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ESTIMATING A NKBC MODEL FOR THE U.S. ECONOMY WITH MULTIPLE FILTERS

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Abstract

This paper estimates a new-Keynesian DSGE model of the U.S. business cycle by employing a variety of business cycle proxies, either *one-by-one* or, following a recent proposal by Canova and Ferroni (2009), in a *joint* fashion. Objects such as posterior densities, impulse-response functions, and forecast error variance decompositions are shown to be remarkably sensitive to different filtering. This uncertainty notwithstanding, shocks to trend inflation are given robust support as the main inflation driver in the post-WWII era.

Keywords: Filtering, business cycle proxies, new-Keynesian business cycle model, trend inflation, estimated dynamics.

JEL classification: C32, E32, E37.

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"There are no innocents ... only different degrees of responsibility."
Lisbeth Salander (in Stieg Larsson, *The girl who played with fire*)

1 Introduction

When willing to take a macroeconomic model of the business cycle to the data, an econometrician has to make a choice on how to filter the raw data in order to work with the frequencies of interest. While some researchers employ statistical filters - e.g. Hodrick-Prescott - to accomplish this task, others make assumptions on processes such as technology and or/preferences to treat the data in a theoretically-consistent manner. Both approaches have pros and cons. Statistical filters are robust to model-misspecification, but are somewhat *ad hoc* - why should one prefer Hodrick-Prescott to linear-detrending? - and may induce 'Slutsky-Yule' effects, i.e. evidence in favor of cyclicalities that are just absent from the original series (Cogley and Nason (1995)). On the other hand, theoretically-consistent detrending is surely appealing, and logically in line with the employment of micro-founded models, but also obviously prone to biases induced by trend misspecification - what if technology is not a log-difference stationary process?[1] Unfortunately, different filtering choices may lead to dramatically heterogeneous representations of the business cycle (Canova (1998)). Moreover, the misspecification of the trend component in rational expectations models may drastically alter policy functions and equilibrium laws of motions, so calling for an 'adjustment' by the structural parameters to compensate for such distortions when the model is confronted with the data (Cogley (2001)). Then, one may very well wonder how sensitive the results obtained with estimated econometric models are to different filtering.[2]

This paper asks the question *'How relevant is filtering to the investigation of the post–WWII U.S. macroeconomic dynamics?'* To answer this question, I estimate a new-Keynesian model of the business cycle (NKBC henceforth) with a variety of filtered output measures to scrutinize the impact of filtering on objects typically investigated by applied macroeconomist. In particular, I aim at assessing how filtering affects i) the posterior densities of the parameters of the structural new-Keynesian model I focus on, ii) the impulse response functions to monetary policy shocks, and iii) the contribution of the estimated shocks to macroeconomic volatilities.

[1] Of course, an econometrician may bet in favor of a 'reference model' for the trend of a series and undertake a 'robust control' approach by minimizing the largest deviations from such a trend induced by a 'evil' agent who works subject to given 'deviation constraints'. I thank Martin Ellison for proposing this idea, the elaboration of which I leave to future research.

[2] Throughout this paper, I will use the terms 'detrending' and 'filtering' interchangeably. In fact, as pointed out by Canova (2007, Chapter 3), 'detrending' refers to the process of making economic series (covariance) stationary, while 'filtering' has a much broader applicability, and refers in general to 'manipulations' operated to the frequencies of the spectrum.

The concern for the first object is easy to justify, in the light of the effort made by econometricians to assess the value of key–parameters such as e.g. the slope of the Phillips curve (key to measure the sacrifice ratio), the degree of 'habit formation', the intertemporal elasticity of substitution (that affects the impact of monetary policy moves on the demand side of the economy), the systematic reaction to inflation and output fluctuations by monetary policy authorities, and the persistence and volatility of structural shocks. Impulse response functions to monetary policy shocks are typically estimated to grasp the quantitative impact that policy surprises may exert on the economy. In undertaking this part of the study, I will distinguish between unexpected monetary policy shifts - i.e. 'standard' monetary policy shocks - and unexpected changes in the inflation target - still a monetary policy shock, but whose origin is conceptually very different. Finally, I assess the role of multiple filtering for the computation of the forecast error variance decomposition, an exercise typically conducted to identify the drivers of the post-WWII U.S. macroeconomic dynamics.

I first estimate the NKBC model by using the filter-specific 'contaminated proxies' of the business cycle *one-by-one*. This can be seen as an extensive robustness-to-filtering exercise, whose documentation is rarely offered in the current applied monetary-macro literature. I then re-estimate the operational NKBC model by employing all the filters *jointly* as recently proposed by Canova and Ferroni (2009), who elaborate a novel methodology (on the lines drawn by Boivin and Giannoni (2006a) with their 'data-rich environment') to efficiently combine differently constructed proxies of the business cycle. This approach has got the potential to eliminate, or at least reduce, filter-specific biases.

My findings read as follows.

- Different filtering techniques lead to remarkably heterogeneous business cycle proxies in terms of turning points, volatility, and persistence. They comove (to some degree) and share low-power when it comes to isolate business cycle frequencies. These findings, obtained with a sample updated to 2008:II, echo those presented by Canova (1998) and Proietti (forthcoming), and offer solid support to the research question asked in this paper. This suggests that these cyclical representations are 'contaminated proxies' of the actual business cycle, and they can in principle severely bias the estimation of structural parameters.

- Such filter-heterogeneity induces (in some cases dramatically) disparate posterior densities of the parameters of the small-scale, new-Keynesian model I concentrate upon. In particular, I find a substantial amount of 'filter–induced uncertainty' surrounding the slope of the Phillips curve, the degree of 'habit formation', the intertemporal elasticity of substitution, the long-run monetary policy response to inflation and output gap oscillations, and the persistence and volatility of the structural shocks. These results, conceptually in line with those presented in Canova (2009), Ferroni (2009), and Canova and Ferroni (2009), open the issue of robustness to different filtering-choices as regards the identification of the drivers of the U.S. macroeconomic series.

- The diversity in the business cycle proxies remarkably affects the estimated impulse response functions to monetary policy shocks. In particular, the responses of the model-consistent 'output gap' to an unexpected move of the federal funds rate and to shocks to the inflation target are clearly proxy-specific (in terms of magnitude), above all when assessed in the Great Moderation period.[3] Interestingly, filter-uncertainty also affects the reaction of inflation and the policy rate to the identified macroeconomic shocks.

- Filter-induced heterogeneity is also present when looking at the forecast error variance decomposition. However, some commonalities emerge, the most evident being the role of time-varying inflation target shocks for the variance of inflation and the policy rate. This result - above all as regards inflation - lines up with recent findings by Kozicki and Tinsley (2005), Cogley and Sbordone (2008), Ireland (2007), and Cogley, Primiceri, and Sargent (2009), and offers support to recent research that aims at understanding the reasons underlying the drifts in the inflation trends observed in the post-WWII U.S. data. An interesting interpretation for such drifts is learning of some key-features of the economy by the Federal Reserve, a point put forward by Cogley and Sargent (2005b), Primiceri (2006), Sargent, Williams, and Zha (2006), and Carboni and Ellison (2009).

While sharing in part the methodology and well as the modeling assumptions with the authors cited above, this contribution is fundamentally different as regards the object of my investigation, which ultimately aims at understanding how differences in the construction of business cycle proxies may drive conclusions on the U.S. macroeconomic dynamics.

The remainder of the paper is structured as follows. Section 2 proposes the 'operational' new-Keynesian model I focus on. Section 3 presents the different measures of the business cycle I work with, and discusses their properties. In Section 4 I discuss some issues on the estimation of the macroeconomic model I focus on, with a particular emphasis on the multiple filters approach. Section 5 presents my findings concerning posterior densities, impulse response functions, and forecast error variance

[3] In this paper I will interpret the empirical proxies of the business cycle as measures of the 'output gap'. Justiniano and Primiceri (2008a) work with a medium-scale DSGE model and show that the distance between the *theoretically* relevant output gap and the *statistically* constructed one(s) dramatically drops when measurement errors are admitted in the estimation, which is what I do in this paper.

decompositions. Section 6 draws some contacts with the existing literature. Section 7 concludes.

2 The model with time-varying trend inflation

The model I consider is a new-Keynesian business cycle framework:

$$\begin{aligned}
\pi_t &= \pi_t^* + \beta E_t(\pi_{t+1} - \pi_{t+1}^*) + \kappa x_t + \varepsilon_t^{\pi}, && (1)\\
x_t &= \gamma E_t x_{t+1} + (1-\gamma)x_{t-1} - \tau(R_t - E_t \pi_{t+1}) + \varepsilon_t^{x}, && (2)\\
R_t &= (1-\phi_R)[\phi_\pi(\pi_t - \pi_t^*) + \phi_x x_t] + \phi_R R_{t-1} + \eta_t^R, && (3)\\
\pi_t^* &= \rho_* \pi_{t-1}^* + \eta_t^*, && (4)\\
\varepsilon_t^z &= \rho_z \varepsilon_{t-1}^z + \eta_t^z, z \in \{\pi, x\}\, ; \eta_t^j \sim i.i.d.N(0, \sigma_j^2), j \in \{R, *, \pi, x\}\, . && (5)
\end{aligned}$$

Eq. (1) is an expectational new-Keynesian Phillips curve (NKPC). Such curve dictates the evolution of the inflation rate π_t as a function of the contemporaneous inflation target π_t^*, the expected value of the future realization of the inflation gap (the wedge between raw inflation and its target), whose loading is the discount factor β, and the output gap x_t, whose influence on the inflation rate is regulated by the slope κ. The presence of the time-varying inflation target in the NKPC may be rationalized by firms' full indexation to the current inflation target (Woodford (2007)), an assumption empirically corroborated by Ireland (2007).[4] Goodfriend and King (2008) employ a very similar model to analyze the U.S. inflation drift observed in the 1970s.

The NKPC at hand is purely forward looking. This choice is motivated by the sound evidence pointing towards a zero-weight assigned to indexation to past inflation in a model (similar to the one employed here) in which the inflation target is allowed to vary over time (Cogley and Sbordone (2008)). Moreover, indexation to past inflation is hardly structural (Benati (2008), Benati (2009)).[5] Consequently, I refrain from

[4] In presence of partial indexation, the inflation schedule displays extra terms and interactions between the steady-state inflation level and some structural parameters entering the NKPC. For a recent theoretical analysis, see Ascari (2004) and Ascari and Ropele (2007). Cogley and Sbordone (2008) tackle this issue from an empirical standpoint.

[5] To be precise, Benati (2008) proposes a very extensive analysis involving ten OECD countries and the Euro Area aggregate. He shows that under stable regimes with clearly defined nominal anchors (U.K., Canada, Sweden, New Zealand, Switzerland under inflation targeting, the Euro Area under the European Monetary Union), inflation can be modeled with a purely forward looking NKPC. His findings point against the notion of price indexation being a structural parameter. The United States have not officially adopted an inflation targeting monetary policy strategy. However, several contributions have supported the shift towards a more aggressive monetary policy at the end of the 1970s. The association of a lower value for the U.S. price indexation parameter in the Great Moderation subsample to a more aggressive systematic monetary policy by the Federal Reserve Bank is conceptually in line with Benati's (2008) position on the indexation parameter being a reduced-form one.

modeling inflation persistence by means of any indexation scheme.

The IS eq. (2) describes the evolution of the *cyclical* component of the real GDP, which is a function of expected and past values - weighted by γ - as well as by the *ex-ante* real interest rate, the latter loaded by the intertemporal elasticity of substitution τ. Strictly speaking, γ is a convolution involving the degree of habit formation of the representative agent, and τ a convolution involving the degree of relative risk aversion and that of habit formation. However, some recent contributions (e.g. Fuhrer and Rudebusch (2004)) propose estimates supporting the 'backward-lookingness' of the U.S. aggregate demand that hardly square with the theoretical restrictions imposed by the microfoundation of lagged output in the IS schedule. Following Benati (2008) and Benati and Surico (2008), we then prefer to work with the more flexible semi-structural eq. (2), which is likely to offer a good empirical performance.

Eq. (3) is a Taylor rule that postulates a gradual response by the Fed to oscillations of the gaps in inflation and output. The target (4) is assumed to follow an autoregressive process (with unconditional mean normalized to zero), an assumption I share with a variety of previous studies (Cogley and Sargent (2005a), Ireland (2007), Woodford (2007), Goodfriend and King (2008), and Cogley, Primiceri, and Sargent (2009).[6] Under $\sigma_*^2 = 0$, the inflation target is constant, and this framework collapses to standard AS/AS model of the kind recently employed in empirical analysis (Lubik and Schorfheide (2004), Lubik and Surico (forthcoming), Boivin and Giannoni (2006b), Benati and Surico (2008), Benati (2008)). Standard assumptions on the stochastic processes (5) close the model.

3 Different business cycle proxies: A comparison

How to approximate the model-consistent business cycle measure x_t, which enters eqs. (1)-(3)? To answer this question, one has to extract the cyclical component from the real-GDP raw time series. I concentrate on six different trends, very popular among macroeconomists. First, I consider the measure of potential output provided by the Congressional Budget Office, which employes a production-function approach to compute a measure of sustainable output.[7] I employ such a measure to filter low-frequency

[6] The inflation target π_t^* is assumed to be perfectly observable at time t. Given that the Fed has never officially announced its inflation target, this is a somewhat problematic assumption. As pointed out by Walsh (2008), misperceptions of the inflation target by the private sector may *de facto* be interpreted as inflationary shocks by an econometrician who assumes trend inflation to be perfectly known. To tackle this issue, one should model the signal-extraction problem faced by the private sector (Erceg and Levin (2003)), or allow for a learning process over the inflation target (for an empirical contribution along this latter line, see Milani (2006)). Kozicki and Tinsley (2005) embed an imperfectly perceived inflation target in a VAR framework.

[7] A detailed explanation on the computation of the CBO potential output may be found at http://www.cbo.gov/ftpdocs/30xx/doc3020/PotentialOutput.pdf.

movements of the real GDP out of the raw series, and I label this empirical proxy 'CBO'. The second transformation is obtained by applying the popular Hodrick-Prescott ('HP') filter with standard weight 1,600. The third transformation is a classical trend-cycle decomposition obtained by fitting a constant and a linear trend to the raw series without allowing for any break in the sample, and taking the residuals as indicator of the business cycle ('LIN'). By contrast, the fourth manipulation ('LBR') fits a piecewise linear trend with a break in 1980:III in both the constant and the slope parameter. Another proxy I consider is constructed by applying the Baxter and King (1994) band-pass filter ('BP') to the log-real GDP so to extract cycles within the [8,32] quarters periodicity (with 12 quarters left as leads/lags). Finally, I take the growth rate of the raw series ('FD') as an indicator of GDP's cyclical component, a choice that relies upon the random walk with drift as a model for the real GDP trend. I perform all these transformations by considering the sample 1954:III-2008:II, a span longer than the one I employ to estimate the NKBC model. This choice's aim is that of tackling initial-condition issues concerning some of the filters at hand.

The filters I consider are very widely employed in the macroeconomic literature.[8] Importantly, they are heterogeneous along different dimensions. Some filters compute the non-cyclical component with quasi-deterministic procedures (LIN, LBR), some assume it is stochastic but very smooth (HP, BK), some very volatile (FD). Some procedures employ univariate information, others a larger set (CBO). Some are one-sided (FD), others two-sided (LIN, LBR, HP, BP). As regards low-frequency distortions, some are likely to overestimate the contribution of the low frequency variability on the business cycle (LIN, LBR), others underestimate it or possibly estimate it fairly precisely (BP).

Figure 1 - left column displays the business cycle empirical proxies obtained with the six filters described above. One may spot similarities and differences across these proxies. Some comments are in order. First, 'eyeball econometrics' suggests a positive correlation across proxies, which is also confirmed by the figures reported in Table 1. However, such correlation varies - in some cases, dramatically - when moving from a pair to another. The highest correlation - 0.94 - regards the pair (HP,BP), while the lowest - 0.10 - involve (LIN,FD). In general, FD is poorly correlated with the rest of the business cycle indicators. This is due to the somewhat erratic behavior displayed by this proxy, which also signals shorter cycles with respect to alternatives. The different proxies under investigation display a relevant amount of heterogeneity also in terms of business cycle dating. Taking the NBER recessions (identified by the grey bars in Figure 1) as reference, one may observe that CBO and HP perform reasonably well. By contrast, LIN just misses to capture the 1969:IV-1970:IV, 1973:IV-1975:I, and 1980:I-1980:III

[8] Of course, the list of filters one may think of is much larger. Canova (1998), Canova (2007) (Chapter 3), Cogley (2008), and Proietti (forthcoming) consider a set of alternative filters and discuss the pros and cons of different filtering strategies at length.

recessions, which are considered as simple slowdowns - i.e. realizations of decreasing but positive output gaps, while LBR shows a somewhat better ability in matching such recessions. Still sticking to the dating issue, FD shows the worst performance, with no clear indication of any particular recession, with the exception of the early 1980s one, indeed caught by all the proxies at hand. The magnitude of booms and busts is clearly filter-dependent, with some filters - e.g. LIN - possibly magnifying the deviations with respect to 'potential' output and others - e.g. FD - dampening them. Table 1 confirms the high volatility in terms of estimated variance of the cyclical component of output. The highest figure - 11.61 - is associated to the LIN filtered proxy, whose variance is much larger than those of the widely employed CBO and HP- respectively 5.76 and 2.90 - and definitely greater than the one of the real GDP growth rate, with the ratio between the two being close to sixteen! Interestingly, when allowing for a break in the trend coefficients, the variance of the linearly detrended business cycle proxy drops of about 40%, so getting much closer to those of HP and CBO. The FD indicator returns the lowest variance - 0.73, and the BP filter induces the second lowest variance - 1.68.

Such heterogeneity is also reflected by the AutoCorrelation Functions depicted in Figure 1 - middle panel. In terms of autocovariance structure, a very different story is told by filters like HP and BP when contrasted to FD, with the latter showing a very quick drop of persistence after a few lags and a mild oscillatory behavior around zero thereafter, while the former display higher persistence and wide oscillations over the twenty-five lags considered. Accounting for the break in the linear trend induces a switch of the sign for most of the autocovariances of LBR with respect to LIN. Table 1-last row, however, suggests that the estimated persistence of the business cycle is very high, with the exception of the FD manipulation. Figure 1 - right panel depicts the log-Spectra of the proxies at hand. It is easy to spot significant errors in terms of identification of the frequencies of interest. Ideally, business cycle indicators should retain frequencies corresponding to the range 8 to 32 quarters (identified by the vertical black dotted bars in the normalized frequency domain). Notably, our proxies tend to attribute an excessive power to low-frequencies, but the error is clearly heterogeneous across filters, with the BP filter performing (by construction) better than all other filters, the HP filter offering an 'intermediate' performance, and others - among which the CBO filter - overemphasizing the relevance of low-frequency fluctuations for the business cycle.[9] In general, problems of leakage (loss of power at the edges of the business cycle frequency band) and compression (increase of power in the middle of the band) are pervasive, a result already pointed out by, among others, Canova (1998), Canova (2007), Chapter 3), Canova (2009), Proietti (forthcoming), and Canova and Ferroni (2009).

[9] The log-Spectra is computed with the 'pwelch' Matlab function. A Bartlett window kernel of size 21 was employed to smooth the periodogram and obtain a consistent estimation of the spectra.

In short, commonly applied filters tend to comove but are very heterogeneous across some dimensions - dating, magnitude, average length, and persistence of the business cycle. These differences are key. One the one hand, they may trigger a 'filter-induced' heterogeneity in results, the quantification of which is ultimately what this paper is after. But this heterogeneity is also a source of relevant information. As stressed by Canova and Ferroni (2009), heterogenous business cycle representations in the frequencies of interest enable the econometrician to optimally extract the relevant information embedded by each 'contaminated proxy' in the estimation phase. Which are the implications of using different filters in terms of model estimation? The next Sections tackles this issue.

4 Model estimation with multiple filters

To appreciate to what extent filtering may be econometrically relevant, I first estimate the NKBC model (1)-(5) by using all the proxies scrutinized in the previous Section *one-by-one*. This exercise will provide information on the *filter-induced heterogeneity* in the estimated objects of interest. Then, I perform estimations by considering the different proxies *jointly*. Canova and Ferroni (2009) point out that this procedure has three main advantages. First, it does not require the researcher to take a strong *a-priori* stand on how to model the trend and the shocks driving it. Given the uncertainty surrounding the evolution of factors like technology and preferences, the fact of being able to remain agnostic on which filter to use is likely to work towards the reduction of biases due to trend misspecification. Second, this methodology allows to employ cyclical data computed with filters having very different features, e.g. one vs. two-sided filters, univariate vs. multivariate, deterministic vs. stochastic, and so on, so making parameter estimates more robust to filter misspecification. Third, errors in the attribution of the business cycle frequencies are proxy-specific. If such errors display a somewhat common pattern across proxies, the joint employment of different empirical indicators of the business cycle should reduce small sample biases in parameters estimates. If such errors are more idiosyncratic, this estimation procedure should wash them out so delivering more precise estimates. Canova and Ferroni's (2009) Monte Carlo exercises confirm that the joint employment of multiple filters reduce the biases of the estimated parameters as well as impulse response functions.

To estimate the model (1)-(5), I therefore set up the following encompassing measurement equation:

$$
\begin{bmatrix} FFRATE_t \\ INFLGDP_t \\ \underset{[Nx1]}{\begin{bmatrix} \widetilde{x}_{1t} \\ \vdots \\ \widetilde{x}_{Nt} \end{bmatrix}} \end{bmatrix} = \begin{bmatrix} \overline{R} \\ \overline{\pi} \\ \underset{[Nx1]}{\begin{bmatrix} \overline{\widetilde{x}}_1 \\ \vdots \\ \overline{\widetilde{x}}_N \end{bmatrix}} \end{bmatrix} + \begin{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} & \underset{[2xN]}{\mathbf{0}} \\ \underset{[Nx2]}{\mathbf{0}} & \underset{[NxN]}{\begin{bmatrix} \lambda_1 & ... & 0 \\ 0 & \ddots & 0 \\ 0 & ... & \lambda_N \end{bmatrix}} \end{bmatrix} \begin{bmatrix} R_t \\ \pi_t \\ \underset{[Nx1]}{\begin{bmatrix} x_t \\ \vdots \\ x_t \end{bmatrix}} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \underset{[Nx1]}{\begin{bmatrix} u_{1t} \\ \vdots \\ u_{Nt} \end{bmatrix}} \end{bmatrix}, \tag{6}
$$

where $FFRATE_t$ is the quarterly federal funds rate at time t, $INFLGDP_t$ is the quarterly GDP deflator inflation, $\widetilde{x}_t = [\widetilde{x}_{1t}, ..., \widetilde{x}_{Nt}]'$ is the $(Nx1)$ vector of empirical proxies of the business cycle computed with N different approximations of the trend, $\overline{\widetilde{x}} = [\overline{\widetilde{x}}_1, ..., \overline{\widetilde{x}}_N]'$ is a $(Nx1)$ vector of proxy-idiosyncratic constants to demean the filters, λ is a (NxN) diagonal matrix of 'loadings' relating the model consistent cyclical component x_t to the N empirical proxies $\widetilde{x}_t$, and $u_t = [u_{1t}, ..., u_{Nt}]' \sim i.i.d.(0_{Nx1}, diag(\sigma^2_{u1}, ..., \sigma^2_{uN}))$ is a $(Nx1)$ vector of serially and mutually uncorrelated filter-specific measurement errors. If a given filtered measure $\widetilde{x}_{nt}, n \in \{1, ..., N\}$ represented exactly the model consistent business cycle, one should expect the slope λ_n to be statistically equal to one, and the volatility of the measurement error σ^2_{un} to be close to zero. Then, the slope parameters indicate the weights assigned by the data to the 'signals' delivered by a given filter as regards the cyclical component of real GDP when contrasted with the model-consistent business cycle indicator. The associated measurement errors indicate the uncertainty surrounding such signals. When implementing the multiple filter strategy, I normalize $\lambda_{CBO} = 1$, and I interpret the remaining λ_s as relative loadings with respect to the first one. By contrast, when estimating the model with a single proxy, the measurement equation (6) features $N = 1$, $\widetilde{x}_t = [\widetilde{x}_{nt}]', u_t = [u_{nt}]'$, and the restriction $\lambda = [\lambda_n]' = 1$ is imposed. A measurement error to the business cycle equation in (6) is allowed also when a single proxy is employed.

Notice that pre-filtering is applied neither to inflation nor to the federal funds rate. In the model at hand, inflation is filtered by the inflation target process (4), which allows to construct a model consistent inflation *gap* measure, i.e. $\pi_t - \pi^*_t$. As for the federal funds rate, the absence of pre-filtering enables a consistent comparison of the results of this paper to those offered by previous contributions, which typically do not perform any manipulation on the raw nominal rate (for further discussions, see Section 5.4).

Bayesian estimation

I perform econometric estimations by relying upon Bayesian techniques, widely employed in the applied macroeconomic literature (see An and Schorfheide (2007) and Fernandez-Villaverde (2009) for detailed reviews, and Canova and Sala (2009) for a discussion of the pros and cons of this methodology vs. alternatives). I then need to set priors so to augment the likelihood of the model with some a-priori knowledge. Following Cogley, Primiceri, and Sargent (2009), I set the autoregressive parameter ρ_* of the inflation target process (4) to 0.995 to capture *low-frequency* movements in inflation. Consequently, the zero-frequency of the inflation process is almost entirely explained by shocks to trend inflation. This does not necessarily imply, however, that shocks to trend inflation are, by construction, the main driver of the conditional volatility of inflation. By contrast, the standard monetary policy shock is assumed to be white-noise. This difference enhances the identification of the two monetary policy shocks. As it is customary in the literature, I calibrate the discount factor β to 0.99.

The remaining priors - reported in Table 2 - are fairly standard, and roughly in line with Benati and Surico (2008), Benati (2008), Benati (2009), and Cogley, Primiceri, and Sargent (2009) as regards the parameters in common between their models and the one under investigation. In particular, I aim to be relatively uninformative as far as the persistence parameters are concerned, and I allow the domain of the volatilities of the model to be wide enough to let the data free to indicate the relative impact of the various shocks on the U.S. economic system. Finally, I assume the loadings of the empirical proxies to be independently distributed as $\lambda_i \sim N(1, 0.5)$. Measurement errors are also assumed to be independently distributed and follow $u_{it} \sim Inverse\ Gamma(0.25, 2)$.[10]

I use as raw data the U.S. GDP deflator, the log-real GDP, and the federal funds rate (average of monthly observations), all downloaded from the website of the Federal Reserve System.[11] In line with e.g. Cogley, Primiceri, and Sargent (2009), I consider the following two subsamples: 1960:I-1979:II, which corresponds to the 'Great Inflation' period before the appointment of Paul Volcker as Fed's chairman, and 1982:IV-2008:II, which corresponds to the post-'Volcker experiment'/'Great Moderation' sample. All series (filtered outputs, inflation, and the policy rate) are demeaned prior to estimation. Consequently, I set $\overline{R}$, $\overline{\pi}$, and the vector $\overline{\overline{x}}$ to zero.[12]

[10] The figures reported in brackets refer to the mean and standard deviation of the distributions of interest.

[11] URL: http://research.stlouisfed.org/fred2/ .

[12] To perform Bayesian estimation I employed Dynare 4.0, a set of algorithms developed by Michel Juillard and collaborators and freely available at http://www.cepremap.cnrs.fr/dynare/. The mode of each parameter's posterior distribution was computed by using the 'csminwel' algorithm elaborated by Chris Sims. A check of the posterior mode, performed by plotting the posterior density for values around the computed mode for each estimated parameter in turn, confirmed the goodness of the optimizations. I employed such modes to inizialize the random walk Metropolis-Hastings algorithm to simulate the posterior distributions. The inverse of the Hessian of the posterior distribution evaluated at the posterior mode was used to define the variance-covariance matrix of the chain. The initial VCV matrix of the forecast errors in the Kalman filter was set to be equal to the unconditional variance of the state variables. I used the steady-state of the model to initialize the state vector in the Kalman filter. I simulated two chains of 200,000 draws each, and discarded the first 75% as burn-in. To scale the variance-covariance matrix of the random walk chain I used a factor so to achieve an acceptance rate belonging to the [23%,40%] range. To assess the stationarity of the chains, I considered the convergence checks proposed by Brooks and Gelman (1998). I conditioned the estimation of the model

5 Empirical results

Canova and Ferroni (2009) show that the MF approach is superior to single-filter alternatives in presence of sufficient idiosyncratic information in the set of contaminated proxies of the business cycle employed in the estimation. The loadings of such proxies (posterior median values) range from 0.85 (LBR) to 4.34 (FD) in the Great Inflation sample, and from 0.80 (LBR) to 4.88 (FD) in the more recent period, confirming the presence of heterogeneous information provided by the different filters. I then take the estimates obtained with MF as a reference when conducting comparisons across filters.

Tables 3 and 4 collect figures concerning the posterior distributions of some representative models. To have a complete screening of the results, Figure 2 plots the densities of all estimated models across the two subsamples. All the posterior medians appear to be economically sensible. Indeed, one may spot striking differences across filter-induced estimates and in contrast to the MF's median. Remarkable filter-specific uncertainty surrounds the intertemporal elasticity of substitution, the extent to which agents are forward-looking in the IS curve, the long-run reaction of the Fed to inflation and output gap fluctuations, the persistence of the shocks, and their volatilities (with the exception of the volatility of the trend inflation shock, which appears to be fairly stable across filters). Given that counterfactuals are typically run by relying on such densities or, often, by conditioning on their means/medians, one may very well wonder how reliable the conclusions of such exercises should be considered in the light of the just documented proxy-induced uncertainty.

Interestingly, there are also similarities across the estimated models. The long-run reaction to inflation gap oscillations increase when moving to the Great Moderation subsample, even if not necessarily so in a statistical sense. This finding is in line with Cogley, Primiceri, and Sargent (2009), and resembles the one proposed by Clarida, Gali, and Gertler (2000), Lubik and Schorfheide (2004), and Boivin and Giannoni (2006b). Notice that, as in Cogley, Primiceri, and Sargent (2009), the difference between the systematic reactions to inflation gap fluctuations in the two subsamples is not large. This might be due to the imposition on equilibrium uniqueness in the estimation phase.[13] Another possible explanation could be the different object at hand, i.e. the inflation

to the unique-solution parameter region.

[13] The debate on the evidence in favor of an indeterminate equilibrium in the pre-Volcker subsample is very lively. On the one hand, Clarida, Gali, and Gertler (2000), Lubik and Schorfheide (2004), and Boivin and Giannoni (2006b) lends support to indeterminacy. Castelnuovo and Surico (2009) show that indeterminacy may offer a rationale for the price puzzle typically found when estimating the effects of a monetary policy shocks with VAR models. Surico (2006) discusses the perils coming from merging two subsamples characterized by different equilibria when conducting empirical exercises on NKPCs. By contrast, Sims and Zha (2006), Justiniano and Primiceri (2008b), Cogley, Primiceri, and Sargent (2009), and Canova and Gambetti (2009) cast doubs on multiple equilibria as a relevant feature to describe the economic situation in the 1960s and 1970s.

gap in this study vs. raw inflation in Clarida, Gali, and Gertler (2000), Lubik and Schorfheide (2004), Boivin and Giannoni (2006b). With a model similar to the one employed in this paper, Castelnuovo (2009) obtains 'more conventional' estimates for the Taylor parameters under the assumption of a constant inflation target.[14]

A robust result I obtain is the generalized reduction of the volatilities of the structural shocks in the second subsample, a finding that captures in first approximation the evidence put forward by Justiniano and Primiceri (2008b) with a framework allowing for time-varying conditional volatilities. Notably, the variance of the inflation target shock is lower in the second subsample. This finding, which I share with Stock and Watson (2007) and Cogley, Primiceri, and Sargent (2009), candidates the reduction in trend inflation volatility as one of the possible drivers of the Great Moderation.[15]

5.1 Comparison with the standard price indexation model

It is worth scrutinizing how the model I focus on performs with respect to the standard price-indexation model displaying no time-varying inflation target. To do so, I consider a version of the model featuring the following version of the NKPC and Taylor rule:

$$\pi_t = \frac{\beta}{1+\alpha\beta}E_t\pi_{t+1} + \frac{\alpha}{1+\alpha\beta}\pi_{t-1} + \kappa x_t + \varepsilon_t^{\pi}, \quad (7)$$

$$R_t = (1-\phi_R)(\phi_\pi \pi_t + \phi_x x_t) + \phi_R R_{t-1} + \eta_t^R. \quad (8)$$

Eq. (7) displays the parameter α, which identifies non-reoptimizing firms' indexation to past inflation. Eq. (8) is a standard Taylor rule postulating a systematic reaction to inflation oscillations by the Fed. In a constant-inflation target (demeaned) world, inflation and inflation gap are coincident objects. As already mentioned, inflation target shocks have been found to be empirically relevant as drivers of the post-WWII U.S. inflation (Cogley and Sargent (2005a), Ireland (2007), Castelnuovo, Greco, and Raggi (2008), and Cogley, Primiceri, and Sargent (2009)). If this is the case, a standard Taylor rule with a constant inflation target is likely to offer a misspecified representation of the U.S. monetary policy conduct.

To engage in a formal comparison between my benchmark (NKBC) model (1)-(5) model and the alternative indexation (IND) framework, I estimate also the latter (composed by eqs. (2), (5), (7), (8)) with different proxies of the business cycle. In so doing, I follow Benati (2008) and model the inflation shifter ε_t^{π} as a white noise, so

[14] Further investigations on this issue are conducted, in the context of regime-switching Taylor rule models, by Castelnuovo, Greco, and Raggi (2008).

[15] The drop of the trend inflation volatility shock may at a first glance appear to be negligible. However, one must bear in mind that the autoregressive root $\rho_* = 0.995$, then a drop of ε in the volatility of the trend inflation shock translates into a reduction of about $\frac{1}{1-0.995^2} \approx 100\varepsilon$ in the unconditional volatility of trend inflation.

giving the indexation parameter α the highest chance of grasping the U.S. inflation persistence. Tables 3 and 4 (ast two rows) collect the (log) Marginal Likelihoods of the NKBC and IND models.[16] Some comments are in order. First, the NKBC model with trend inflation is clearly preferred in four of the five comparisons reported in Table 3 - Great Inflation. Indeed, price indexation acts as an imperfect 'substitute' of the time-varying inflation target. This result squares up with those put forward by Ireland (2007) and Cogley and Sbordone (2008), which favor a new-Keynesian Phillips curve formulation with trend inflation and no indexation when contrasted to a model endowed with price indexation. The only exception is represented by the FD scenario, which supports instead the IND model. This is possibly due to the low volatility of the FD cyclical component, which may perhaps capture some of the low frequencies in inflation otherwise caught by trend inflation. Notably, the posterior odd clearly favors the NKBC model when multiple filters MF are considered.

A somewhat less defined picture arises when considering the Great Moderation subsample. In this latter case, three models out of five - HP, LIN, FD - support the price indexation model. This is perhaps not too surprising. The Great Moderation period is characterized by low and fairly stable inflation, and the role of trend inflation for the dynamics of raw inflation is possibly less relevant. However, the CBO filter and, importantly, the MF panel of filters support the NKBC model with time-varying trend inflation. This latter result casts doubts on the ability of a single filter to identify the shocks driving the U.S. macroeconomic processes. Overall, when considering both subsamples, the trend inflation model appears to be preferrable. Moreover, it is naturally suited to investigate the role played by trend inflation shocks in shaping the post-WWII U.S. macroeconomic environment. Then, in the reminder of the paper I will exclusively focus on such a model.[17]

5.2 Impulse response functions

Figure 3 displays the impulse response functions to the two monetary policy shocks affecting the system, the 'traditional' shock to the nominal interest rate in the Taylor rule (3) and the shock to the trend inflation process (4). In all cases, the reactions have the expected sign. A monetary policy tightening induces an increase in the policy

[16] Preliminary attempts to estimate the IND model with the priors reported in Table 2 failed due to the difficulty of computing posterior modes. I verified that a smooth convergence was instead possible by manipulating the prior mean of the slope of the NKPC. The estimations of the IND model are then conditional on $\kappa \sim Gamma(0.035, 0.01)$.

[17] Notice that, given the difference in terms of 'observables', I *cannot* perform Marginal-Likelihood based comparisons across filters. This is due to the procedure at hand, which implies a filter-specific dataset. Differently, Ferroni (2009) and Canova (2009) filter raw data and estimate the DSGE cyclical model *jointly*, i.e. in a single-step fashion. This strategy enables them to compare the empirical performance of different filters.

rate as well as in the real interest rate, a decrease in the output gap, and a demand-driven deflation. A positive inflation target shock triggers a take-off in inflation and calls for a monetary policy tightening. Given that policymakers react with gradualism, the real interest rate takes negative values in the short run, which leads to a temporary expansion. These reactions are qualitatively in line with those put forward by Ireland (2007) and Cogley, Primiceri, and Sargent (2009).

However, while the dynamics of the system are qualitatively clear, Figure 3 also shows that the situation is quite shaded when seen from the quantitative angle. In fact, the business cycle reaction to both shocks in both subsamples is extremely heterogeneous.[18] To fix ideas on this concept, I compute the percentage deviations of each estimated reaction with respect to the MF filter. Table 5 collects the figures regarding the 4 and 8-quarter ahead percentage deviations. The estimated differences across filters and between each filter and the MF representation are striking. As regards the standard policy shock, figures related to the 4-quarter horizon range from the zero deviation suggested by the CBO filter to the 50% of FD, with HP and LIN associated to a deviation of about 30% under the Great Inflation sample. Interestingly, when accounting for the break, the linear trend lines up (in terms of deviations) to the CBO trend. Figures are somewhat magnified under the Great Moderation sample, with FD's deviation reading 75%. 8-quarter ahead predictions suggest larger figures for all the filters but BP under the Great Moderation.

Filter-uncertaintly clearly affects also the estimated reaction of inflation to a standard monetary policy shock. Again, CBO suggests milder deviations when contrasted to HP and LIN, and LBR somewhat dampens the effects induced by LIN. Notably, the widely employed HP filter is associated to a percentage deviation of about 40% (8-quarter ahead), a very large departure indeed. The growth rate, once more, turns out to be the filter deviating the most with respect to the MF 'weighted average', with figures over 80%.

Also inflation target shocks trigger quantitatively very different business cycle responses. Under Great Inflation, the 4-quarter ahead business cycle reaction to a trend inflation shock inducing a 1% on impact hike in the inflation rate reads 17%, 34%, and 44% when - respectively - HP, LIN, and FD filters are considered under the Great Inflation, and even larger under the Great Moderation, with FD's departures peaking 75% in the 8-quarter ahead scenario. Interestingly, inflation reactions turn out to be much more homogeneous, with the highest deviation being 5.78% (8-quarter ahead). This might be due to the role played by the direct impact exerted by inflation target shocks on the inflation rate via the NKPC (1).

[18] Credible sets (confidence bands) are *intentionally* not displayed. The point here is that of assessing the heterogeneity due to the filtering choice, and not the sample uncertainty surrounding objects like impulse responses or forecast error variance decompositions.

5.3 Forecast error variance decomposition

To gain some information on the role that filtering may play for the identification of the shocks driving the U.S. macroeconomic dynamics, I estimate the forecast error variance decomposition at different horizons.[19] Figures 4 and 5 show this information for the two subsamples of interest. Once again, filtering matters. A few striking examples support this statement. If one wants to assess the contribution that 'inflation' shocks have had on output dynamics at - say - a forty-quarter horizon, she has to face the rather puzzling situation of choosing between the 100% contribution suggested by LIN versus the virtually 0% contribution proposed by the HP filter (both during the Great Inflation and under Great Moderation). Filter-induced heterogeneity is visually detectable in both subsamples when looking at inflation in reaction to monetary policy shocks, output to output and inflation shocks, the policy rate and the inflation gap to basically all shocks. The contribution of the inflation shock to the policy rate tells a story similar to that of the contribution of the very same shock to the business cycle. The standard monetary policy shock turns out to be relevant for the dynamics of the policy rate and for the business cycle, with the latter being mainly affected under the Great Moderation. By contrast, the direct impact of the traditional policy shock appears to play a negligible role for inflation and the inflation gap. Also the contribution to inflation target shocks to inflation, the inflation gap, and the policy rate is subject to a considerable amount of uncertainty in absolute terms, but tends to be relatively large and increasing over subsamples. By contrast, the impact of trend inflation shocks on the business cycle appears to be negligible in both subsamples.

Table 6 collects percentage deviations of the filter-specific contributions of the two monetary policy shocks on inflation and output with respect to the one associated to MF. Some common patterns with the previously analyzed filter-specific impulse response function arise. In fact, one may notice that HP, LIN, and FD suggest decompositions that are percentually very different with respect to the one proposed by MF, both when looking at 16-quarter ahead and when going for the 'long run' - 40-quarter ahead. Percentage deviations are relatively less important in the case of inflation under the Great Inflation period for most of the filters but HP and LIN. Again, accounting for the break in the linear trend lines remarkably dampens the departures from MF, which are anyhow still present. Interestingly, while the standard monetary policy shock is subject to a very large amount of filter-induced uncertainty, that surrounding the contribution of trend inflation shocks for the inflation process is much lower. Indeed, the highest departure concerning this latter shock is that of LIN under the Great Moderation - about 35%. Much larger figures are those associated to the reactions to a standard unexpected policy rate hike, a chief example being the contribution of the

[19] I thank Marco Ratto for kindly providing me with the 'vardec.m' code to compute the forecast error variance decomposition at different horizons.

standard monetary policy shock for output under the Great Inflation sample - 340%! This suggests that the large contribution assigned to trend inflation shocks by all filters as regards inflation is a very robust fact. This finding lines up with recent research -Ireland (2007), Cogley, Primiceri, and Sargent (2009) pointing towards trend inflation shocks as the main inflation driver of the post-WWII U.S. period. This is relevant, because it lends support to studies aiming at understanding the reasons behind trend inflation, one of the possible reasons being learning of the structure of the economy by the U.S. monetary policy authorities (Cogley and Sargent (2005b), Primiceri (2006), Sargent, Williams, and Zha (2006), and Carboni and Ellison (2009)).

Wrapping up, the evidence presented above clearly points towards a marked filter-induced heterogeneity in the posterior densities and, consequently, dynamic responses and variance decompositions when a standard, 'operational' business cycle model is taken to the data.

5.4 Robustness checks

I ran some checks to verify the solidity of the previously discussed empirical findings. In particular,

- I re-estimated the model with multiple filters by dropping the FD filter, which appears to be an outlier when contrasted to the other filters at hand. Indeed, the presence of the FD filter enhances the heterogeneity of the filters across the frequencies of interest. On top of that, the information content of the FD business cycle proxy is weighted 'endogenously' via the estimated λ_{FD} per each subsample, and its precision is assessed via its period-specific measurement error variance. However, to be sure that such particular filter is not driving the results in any important manner, I undertook the estimation of the model with the remaining five filters and re-plotted IRFs and FEVDs. The results presented above turns out to be robust to this manipulation;

- I re-estimated the model by considering the cyclical representation also of inflation and the policy rate on top of that of real GDP. E.g., the model 'HP' has been estimated with HP filtered log-real GDP, HP filtered GDP deflator inflation, and the HP filtered federal funds rate (the same holds for the remaining filters).[20] The main conclusion of this paper, i.e. the pervasive heterogeneity induced by different filterings as regards IRFs and FEVDs, is unaffected. Not surprisingly, the impact of trend inflation shocks turns out to be dampened for most of the

[20] The LBR filter was not considered due to multicollinearity issues in the MF application. We did not filter inflation and the policy rate in the CBO case, which is constructed on the basis of the potential output as computed by the Congressional Budget Office.

filters. However, one should take this last result with care. Indeed, the structural model (1)-(5) already displays a filter for raw inflation (and, indirectly, the policy rate), which is the inflation target process. Then, the reduction in the importance of inflation target shocks is likely to be driven by 'over-detrending';

- In the baseline battery of estimations I employed demeaned data and set $\overline{R}$, $\overline{\pi}$, and the vector $\overline{\overline{x}}$ to zero. In fact, as pointed out by Canova and Ferroni (2009), estimating the constants of the model may be informative on the 'level biases' associated to each filter. As a 'quality-check', I re-estimated the MF models by allowing for independently distributed filter-specific constants $\overline{\overline{x}}_n \sim N(0, 0.5)$, $n \in \{1, ..., N\}$. A large departure from the zero-value of a given filter-specific constant would cast doubts on that filter's ability to correctly identify the mean of the business cycle process. However, the vector $\overline{\overline{x}}$ is estimated to be very close to zero, and with small standard errors, a result suggesting the absence of level biases.

These results, not documented here for the sake of brevity, are available upon request.

6 Contacts with the literature

This paper is closely related to some recent contributions regarding filtering and the estimation of DSGE models on the one hand, and the role played by trend inflation shocks on the other. As previously pointed out, Canova and Ferroni (2009) propose a methodology to jointly deal with different contaminated proxies of the cyclical component of the variables of interest when taking the model to the data. They perform a Monte Carlo analysis to study the properties of their proposal, and show that the joint employment of different filters returns estimated parameters and impulse responses much more consistent than those obtained with a standard single-filter approach. Then, they take a new-Keynesian business cycle model of the business cycle to the data, and show that money enters significantly both the inflation schedule and the aggregate demand equation, a finding overturning previous results. The Fed is also shown to have systematically reacted to oscillations in the growth rate of money. While employing Canova and Ferroni's (2009) methodology, my paper focuses on different objects, i.e. ultimately the filter-induced heterogeneity concerning the conditional reaction of inflation and output to two different monetary policy shocks and the contribution of identified structural shocks to the U.S. macroeconomic volatility.

Related papers are Ferroni (2009) and Canova (2009). Ferroni (2009) contrasts the standard 'first filter, then estimate' two-stage approach with a novel 'jointly filter and estimate' one-step strategy. The novelty hinges upon the joint estimation of trend and structural parameters. Importantly, this strategy allows a researcher to exploit the cross-equation restrictions of the DSGE model when performing the trend-cycle decomposition, to compare the descriptive ability of different filters, and to employ the resulting information to construct robust estimates *via* Bayesian averaging. Ferroni's (2008) 'trend agnostic' methodology turns out to be more consistent than alternatives also in case of model misspecification. He also estimates a standard AD/AS model with U.S. data and show that different filters may indeed induce different estimates of the parameters/moments of interest. Canova (2009) also proposes a 'single step' methodology that allows for a flexible link between unfiltered raw data and the theoretical model at hand, and in which cyclical and non-cyclical components are allowed to have power in all the frequencies of the spectrum. Simulations performed by the author show that standard data transformations induce distortions in structural estimates and policy conclusions that are drastically reduced when applying his methodology. With respect to Ferroni (2009) and Canova (2009), I undertake a more conventional 'two-stage strategy' to highlight the consequences of detrending in the context of a modern monetary policy model of the business cycle that embeds, among others, trend inflation shocks, i.e. possibly one of the main drivers of the great moderation in inflation (Cogley, Primiceri, and Sargent (2009)). Moreover, I jointly consider a variety of differently filtered business cycle representations and let the data speak about their relative weights.

Cogley (2001) suggests to estimate the model with GMM techniques before solving the Euler equations for rational expectations, so to avoid to specify the driving processes at the estimation stage. Instead, I stick to the 'first solve, then estimate' sequence typically called for by likelihood-based estimation techniques, also to overcome the weak-instrument problem often arising when employing GMM techniques (e.g. Fuhrer and Rudebusch (2004)).

In terms of empirical application, a recent contribution by Delle Chiaie (2009) contrasts the estimates of a medium-scale DSGE model for the Euro area conditional on the employment of linear vs. HP filter. Dramatic differences in terms of posterior densities and impulse response functions arise. While being quite correlated to Delle Chiaie's (2009) research idea, my paper employes a larger variety of filters, and it combines them according to the proposal by Canova and Ferroni (2009).

From a more exquisitely economic standpoint, my contribution intersects those concerned with the modeling of the U.S. inflation and output. One of the main features of inflation is its persistence, which has often been modeled via somewhat *ad hoc* indexation mechanisms. Going against this tendency, Cogley and Sbordone (2008) and Benati (2009) show that, once trend inflation is embedded in the new-Keynesian Phillips curve, price indexation is statistically not significant. The remarkable evidence supporting the hypothesis of a time-varying inflation target pursued by the Fed (Cogley and Sargent (2001), Cogley and Sargent (2005a), Ireland (2007), Stock and Watson (2007), Cogley, Primiceri, and Sargent (2009), Castelnuovo, Greco, and Raggi (2008), Castelnuovo (2009), and the two previously mentioned papers) motivates my choice of working with a model in which trend inflation is allowed to play an active role in shaping the U.S. inflation process.

7 Conclusions

This paper has estimated an 'operational' new-Keynesian model of the business cycle (NKBC) with single and, following Canova and Ferroni (2009), multiple filters to assess the role that filtering choices may play as regards objects of interest such as posterior densities, impulse response functions, and forecast-error variance decompositions.

My findings read as follows. Different proxies of the 'output gap', widely employed in the applied macroeconomic literature, are remarkably heterogeneous in terms of turning points, volatility, and persistence, and share low-power when it comes to isolate business cycle frequencies. When employed to estimate the NKBC model I consider, I found that the filter-induced uncertainty surrounding the values of some key parameters - slope of the Phillips curve, degree of intertemporal elasticity of substitution, Taylor rule parameters, persistence and volatility of the structural shocks - is substantial. This uncertainty affects also impulse response functions to a standard monetary policy shock and variance decompositions. These results, conceptually in line with those presented in Canova (2009), Ferroni (2009), and Canova and Ferroni (2009), raise the issue of the robustness of the identification of the drivers of the U.S. great moderation to different filtering strategies.

This uncertainty notwithstanding, a very solid finding stands out. Shocks to trend inflation turn out to be the main driver of the post-WWII U.S. inflation. This result squares up with recent findings by Ireland (2007) and Cogley, Primiceri, and Sargent (2009), and it lends support to research investigating the evolution of the low-frequency component of the post-WWII U.S. inflation rate. A possible explanation is learning, i.e. imperfect knowledge of the economic structure and the formation of the beliefs on the evolution of the perceived inflation-output volatility trade-off by the Fed. Cogley and Sargent (2005b), Primiceri (2006), Sargent, Williams, and Zha (2006), and Carboni and Ellison (2009) have proposed interesting investigations along this dimension.

The employment of a rich set of cyclical macroeconomic measures is a promising avenue to perform robust evaluations on the impact of macroeconomic shocks and systematic policies on the macroeconomic dynamics of interest. Two applications come to mind. The recent financial crises has boosted the attention of policymakers and academic scholars on the role that financial indicators play in shaping the macroeconomic environment. Christiano, Motto, and Rostagno (2007) and Castelnuovo and Nisticò (2009) propose and estimate models in which 'Wall Street goes to Main Street', i.e.

in which firms and households cannot fully insure against financial fluctuations, and financial swings may importantly drive aggregate output and inflation. The reaction of inflation to a monetary policy shock has recently been subject of debate. Christiano, Eichenbaum, and Evans (2005) call for an inflation hike after a monetary policy tightening, the hike being justified by a strong cost-channel linking the interest rate paid by borrowing firms to their marginal costs. Rabanal (2007), employing different econometric techniques, reaches an orthogonal conclusion, i.e. a monetary policy tightening induces a deflation due to the strength of the standard demand channel. One may very well wonder how robust these results are to different filtering strategies, and which are the indications coming from the employment of multiple filtering. I plan to answer these questions with future research.

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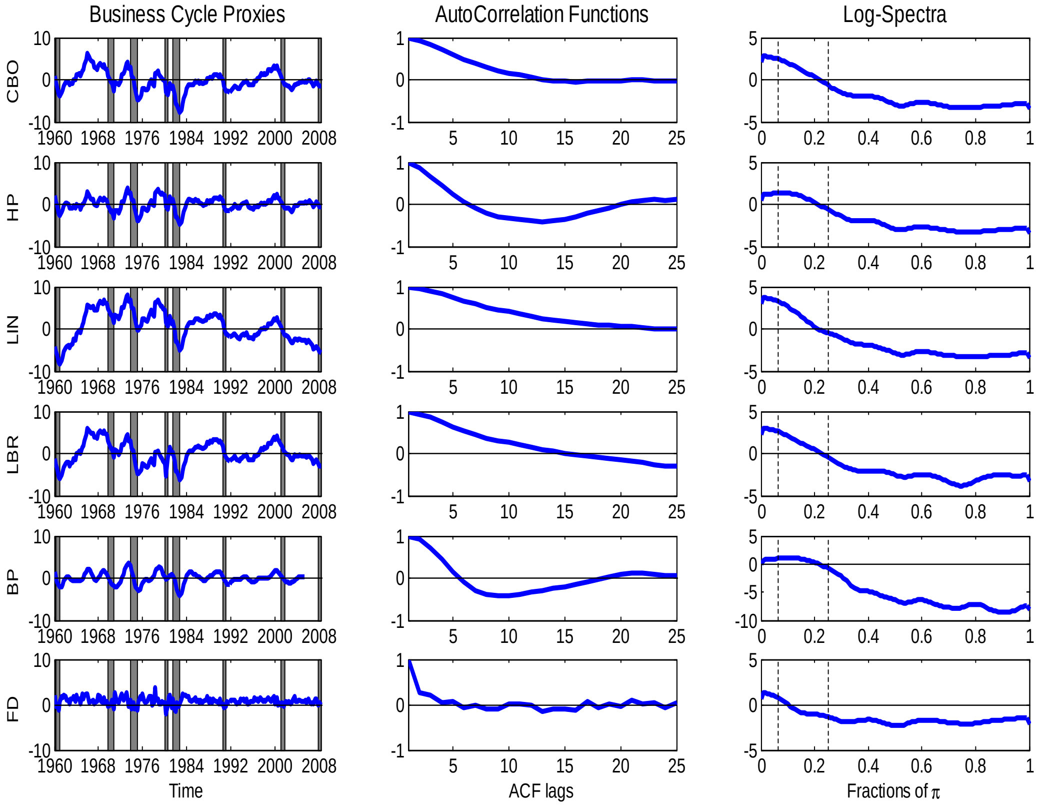

Figure 1: **Proxies of the Business Cycle: Multiple Filters.** Left column: U.S. real GDP filtered with different proxies of the low-frequency component ('trend'). List of filters indicated in the text. Grey vertical bars identify recessions (from peak to through) as dates by the NBER. Middle column: AutoCorrelation Functions of the business cycle proxies. Right columnt: Log-Spectral Density of the business cycle proxies. Blue vertical bars identify the normalized business cycle frequencies in the range [1/16, 1/4] corresponding to 8-32 quarters.

$SCENARIOS$	CBO	HP	LIN	LBR	BP	FD
CBO	*5.76*					
HP	0.79	*2.30*				
LIN	0.64	0.63	*11.62*			
LBR	0.88	0.70	0.72	*6.95*		
BP	0.26	0.94	0.61	0.69	*1.68*	
FD	0.27	0.26	0.10	0.19	0.12	*0.73*
$\widehat{\rho}$	0.94	0.86	0.96	0.94	0.92	0.27

Table 1: **Business Cycle Proxies: Descriptive Statistics.** Main diagonal cells: Variance of the business cycle proxy. Off-diagonal cells: Pairwise correlations. last row: OLS estimated persistence of the business cycle proxies (reference model: AR(1)). Moments computed on the sample 1960:I-2005:2 to account for sample choice and loss of degrees of freedom due to the computation of the Band-Pass filtered proxy.

COEFF.	*INTERPRETATION*	*PRIOR*		
		Density	*Mean*	*St. Deviation*
β	Discount factor	*Calibrated*	0.99	–
κ	NKPC, slope	*Gamma*	0.05	0.01
γ	ISC, forw. look. degree	*βeta*	0.5	0.2
τ	Intertemp. Elasticity of Subst.	*Gamma*	0.1	0.05
ϕ_π	TRule, react. to inflation	*Normal*	1.5	0.3
ϕ_x	TRule, react. to detr. output	*Gamma*	0.3	0.2
ϕ_R	TRule, interest rate smoothing	*βeta*	0.5	0.2
ρ_π	Infl. shock, persistence	*βeta*	0.5	0.2
ρ_x	Output shock, persistence	*βeta*	0.5	0.2
ρ_*	Infl. target, persistence	*Calibrated*	0.995	–
σ_π	Infl. shock, variance	*Inverse Gamma*	0.25	2
σ_x	Output shock, variance	*Inverse Gamma*	0.25	2
σ_R	MP shock, variance	*Inverse Gamma*	0.25	2
σ_*	Infl. target shock, variance	*Inverse Gamma*	0.25	2

Table 2: **Structural Parameters, Prior Densities.**

$COEFF.$	$POSTERIORS$				
	CBO	HP	LIN	FD	MF
κ	0.03 [0.02,0.04]	0.03 [0.02,0.04]	0.04 [0.03,0.06]	0.05 [0.03,0.06]	0.03 [0.02,0.04]
γ	0.54 [0.46,0.62]	0.57 [0.47,0.68]	0.58 [0.50,0.68]	0.59 [0.43,0.80]	0.58 [0.46,0.63]
τ	0.14 [0.06,0.23]	0.12 [0.04,0.21]	0.14 [0.07,0.23]	0.13 [0.06,0.22]	0.13 [0.05,0.22]
ϕ_π	1.69 [1.36,2.07]	1.51 [1.15,1.85]	2.00 [1.68,2.32]	1.69 [1.34,2.06]	1.66 [1.32,2.03]
ϕ_x	0.29 [0.16,0.45]	0.51 [0.29,0.79]	0.14 [0.05,0.23]	0.88 [0.35,1.40]	0.29 [0.15,0.44]
ϕ_R	0.82 [0.75,0.90]	0.84 [0.77,0.90]	0.77 [0.69,0.85]	0.82 [0.75,0.88]	0.82 [0.74,0.90]
ρ_π	0.68 [0.47,0.85]	0.45 [0.19,0.69]	0.95 [0.89,0.99]	0.59 [0.38,0.78]	0.66 [0.38,0.85]
ρ_x	0.53 [0.30,0.73]	0.50 [0.28,0.69]	0.62 [0.41,0.80]	0.40 [0.14,0.64]	0.52 [0.30,0.73]
σ_π	0.12 [0.07,0.17]	0.15 [0.09,0.21]	0.07 [0.05,0.09]	0.13 [0.08,0.18]	0.12 [0.07,0.18]
σ_x	0.28 [0.16,0.42]	0.31 [0.18,0.43]	0.20 [0.10,0.32]	0.14 [0.06,0.24]	0.29 [0.16,0.42]
σ_R	0.19 [0.17,0.22]	0.17 [0.15,0.20]	0.21 [0.17,0.24]	0.21 [0.18,0.25]	0.19 [0.17,0.22]
σ_*	0.08 [0.05,0.11]	0.09 [0.06,0.13]	0.10 [0.07,0.14]	0.08 [0.05,0.11]	0.08 [0.05,0.12]
ML_NKBC	-142.81	-126.25	-157.26	-141.48	-854.24
ML_IND	-147.26	-142.44	-166.83	-137.98	-893.86

Table 3: **Structural Parameters, Posterior Densities Conditional on Different Filters: Great Inflation.** Figures reported in the Table refer to posterior medians and [5th,95th] posterior percentiles. Last two rows: Figures concerning log-Marginal Likelihoods of the benchmark model with trend inflation (BMK) and the standard model with price-indexation (IND). Marginal-Likelihoods computed with the Modified Harmonic Mean approach proposed by Geweke (1998).

$COEFF.$	$POSTERIORS$				
	CBO	HP	LIN	FD	MF
κ	0.02 [0.01,0.03]	0.03 [0.01,0.04]	0.02 [0.01,0.03]	0.04 [0.03,0.05]	0.02 [0.01,0.03]
γ	0.53 [0.46,0.59]	0.57 [0.49,0.66]	0.52 [0.46,0.57]	0.36 [0.08,0.83]	0.43 [0.21,0.59]
τ	0.04 [0.01,0.08]	0.03 [0.01,0.07]	0.05 [0.01,0.09]	0.07 [0.02,0.14]	0.08 [0.02,0.15]
ϕ_π	1.80 [1.39,2.23]	1.81 [1.41,2.22]	2.08 [1.67,2.51]	1.59 [1.16,2.02]	1.68 [1.25,2.12]
ϕ_x	0.58 [0.21,1.06]	0.71 [0.32,1.16]	0.23 [0.10,0.38]	2.06 [1.42,2.73]	0.99 [0.35,1.70]
ϕ_R	0.95 [0.93,0.97]	0.94 [0.91,0.96]	0.91 [0.86,0.95]	0.88 [0.84,0.92]	0.96 [0.93,0.98]
ρ_π	0.20 [0.04,0.39]	0.18 [0.04,0.35]	0.63 [0.58,0.73]	0.18 [0.04,0.34]	0.24 [0.07,0.46]
ρ_x	0.67 [0.54,0.78]	0.63 [0.49,0.76]	0.71 [0.58,0.81]	0.47 [0.16,0.84]	0.77 [0.63,0.87]
σ_π	0.14 [0.11,0.18]	0.14 [0.11,0.18]	0.09 [0.07,0.11]	0.14 [0.11,0.17]	0.13 [0.09,0.16]
σ_x	0.10 [0.06,0.14]	0.11 [0.07,0.15]	0.09 [0.06,0.12]	0.09 [0.06,0.13]	0.09 [0.05,0.13]
σ_R	0.14 [0.12,0.15]	0.13 [0.12,0.15]	0.13 [0.11,0.15]	0.10 [0.08,0.12]	0.13 [0.12,0.15]
σ_*	0.06 [0.05,0.08]	0.06 [0.05,0.08]	0.06 [0.05,0.08]	0.06 [0.04,0.08]	0.07 [0.05,0.08]
ML_NKBC	−51.74	−37.79	−61.02	−24.90	−559.08
ML_IND	−54.09	−36.98	−52.06	−22.61	−563.43

Table 4: **Structural Parameters, Posterior Densities Conditional on Different Filters: Great Moderation.** Figures reported in the Table refer to posterior medians and [5th,95th] posterior percentiles.

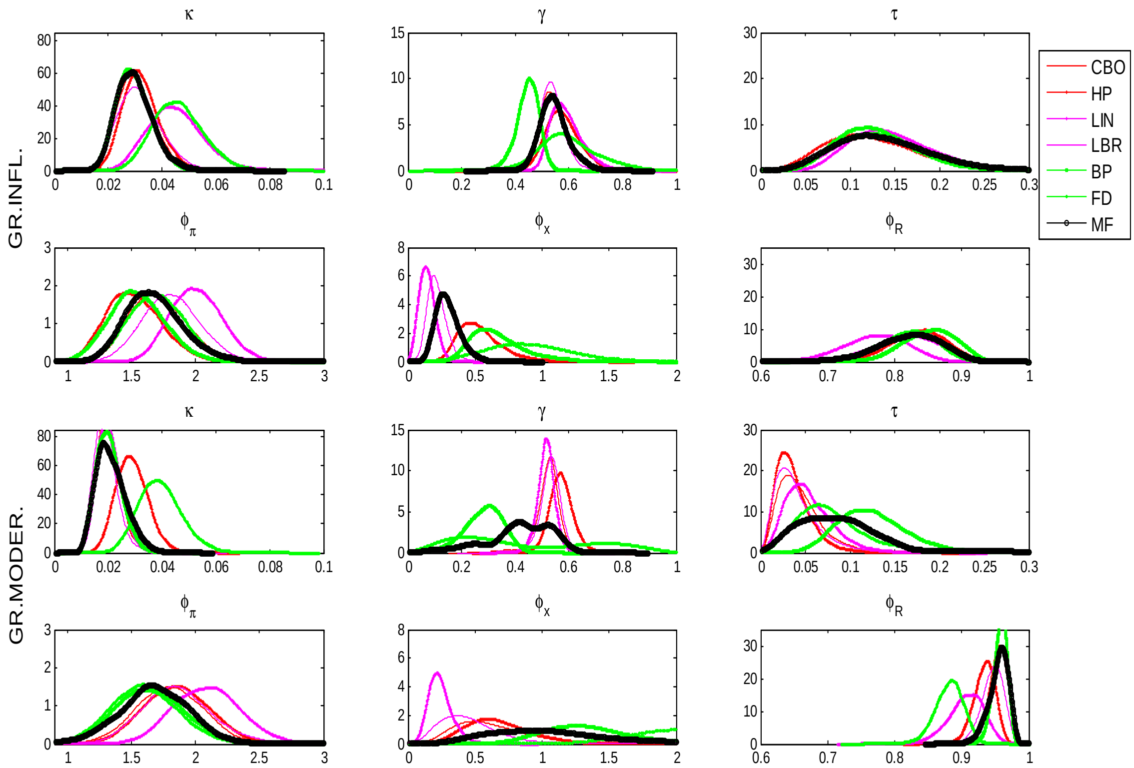

Figure 2: **Structural Parameters, Posterior Densities.** Filters described in the text.

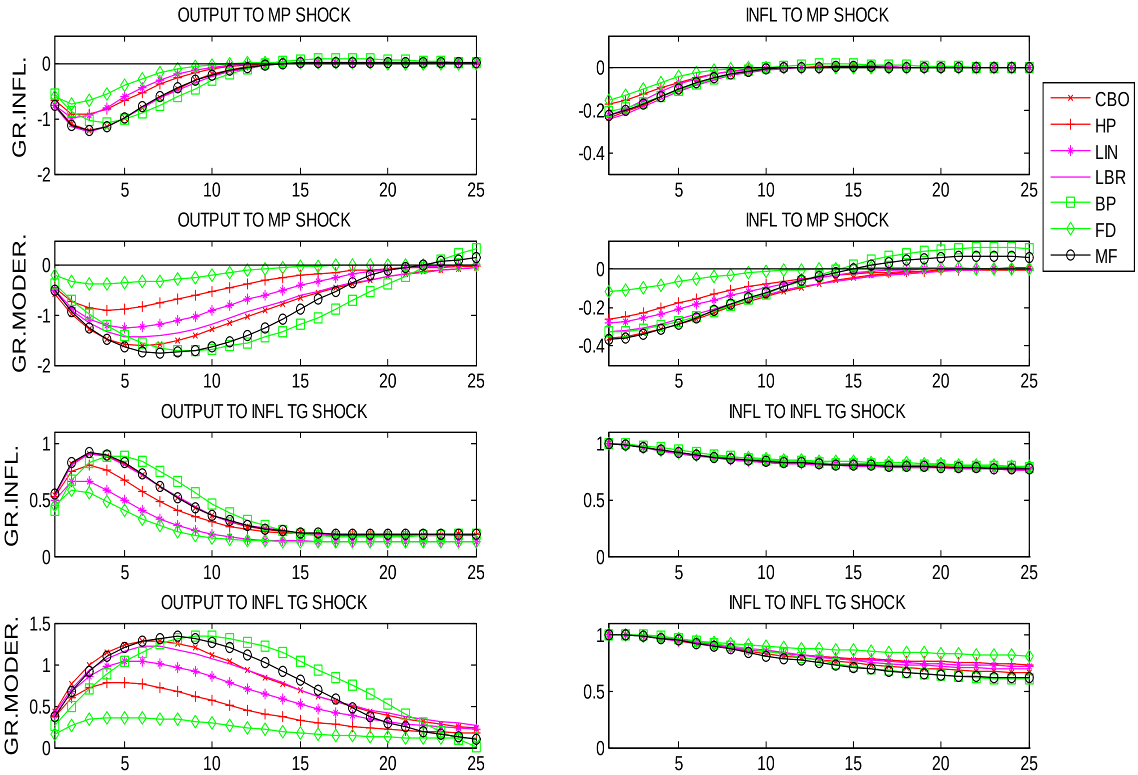

Figure 3: **Impulse Response Functions to Monetary Policy Shocks.** First two rows: Responses to a standard monetary policy shock - normalized to induce a 1% on-impact increase in the policy rate. Last two rows: Responses to a trend inflation shock - normalized to induce a 1% on-impact increase in the inflation rate. Median Bayesian impulse responses based on 500 draws from the posterior densities.

SCENARIOS		*CBO*	*HP*	*LIN*	*LBR*	*BP*	*FD*
		Standard mon. pol. shock - 4-quarter ahead					
GR.INFL.	*Output*	-0.13	-27.93	-30.16	-0.08	-5.90	-51.66
	Inflation	1.75	-29.41	-17.81	9.46	1.26	-49.67
GR.MODER.	*Output*	-0.78	-39.81	-18.57	-10.73	-18.42	-75.16
	Inflation	0.59	-35.29	-25.18	-9.15	-5.00	-74.32
		Standard mon. pol. shock - 8-quarter ahead					
GR.INFL.	*Output*	4.15	-40.56	-53.68	9.41	38.06	-77.24
	Inflation	-4.75	-44.21	-38.63	20.72	-4.47	-82.06
GR.MODER.	*Output*	-12.31	-60.99	-36.07	-21.47	-1.73	-83.81
	Inflation	9.46	-38.66	-24.99	-0.59	5.24	-84.62
		Trend inflation shock - 4-quarter ahead					
GR.INFL.	*Output*	-2.01	-16.97	-34.04	-2.58	-3.36	-44.00
	Inflation	-1.04	-0.58	-1.18	0.25	2.11	-0.33
GR.MODER.	*Output*	6.02	-26.47	-7.55	1.02	-16.53	-65.84
	Inflation	-0.09	-0.32	-0.23	0.11	1.34	0.38
		Trend inflation shock - 8-quarter ahead					
GR.INFL.	*Output*	-2.66	-22.43	-47.15	0.42	22.24	-57.83
	Inflation	-1.28	-0.23	-0.96	-0.38	2.28	1.50
GR.MODER.	*Output*	-4.59	-47.55	-21.68	-9.62	-0.13	-75.01
	Inflation	0.07	1.76	1.97	2.54	2.76	5.78

Table 5: **Impulse Response Functions to a Monetary Policy Shock: Percentage Deviations with respect to Multiple Filters Models.** Figures computed by relying on median responses.

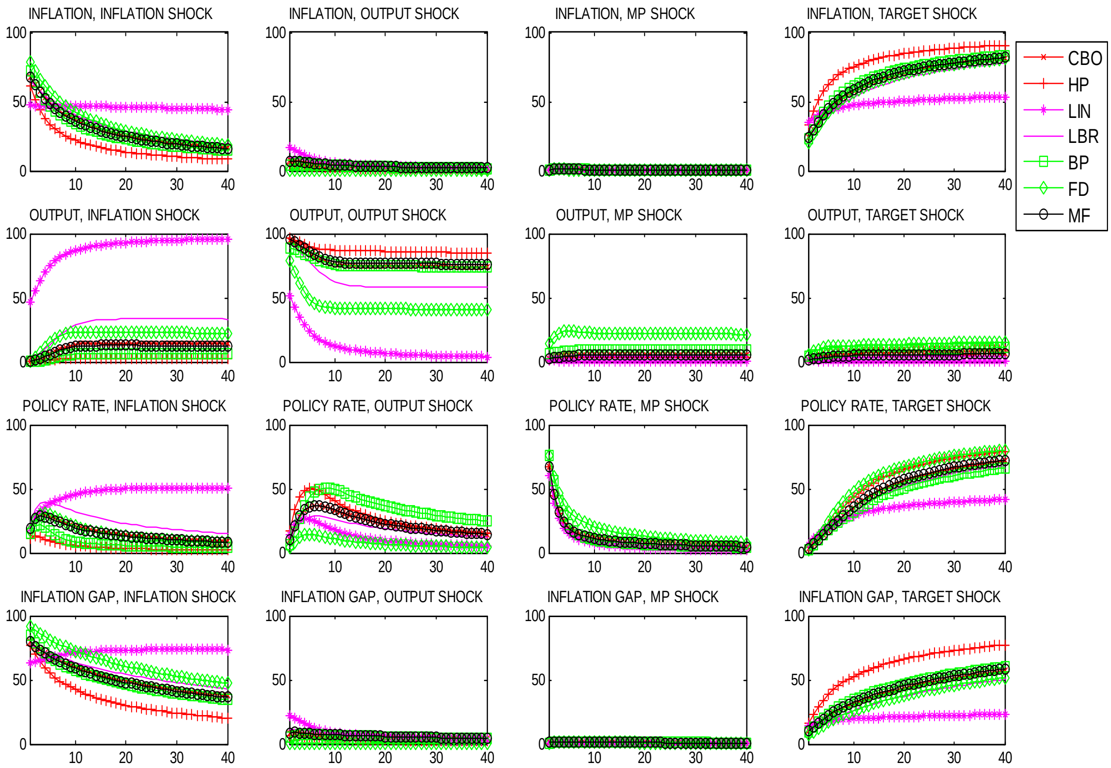

Figure 4: **Forecast Error Variance Decomposition: Great Inflation.** Forecast errors computed on the horizons [1,40] on the basis of posterior mode values.

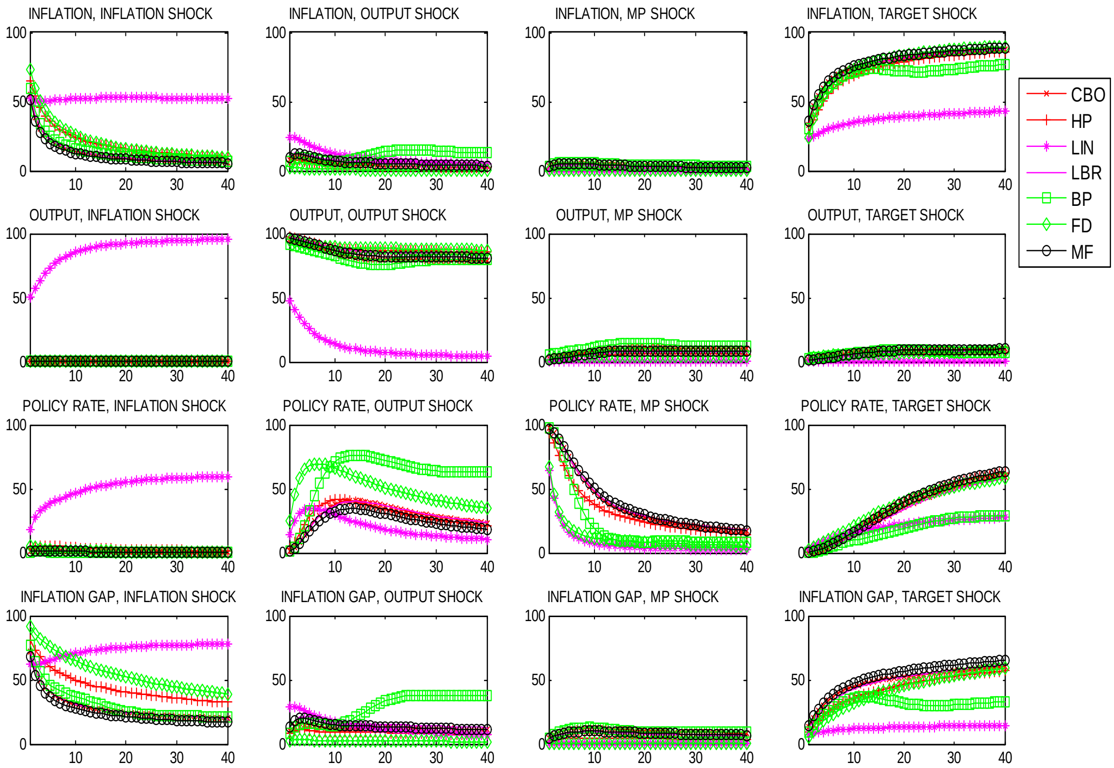

Figure 5: **Forecast Error Variance Decomposition: Great Moderation.** Forecast errors computed on the horizons [1,40] on the basis of posterior mode values.

SCENARIOS		*CBO*	*HP*	*LIN*	*LBR*	*BP*	*FD*
		Standard mon. pol. shock - 16-quarter ahead					
GR.INFL.	*Output*	3.49	−23.01	−95.72	−13.58	80.08	341.70
	Inflation	6.62	−53.01	−78.78	14.69	10.72	−13.51
GR.MODER.	*Output*	28.96	−16.51	−92.61	−13.49	78.54	−18.48
	Inflation	22.60	−48.21	−92.41	−9.80	23.80	−94.59
		Standard mon. pol. shock - 40-quarter ahead					
GR.INFL.	*Output*	3.53	−23.79	−97.89	−13.88	78.36	333.96
	Inflation	7.49	−57.38	−81.33	19.28	9.82	−13.90
GR.MODER.	*Output*	23.09	−32.21	−99.04	−13.65	46.64	−52.45
	Inflation	22.37	−51.38	−94.57	−8.62	43.57	−96.27
		Trend inflation shock - 16-quarter ahead					
GR.INFL.	*Output*	−1.41	40.42	−94.14	−24.91	79.63	152.58
	Inflation	−1.62	20.67	−27.25	−8.17	2.84	−2.50
GR.MODER.	*Output*	6.97	−24.02	−97.24	−17.14	8.18	−20.93
	Inflation	−1.84	−6.31	−53.37	−2.32	−9.60	−0.82
		Trend inflation shock - 40-quarter ahead					
GR.INFL.	*Output*	−2.03	48.91	−96.92	−27.00	75.37	151.42
	Inflation	−0.95	10.91	−34.46	−4.93	1.55	−1.08
GR.MODER.	*Output*	0.94	−25.36	−98.66	−16.02	−23.23	−15.40
	Inflation	−1.39	−2.89	−51.55	−1.29	−13.48	1.24

Table 6: **Forecast Error Variance Decomposition to Monetary Policy Shocks: Percentage Deviations with respect to Multiple Filters Models.** Figures computed by relying on posterior modes.