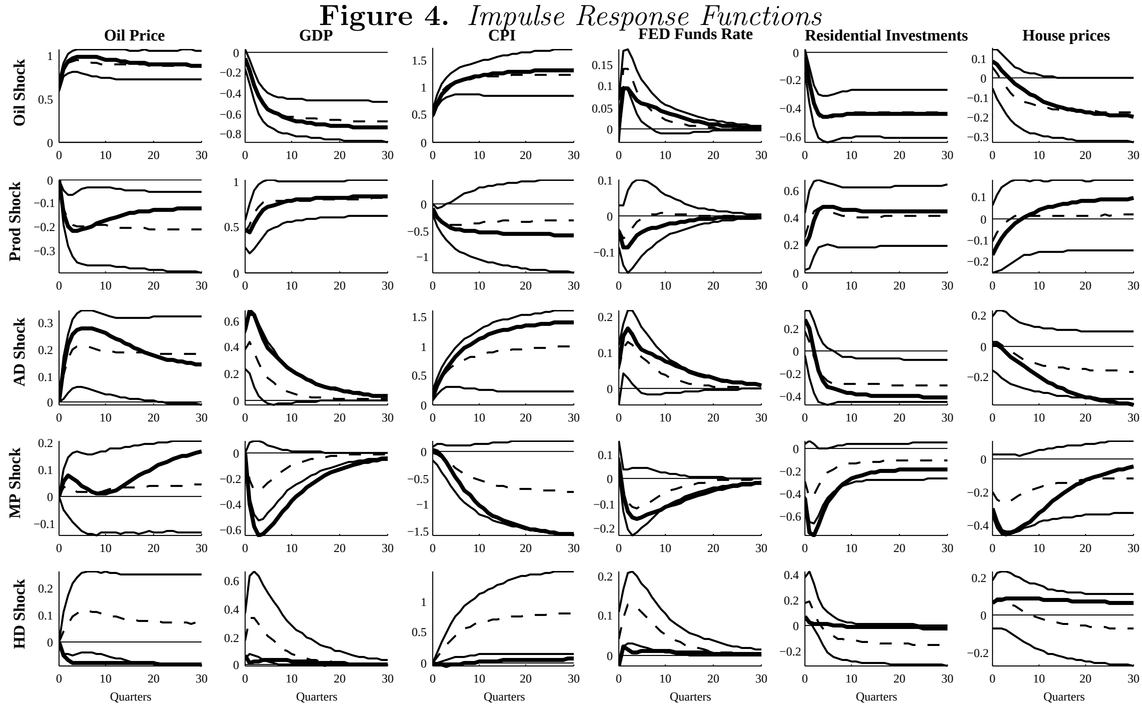
Straight lines are the number of selected factors by each criteria as the value of the penalty function changes. Dotted lines is the variance of the number of factors selected in each subsample (see Alessi et al. 2008)

Figure 3. *Determining the Number of Dynamic Factors*
Hallin and Liška (2007)



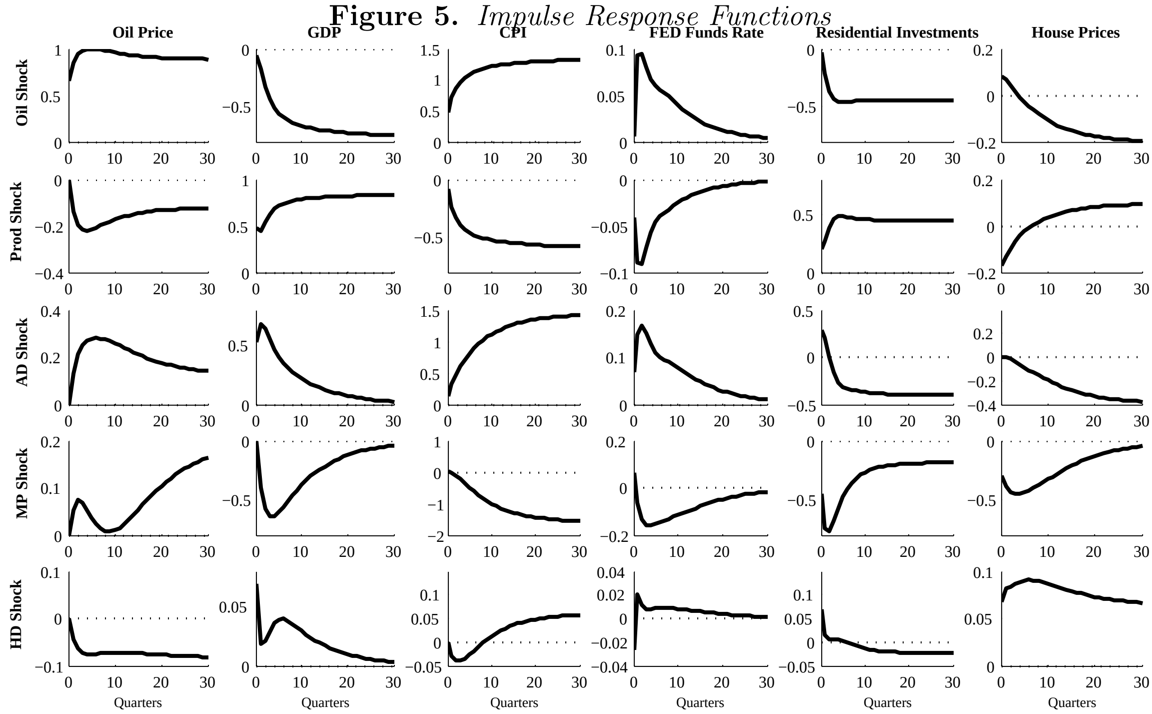
Straight lines are the number of selected factors by each criteria as the value of the penalty function changes. Dotted lines is the variance of the number of factors selected in each subsample (see Hallin and Liška 2007)

Figure 4. *Impulse Response Functions*



Thick straight lines are the Impulse Responses, thin straight lines are the 68% bootstrap confidence band, while dashed line are the median of the bootstrap distribution. All Responses are cumulated but for the FED Funds rate.

Figure 5. *Impulse Response Functions*



All Responses are cumulated but for the FED Funds rate.

Figure 6. *Impulse Response to a Contractionary Monetary Policy Shock*

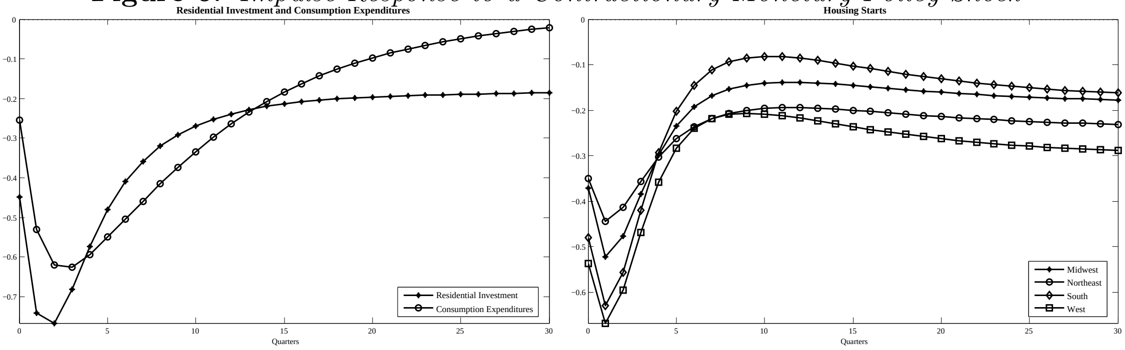
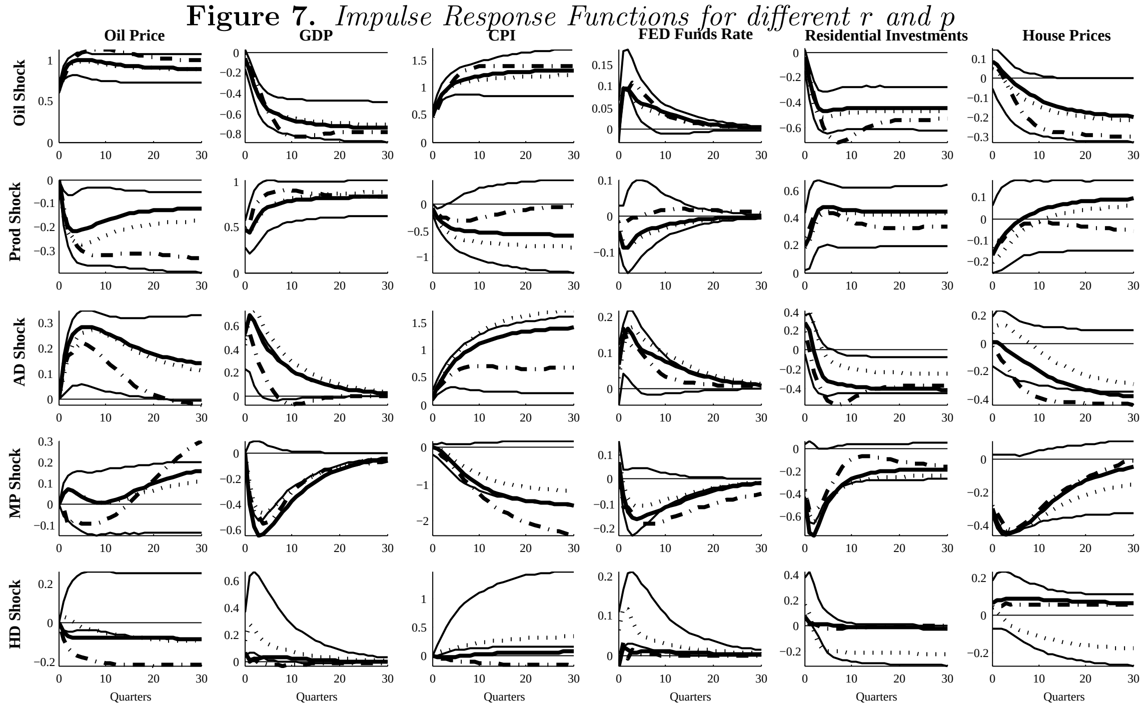
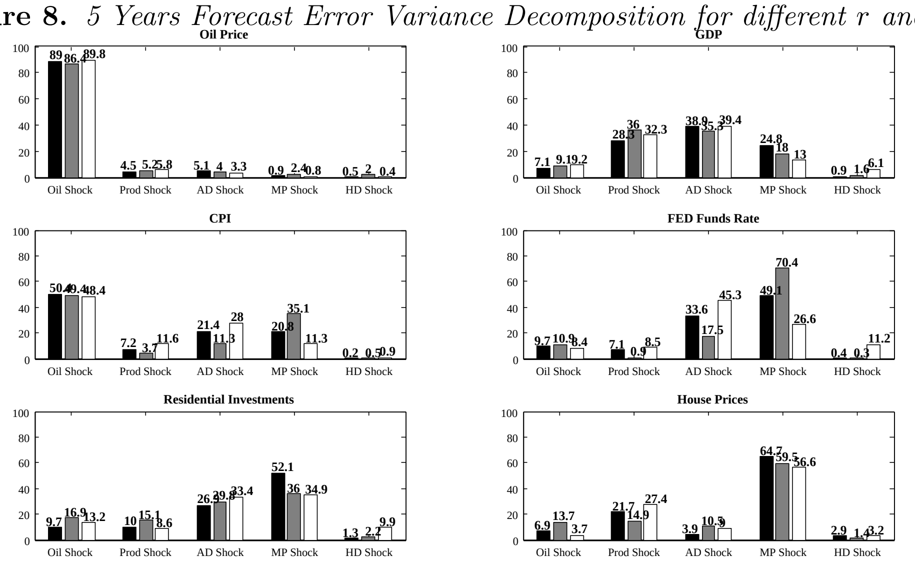


Figure 7. *Impulse Response Functions for different r and p*



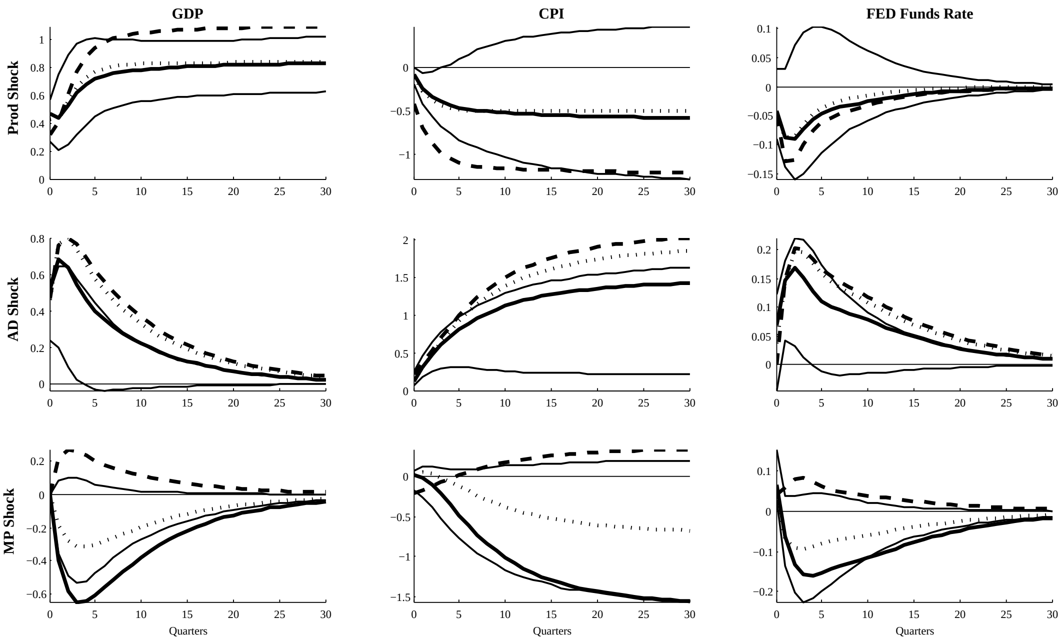
Solid thick lines are IRF with $r = 8$ and $p = 1$, dashed thick lines are IRF with $r = 8$ and $p = 2$, dotted tick lines are IRF with $r = 9$ and $p = 1$, and thin straight lines are 68% bootstrap confidence band obtained over the whole sample. All Responses are cumulated but for the FED Funds rate.

Figure 8. *5 Years Forecast Error Variance Decomposition for different r and p*



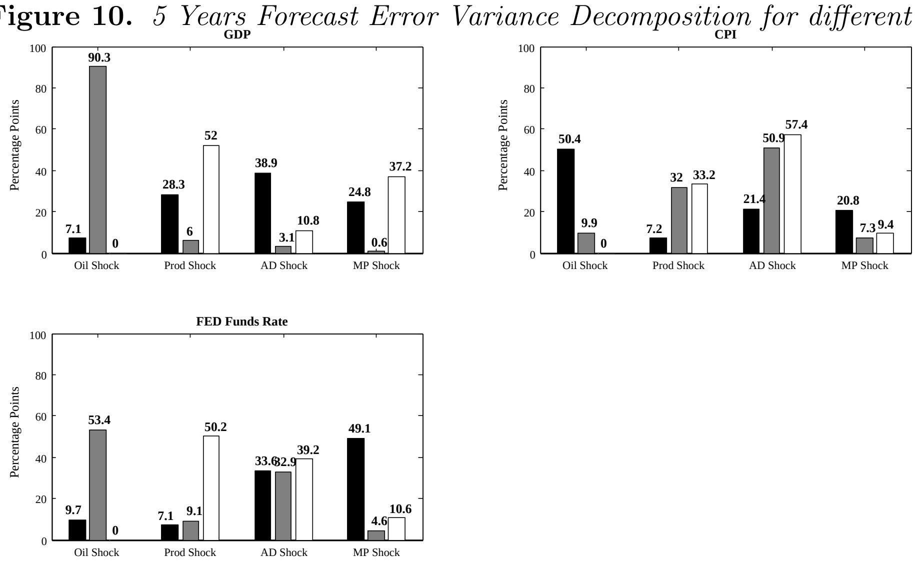
Black bars are FEVD with $r = 8$ and $p = 1$, gray bars are FEVD with $r = 8$ and $p = 2$, and white bars are FEVD with $r = 9$ and $p = 1$. Results refer to common components.

Figure 9. *Impulse Response Functions for different q*



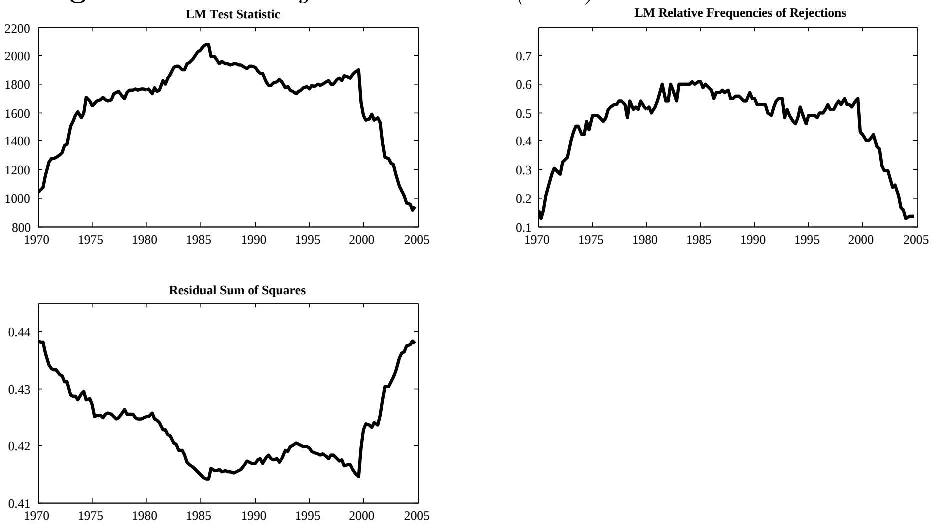
Solid thick lines are IRF with $q = 5$, dotted thick lines are IRF with $q = 4$, dashed thick lines are IRF with $q = 3$, and thin straight lines are 68% bootstrap confidence band obtained over the whole sample. All Responses are cumulated but for the FED Funds rate.

Figure 10. *5 Years Forecast Error Variance Decomposition for different q*



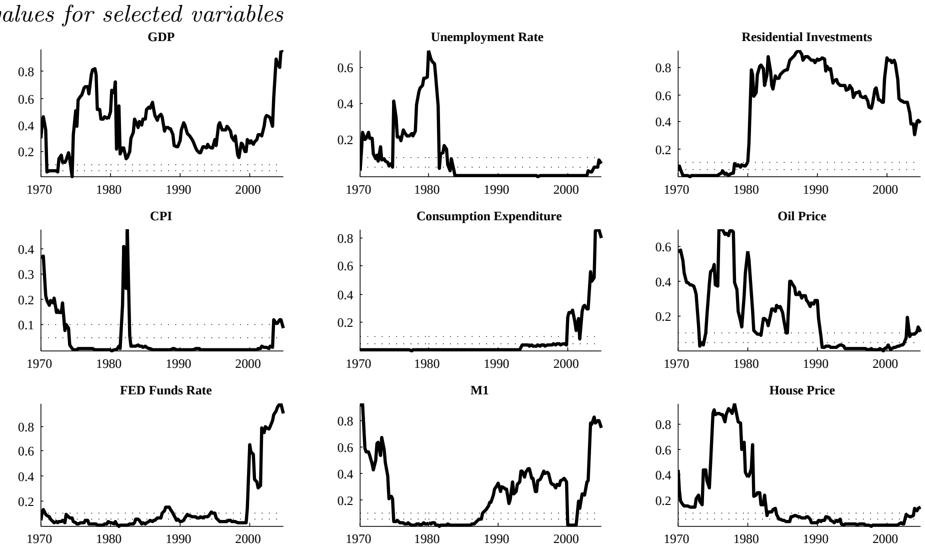
Black bars are FEVD with $q = 5$, gray bars are FEVD with $q = 4$, and white bars are FEVD with $q = 3$. Results refer to common components.

Figure 11. *Breitung and Eickmeier (2009) Structural Break Test*



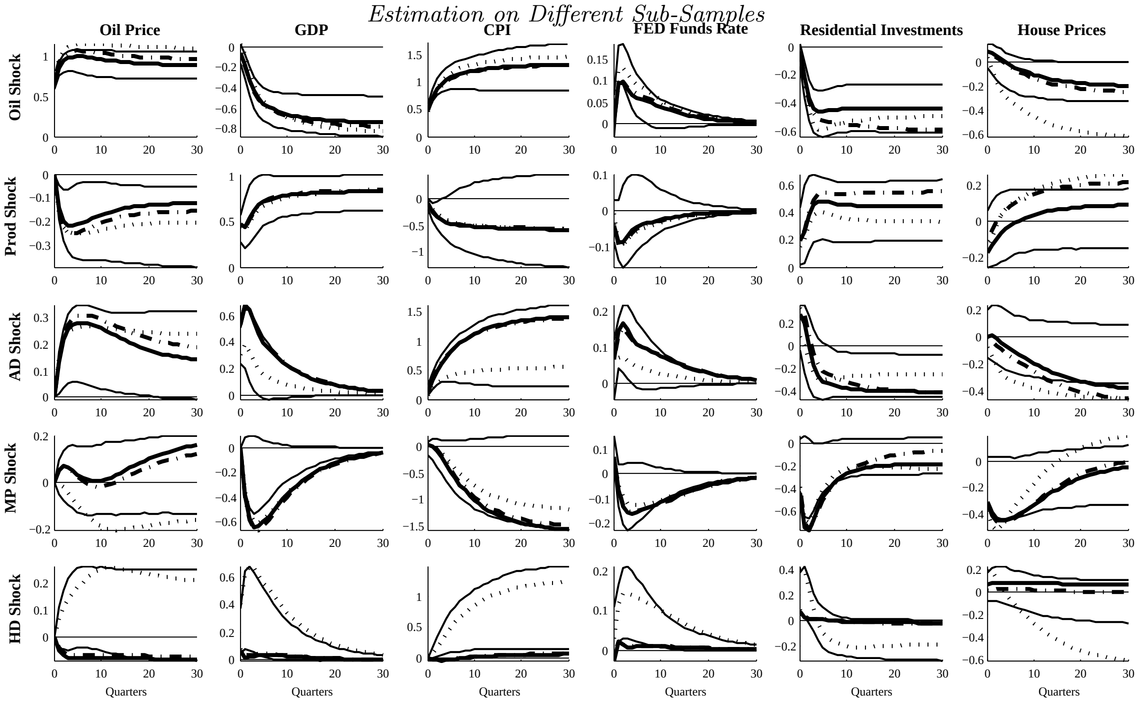
The 1%, 5%, and 10% critical values for the statistics are respectively 904.5,875.25, and 859.93. H_0 = No Break.
The Residual Sum of Squares is the average of RSS_i obtained from the auxiliary regression necessary to compute the statistic s_i. Here, the smaller the sum of square residual, the higher the probability of being in presence of a structural break.
The Relative Frequency of Rejection is the share of variables that at each date reject the null

Figure 12. *Breitung and Eickmeier (2009) Structural Break Test*
p-values for selected variables



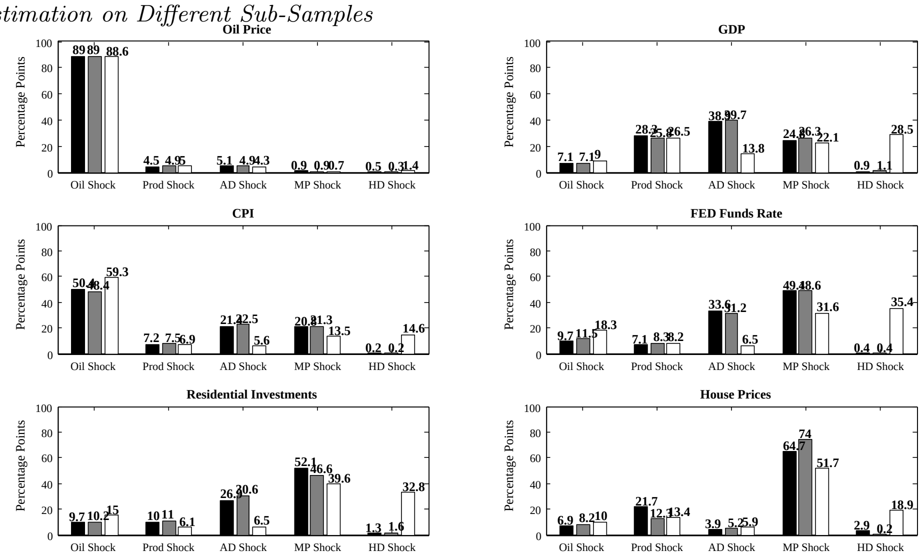
Solid line are p-values, while dotted line indicates 5% and 10%. H_0 = No Break

Figure 13. *Impulse Response Functions*
Estimation on Different Sub-Samples



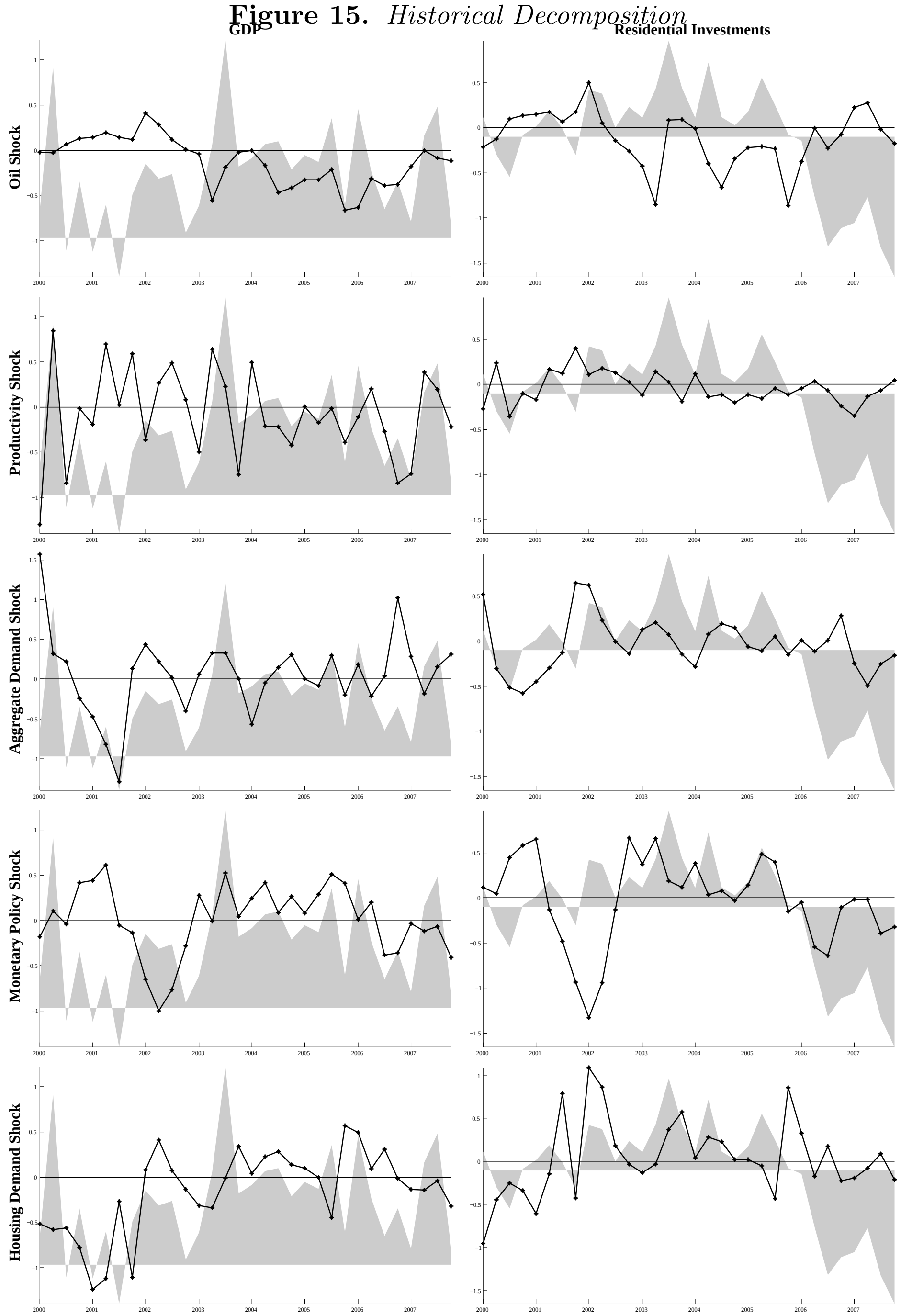
Solid thick line is the benchmark model (whole sample), dashed thick line are obtained over the subsample starting at 1974:1, dotted thick line are obtained cover the subsample starting at 1982:4, and thin straight lines are 68% bootstrap confidence band obtained over the whole sample. All Responses are cumulated but for the FED Funds rate.

Figure 14. *5 Years Forecast Error Variance Decomposition*
Estimation on Different Sub-Samples



Black bars are the benchmark model (whole sample), dark gray bars are obtained over the subsample starting at 1974:1, and white bars are obtained over the subsample starting at 1982:4. Results refer to common components.

Figure 15. *Historical Decomposition*



The shades areas are respectively the GDP and residential investment standardized growth rate. The baseline of the shaded area is fixed so that it correspond to zero in the non transformed series.