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Monetary policy rules:
model uncertainty meets design limits*

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Abstract

We offer a contribution to the analysis of optimal monetary policy. The canonical approach to determine what policy rule a central bank should follow is to take a single structural model and minimize the unconditional volatilities of inflation and real activity. In this paper, we design monetary policy rules that robustly perform well across a wide set of structural models and that minimize the volatilities at those frequencies policymakers are most interested in stabilizing. We find that rules robust to model uncertainty call for much less aggressive responses by policymakers. Frequency-specific stabilization preferences further dampen their optimal policy responses.

JEL classification: C49, E32, E37, E52, E58

Keywords: monetary policy rules, policy evaluation, model comparison, model uncertainty, frequency domain, design limits, DSGE models

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1 Introduction

We propose a new way to design optimal monetary policy rules. The canonical approach to find the interest rate rule a central bank should follow is to take a structural macroeconomic model and find the interest-rate (Taylor) rule coefficients that minimize the central bank's objective function, which is usually a weighted average of the unconditional variances of inflation and real activity. In this paper, we question this approach for two reasons.

First, policymakers have a large number of structural models at their disposal to make their decisions, but none of them is the true model of the economy and none may be ideal for answering a specific policy question. Furthermore, as shown by e.g. Levin, Wieland and Williams (2003), a policy rule that is optimal in one model may lead to poor or even disastrous outcomes in other models, hence the choice of model(s) matters. The lack of robustness of model-specific rules is a recurrent finding in the literature. Relying on a single structural model is thus likely to imply an excessively narrow perspective and model uncertainty should be taken seriously when designing optimal policy rules. To address this issue, the literature on model-robust monetary policy has proposed and identified monetary policy rules whose stabilization properties remain relatively good regardless of the model of the economy used. A common finding in this literature is that simple model averaging offers an effective strategy for improving the robustness of monetary policy rules.[1]

Second, monetary policy, through interest-rate setting, should be used to smooth cyclical fluctuations and not as an instrument to fine-tune high-frequency fluctuations of inflation and real activity or to promote long-term economic growth. Policymakers should thus aim at stabilizing specific frequencies of inflation and real activity, and not their unconditional volatilities, as is commonly done in the literature. By focusing on the weighted average of the unconditional variances of inflation and real activity, policymakers

[1] Levin and Williams (2003), Levin et al. (2003), Taylor and Wieland (2012), Schmidt and Wieland (2013), and Wieland, Afanasyeva, Kuete and Yoo (2016) compute model-robust monetary policy rules using structural models of the United States (US) economy, Côte, Kuszczak, Lam, Liu and St-Amant (2004) analyze the performance and robustness of simple monetary policy rules in models of the Canadian economy, and Adalid, Coenen, McAdam and Siviero (2005), Kuester and Wieland (2010), and Orphanides and Wieland (2013) run the analysis using structural models for the Euro Area (EA) economy.

(and researchers) ignore the different high-, business cycle- and low-frequency (HF, BCF, and LF, respectively) effects of monetary policy on those variables. These frequency-specific effects of monetary policy choices have been emphasized by e.g. Onatski and Williams (2003), Brock, Durlauf, Nason and Rondina (2007), and Brock, Durlauf and Rondina (2008, 2013). These studies, which are based on the design limits theory, show that the choice of a policy rule yields a frequency-by-frequency variance trade-off, whereby reducing the variance of targeted variables at certain frequencies may increase the variances at other frequencies.

Table 1 provides an example of the frequency-by-frequency variance trade-off. The first row reports the volatility of inflation (first column) and the volatility of three of its frequency components (HF, BCF, and LF in the subsequent columns) when the central bank follows a Taylor rule that minimizes the volatility of inflation. The second and third rows report the percentage differences in the volatility of inflation and of its frequency components compared to the first row when the central bank follows a Taylor rule that minimizes the volatility of the BCF or LF components of inflation only, respectively. A Taylor rule that minimizes the variance of inflation at BCF (LF) does so at the expense of increasing the variance of inflation at LF (HF and BCF). Policymakers have to be aware and informed of this trade-off when evaluating and deciding on policies, as they should act to reduce the volatility at frequencies they are most interested in stabilizing.

Against this background, in this paper we depart from the canonical approach and analyze the performance of monetary policy rules in the face of model uncertainty *and* with respect to the frequency-specific behavior of inflation and output growth in a unified framework. Our contribution is twofold. First, we contribute to the literature on model-robust monetary policy rules by designing frequency-based model-robust (and model-specific) policy rules using a wide set of Dynamic Stochastic General Equilibrium (DSGE) models for the US economy, which includes the latest vintage of DSGE models. We also compute optimal policy rules by splitting the models in many different ways according to their key features, and not simply between backward- and forward-looking models as done in most of the literature.[2] Second, we contribute to the literature on design limits in monetary policy by designing optimal frequency-specific monetary policy responses across a large number of DSGE models. Previously, this literature mainly relied on a single simple two-equation New Keynesian (NK) class of inflation and output models. Furthermore, it focused on analyzing the sensitivity of rules to frequency-specific preferences instead of addressing the design of optimal monetary policy responses, as we do in this paper.

In terms of substantive conclusions, we emphasize the following results. Compared to the *status quo* of using a single structural model and minimizing the unconditional variances of inflation and real activity, we find that both model uncertainty and frequency-specific preferences call for less aggressive responses by monetary policymakers. From a quantitative point of view, model uncertainty however plays a much bigger role in the design of optimal monetary policy rules, as it more than halves the optimal policy responses. Frequency-specific preferences have a smaller dampening impact on the optimal policy responses.

The rest of the paper is organized as follows. In Section 2, we introduce the DSGE models used, the central bank objective functions, the monetary policy rule, and the frequency decomposition. In Section 3, we analyze the optimized model-specific and model-robust monetary policy rules, and we conduct various experiments and robustness checks. Section 4 concludes.

2 The setup

2.1 DSGE models

DSGE models are widely used for monetary policy analyses in academia and policy institutions. We take several DSGE models from the *Macroeconomic Model Data Base*.[3] These models share antecedents

[2] Binder, Lieberknecht, Quintana and Wieland (2019) represents an exception, but they only differentiate between models with and without financial frictions.

[3] www.macromodelbase.com/. Wieland, Cwik, Müller, Schmidt and Wolters (2012) and Wieland et al. (2016) explain database developments over the years and provide several applications.

and the same methodological core, but each emphasizes different transmission channels, frictions, and shocks. We started from a larger set of models and eliminated the ones that were not well behaved in terms of volatilities (i.e. they generate too large and implausible volatilities of the key macro variables), the unstable models, as well as different versions of the same models (which were too similar to other models already included). Ultimately, we use 29 US economy models. Some of these models are currently used in policy institutions for forecasting and policy simulations (e.g. the del Negro, Giannoni and Schorfheide, 2015 model is in use at the New York Fed).[4]

About half of the models are either small-scale NK models (e.g. three-equation models) or medium-sized DSGE models (e.g. Smets and Wouters, 2007). We include the small-scale NK models to render policy recommendations more robust to model uncertainty. Furthermore, as del Negro, Hasegawa and Schorfheide (2016) show, these models are more useful than larger models in certain situations and simulations, namely their forecasting performances in tranquil periods are usually better compared to those of larger models with financial frictions. The remaining half are larger models and feature financial frictions in the form of the Bernanke, Gertler and Gilchrist (1999) financial accelerator or financial intermediation along the lines of Gertler and Karadi (2011).

All models feature nominal price rigidity à la Calvo (1983) or Rotemberg (1982), and more than half of them also include nominal wage rigidities following Calvo (1983). One model features an accelerationist Phillips curve that is purely backward-looking with respect to inflation. Every third model incorporates a forward-looking New Keynesian Phillips curve, while the remaining two-thirds contain backward- and forward-looking elements that result in a hybrid Phillips curve. Most models include real rigidities such as habit formation in consumption, and either investment or capital adjustment costs.

Finally, some models provide more detailed modelling of certain sectors of the economy such as the labor market (using search and matching frictions à la Mortensen and Pissarides, 1994) or the housing market (usually by introducing heterogeneity in the households sector following the Iacoviello, 2005 setup with

[4] In a previous version of the paper, we also run the analysis separately for the Euro area using nine DSGE models, which are calibrated or estimated on Euro area data. The results are similar and are available in Dück and Verona (2023).

patient savers and impatient borrowers).

Estimated models differ in the estimation method and the data sample used for estimation. We take the results of the estimation or the calibrated values as provided by the authors. The list of model acronyms and a summary of the key features of each model are provided in Table 8 in Appendix A.

2.2 Central bank preferences and objective functions

Inflation and output (or unemployment) are the key variables central banks usually look at when making their policy decisions. However, stabilizing certain frequencies of these variables seems to be more important for policymakers than stabilizing others.[5]

For instance, Lagarde (2021) and Powell (2021) argue that monetary policymakers should not attempt to offset what are likely to be temporary (i.e. high-frequency) fluctuations in inflation, as these fluctuations may disappear before monetary policy can have any effect on the economy. Likewise, as long-term inflation is ultimately a monetary phenomenon under the control of the central bank, policymakers may be reluctant to make interest-rate decisions that may potentially destabilize low-frequency fluctuations in inflation.[6] Regarding real activity, conventional monetary policy cannot directly affect the long-term growth rate of the economy (Mester, 2023) and should not be used to fine-tune high-frequency fluctuations in the real economy. Overall, as argued by Kažimír (2024), acting based on short-term surprises without having clarity about the medium term would be risky.

Given these clear frequency-specific preferences, in this paper we consider several objective functions for the central bank (reported in Table 2) so that monetary policymakers can act according to their preferences with respect to fluctuations at different cycles.

[5] This is explicitly stated in the mandate of some central banks. For instance, the European Central Bank (ECB) states that "price stability is best maintained by aiming for 2% inflation *over the medium term*", while the Sveriges Riksbank aims at maintaining "low and stable inflation *over the long term*", according to the Sveriges Riksbank Act (italics added).

[6] As reported in Verona, Martins and Drumond (2013, Table 1), the Fed has been using forward guidance (on nominal interest rate) at least since June 2003 to shape inflation expectations and, ultimately, inflation in the long run.

As a starting point, we choose the traditional objective function (OF) that considers the unconditional variances (var) of inflation (π) and output growth (Δy). The literature often refers to the output gap (defined as the deviation of output from potential output) rather than output growth in the central bank's objective function (and in the Taylor rule). As pointed out by Plosser (2010), the use of output gap, however, is problematic for at least two reasons. First, its estimations from the data depend on the empirical method used to compute potential output. Second, different models of the economy can employ different theoretical concepts for the output gap. In contrast, output growth is easy to compute from the data and is consistently defined across models.

We then consider several objective functions that include only some frequencies of the relevant variables. In particular, given the discussion above, we ignore altogether the HF fluctuations of inflation and output growth, as well as the LF fluctuations of output growth. Instead, we consider different combinations of BCF and LF volatilities of inflation and the BCF volatility of output growth.

We follow the norm in the business-cycle literature (e.g. Brock et al., 2013) and define BCF fluctuations as those with a period of two to eight years. Hence, we consider all frequencies below two years and above eight years as HF and LF fluctuations, respectively. In the robustness section, we consider different ways of computing BCF fluctuations.

We attach a relative weight λ_y to output growth and consider different values for this parameter. Notably, $\lambda_y > 0$ seems to be more in line with the Fed's dual mandate of price stability and maximum employment, while $\lambda_y = 0$ more closely characterizes the ECB's strict inflation target regime. Furthermore, in all objective functions, following common practice in the literature (see e.g. Smets, 2003 and Kuester and Wieland, 2010), we introduce a preference for restraining the variability of changes to nominal interest rates (Δr) with a weight of 0.5. This term is intended to capture the tendency of central banks to smooth interest rates and avoid extreme values of optimized response coefficients that would be very far from empirical observation and may (frequently) violate the zero lower bound constraint on nominal interest rates.

2.3 Taylor rules

We assume that policymakers try to achieve their targets by setting the nominal interest rate according to the following Taylor rule:

$$r_t = \rho r_{t-1} + \alpha_\pi \pi_t + \alpha_y \Delta y_t \ ,$$

where r_t is the quarterly annualized nominal interest rate, π_t is the quarterly annualized inflation rate, Δy_t is the quarter-on-quarter output growth, α_π and α_y are the interest rate responses to current inflation and output growth, respectively, and ρ captures the degree of interest rate smoothing.

This rule belongs to the class of simple and implementable Taylor rules (Schmitt-Grohe and Uribe, 2007 and Faia and Monacelli, 2007) and is widely used in the literature (see e.g. Gilchrist and Zakrajsek, 2011 and Carrillo and Poilly, 2013). We focus on interest-rate feedback rules belonging to this class because they are defined in terms of readily available macroeconomic indicators, i.e. the central bank sets the short-run nominal interest rate by responding only to observable variables.

2.4 Frequency decomposition

To extract the different frequency components from the time series of inflation and output growth, we use the Maximal Overlap Discrete Wavelet Transform (MODWT). This approach permits the decomposition of any variable, regardless of its time series properties, into a trend and several cycles in a manner similar to the traditional Beveridge and Nelson (1981) time series trend-cycle decomposition approach.

By using the MODWT with the Haar filter, any variable X_t can be decomposed as:

$$X_t = \sum_{j=1}^{J} X_t^{D_j} + X_t^{S_J} \ , \tag{1}$$

where $X_t^{D_j}$ are the wavelet coefficients at scale j, and $X_t^{S_J}$ is the scaling coefficient. These coefficients are given by

$$X_t^{D_j} = \frac{1}{2^j}\left[\sum_{i=0}^{2^{(j-1)}-1} X_{t-i} - \sum_{i=2^{(j-1)}}^{2^j-1} X_{t-i}\right] \tag{2}$$

and

$$X_t^{S_J} = \frac{1}{2^J}\sum_{i=0}^{2^J-1} X_{t-i} \ . \tag{3}$$

Equations (1)-(3) show that the original series X_t can be decomposed (by means of an appropriate sequence of band-pass filters) in different time series components, each defined in the time domain and representing the fluctuation of the original time series in a specific frequency band. The coefficients $X_t^{D_j}$ can then be viewed as components with different levels of persistence operating at different frequencies, whereas the scaling coefficient $X_t^{S_J}$ corresponds to the LF trend of the series. We note that the Haar filter is a one-sided filter, so it can be used in real time by policymakers to disentangle the frequency of the fluctuations of the variables of interest.[7]

In this paper we compute a J=4 level decomposition of our time series. The time period in the models is usually a quarter, hence the first component ($X_t^{D_1}$) captures fluctuations with a period between 2 and 4 quarters, while the components $X_t^{D_2}$, $X_t^{D_3}$, and $X_t^{D_4}$ capture fluctuations with periods of 1-2, 2-4, and 4-8 years, respectively. Finally, the scale component $X_t^{S_J}$ captures fluctuations with a period longer than 8 years.[8] Subsequently, we define the HF component of inflation and output growth (e.g. inflation, π_t) as $\pi_t^{HF} = \pi_t^{D_1} + \pi_t^{D_2}$, the BCF component ($\pi_t^{BCF}$) as $\pi_t^{BCF} = \pi_t^{D_3} + \pi_t^{D_4}$, whereas its LF components correspond to $\pi_t^{S_4}$. That is, cycles with periodicity below (above) two (eight) years are considered as HF (LF) fluctuations, whereas BCF fluctuations as those with a period of two to eight years.

Even though our analysis is purely theoretical, for illustrative purposes we show the frequency decomposition using US data from 1990Q1 to 2017Q4 for two variables: year-on-year Personal Consumption

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[7] The Haar filter is widely used in macro and finance applications (see e.g. Faria and Verona, 2018, 2020, 2021, Bandi, Perron, Tamoni and Tebaldi, 2019, Kilponen and Verona, 2022, Martins and Verona, 2023, and Stein, 2024). It has some intuitive advantages over band-pass filters, as it operates in the time domain and the number of moving average terms is finite.

[8] In the MODWT, each wavelet component at frequency j approximates an ideal high-pass filter with passband $f \in \left[1/2^{j+1}, 1/2^j\right]$. Hence, they are associated with periodicity fluctuations $\left[2^j, 2^{j+1}\right]$ (quarters, in our case). We provide the analytical expressions for these components in Appendix B, .

Expenditures (PCE) inflation rate and quarter-on-quarter real output growth. The first row in Figure 1 reports the time series of the variables, along with business-cycle recessions (depicted as gray-shaded areas). The US economy experienced three recessions over the sample period, with negative GDP growth around those recessions. Inflation mostly fluctuates around 2 %, with some larger swings around the global financial crisis (GFC) of 2007-2008.

The second to fourth rows in Figure 1 report the time series of the frequency components for both variables. Most of the volatility of GDP growth during the GFC is due to its HF and BCF fluctuations, whereas its LF component seems to have shifted to a somehow lower level after the GFC (from 2.5 % to 1.5 %). Similarly, the large swings of inflation during and after the GFC are mainly due to its HF and BCF components, while the LF component of inflation (often interpreted as the inflation target or the perception thereof) has been remarkably anchored to the 2 % inflation target of the Fed since the late-1990s.

3 Optimized monetary policy rules

In this section, we first analyze the optimized monetary policy rule for each DSGE model separately (Sub-section 3.1), and then we evaluate the implications of model uncertainty for the design of monetary policy rules (Sub-section 3.2). In Sub-section 3.3, we quantify the costs of model uncertainty and of ignoring frequency-specific preferences in terms of increase in the OF of the central bank. In Sub-section 3.4, we split the models according to their key features and compute model-robust rules for each group of models separately. Finally, in Sub-section 3.5, we report the results of some robustness tests.

3.1 Model-specific rules

For each model $m \in M$, we solve the following optimization problem:

$$\min_{\{\rho, \alpha_\pi, \alpha_y\}} \quad Var_m\left(\pi^{freq}\right) + \lambda_y Var_m\left(\Delta y^{freq}\right) \quad freq = BCF, LF, all$$

$$s.t. \;\; r_t = \rho r_{t-1} + \alpha_\pi \pi_t + \alpha_y \Delta y_t$$

$$E_t\left[f_m\left(x_t^m, x_{t+1}^m, x_{t-1}^m, z_t, \Theta^m\right)\right] = 0$$

and there exists a unique and stable equilibrium for that model (that is, the Taylor principle is verified), where f_m is the set of all model-specific equations besides the policy rule. x^m and Θ^m are model-specific endogenous variables and parameters, while z are common endogenous variables in all models. When computing the optimized model-specific (and model-robust) rules, we set the limits for each policy rule coefficient ($\rho \in [0, 0.9]$, $\alpha_\pi \in [0.1, 5]$, and $\alpha_y \in [0, 2]$) and run a grid search (with steps of size 0.1 (0.2) below (above) 1 for all grids) to minimize the objective function.

We run the analysis considering the unconditional volatilities of the variables of interest (denoted *all*, because all frequencies are implicitly included in this case), as well as for different frequency combinations in the objective function (as reported in Table 2). In the baseline case, we consider $\lambda_y = 0$ and $\lambda_y = 1$.

The first three columns in Table 3 show the averages of the optimized model-specific coefficients. We emphasize four main results. First, the average smoothing coefficient on the nominal interest rate is 0.9 regardless of the objective function. Second, if the central bank cares about stabilizing only one frequency fluctuation of inflation (either the BCF or the LF), then the optimized model-specific rules imply smaller or similar average response coefficients to inflation. However, stabilizing both frequencies of inflation leads to an average inflation response higher or similar to that of stabilizing aggregate inflation. Third, if the central bank is concerned about output growth stabilization, the average response to output growth is larger (as one would expect), while the response to inflation is smaller. Fourth, when the central bank aims at stabilizing the BCF of GDP growth, then its average response to GDP growth is lower than in the case when it aims at stabilizing the volatility of aggregate GDP growth.

In Figure 2, we plot the distribution of optimized model-specific coefficients. It is clear that not only the average model-robust coefficients (red crosses) are lower when the policymaker aims at stabilizing only some frequencies of inflation and output growth, but the entire distributions of the optimized model-specific coefficients shift downwards. Frequency-specific preferences thus call for somehow more restrained responses by policymakers.

Next, we analyze the extent to which optimized model-specific rules are robust to model uncertainty or, in other words, the cost of ignoring model uncertainty. We do so by evaluating the performance of rules optimized for one model in the other models. Table 4 reports the percentage increase in objective function 1 (% L) when using a rule optimized for model X in model Y relative to using the rule that is optimized for model Y.[9] To interpret the economic significance of this metric, Levin and Williams (2003) looked at historical variations in the value of % L and conclude that a rule generating % L up to 50 % might be viewed as yielding satisfactory performance, whereas a rule yielding % L greater than 100 percent would suggest that insurance against model-uncertainty is prohibitively costly.

This exercise reveals that rules optimized for a specific model generate substantial losses (but never explosiveness / indeterminacy or multiple equilibrium) in several other models. This finding comports with earlier results in the literature. In more detail, we find that the majority of optimized model-specific rules (displayed in the rows of Table 4) trigger steep increases in many other models, and are hence considered to be unsuitable in the presence of model uncertainty. However, two model-specific rules (M_1 and M_2) are robust to model uncertainty as they do not cause loss increases above 65 %, while four other rules (M_3, M_13, M_22, and M_24) perform fairly well across all models. Similarly, as displayed in the columns of Table 4, only few models (especially M_12) are not too sensitive to other optimized model-specific rules, whereas most models generate high % L increases for various rules optimized for other models.

[9] The results hold for all the other objective functions of the central bank.

3.2 Model-robust rules

Given the lack of robustness of the optimized model-specific rules discussed in the previous sub-section, we now search for the rules that perform well across all models. We do so by following Levin et al. (2003), Taylor and Wieland (2012), and Orphanides and Wieland (2013), among others, and apply simple model averaging.[10]

Formally, the model-robust rules are obtained by choosing the coefficients of the monetary policy rule that solve the following optimization problem:

$$\min_{\{\rho,\alpha_\pi,\alpha_y\}} \sum_{m=1}^{M} \omega_m \left[Var_m\left(\pi^{freq}\right) + \lambda_y Var_m\left(\Delta y^{freq}\right)\right] \quad freq = BCF, LF, all$$

$$s.t.\ \ r_t = \rho r_{t-1} + \alpha_\pi \pi_t + \alpha_y \Delta y_t$$

$$E_t\left[f_m\left(x_t^m, x_{t+1}^m, x_{t-1}^m, z_t, \Theta^m\right)\right] = 0 \quad \forall m \in M$$

where there exists a unique and stable equilibrium $\forall m \in M$ (that is, the Taylor principle is always verified) and $\omega_m = 1/M$.

Columns 4 to 6 in Table 3 report the optimized model-robust coefficients for each objective function. We emphasize the following results. First, all model-robust rules feature the same degree of interest rate smoothing, which also coincides with the optimized average model-specific coefficient. Second, compared to the average model-specific coefficients and regardless of the objective function, model-robust rules prescribe much smaller responses to inflation and smaller reactions to output growth. That is, rules robust to model uncertainty generally imply much less aggressive responses of central banks. Third, similar to the model-specific rules, if the policymaker cares about stabilizing a subset of inflation and output growth frequencies, then the robust responses to inflation and output growth are reduced even further.

[10] Alternative approaches to robust policy making include Bayesian model averaging (e.g. Kuester and Wieland, 2010), robust Bayesian rule (e.g. Levine, McAdam and Pearlman, 2012), and non-Bayesian approaches based on minimax and minimax regret criteria (e.g. Brock et al., 2007 and Levine and Pearlman, 2010).

Looking at Figure 2, the model-robust coefficients (black crosses) are on the lower side of the boxes, thus implying much smaller than average (and smaller than median) responses by the central bank in the face of model uncertainty.

Overall, policymakers uncertain about which model(s) to use have to be much more cautious in their policy responses than what the *status quo* of using one single model would, on average, prescribe. Additional caution is needed for those policymakers who have preferences for stabilizing specific frequencies of inflation and output growth.

3.3 Quantifying the costs of insurance against model uncertainty and of ignoring frequency-specific fluctuations

3.3.1 The cost of insurance against model uncertainty

The model-robust rule is designed in such a way that it performs well across all models, but it is rarely the best rule for any model. To provide a measure of the relative performance of the model-robust policy rule in a particular model, we compute the % increase of each objective function (% L) when using the optimized model-robust rule relative to the first-best outcome obtainable in that model (that is, the optimized model-specific rule for that model).

Results are reported in Table 5. Even though some of the individual % L are above the 50 % threshold considered to be acceptable (as mentioned in Sub-section 3.1), the average losses are well below that threshold. Furthermore, when the policymaker is concerned about stabilizing specific frequencies of inflation and output growth (OFs 2-4 and 6-8), then the cost of insuring against model uncertainty is significantly lower, both on average and for nearly all models separately. For instance, comparing the cost implied by objective function 5 with those of objective functions 6 to 8, the average cost of insurance against model uncertainty is halved.

This analysis shows that policymakers can insure against model uncertainty at reasonable cost in each model of the economy.

3.3.2 The cost of ignoring frequency-specific fluctuations

What if policymakers ignore (or are not informed about) the frequency-specific trade-offs we mentioned in the introduction and set their policies looking at the aggregate volatilities of the variables of interest instead?

We report the cost of doing this in Table 6. Each value is the table displays the increase of each objective function (in %) when using the optimized model-specific (m-s) or model robust (m-r) rule of objective function 1 (5) in objective function 2 to 4 (6 to 8), relative to its own optimized rule. On average, as reported in the last row of the table, the % increases of objective functions are not remarkably higher (at most 10 %). Only two models (M_8 and M_14) are more sensitive when stabilization of real activity is a concern (objective functions 5 to 8).

Hence, ignoring these frequency-specific trade-offs does not significantly worsen the outcome for policymakers.

3.4 Model-robust monetary policy rules and models' features

The DSGE models used in this paper feature different frictions and transmission mechanisms. In this sub-section, we investigate if and how specific features of the models affect the size of the model-robust policy responses.

In Table 7, we report the model-robust coefficients separately for i) calibrated and estimated models (8 and 21 models, respectively), ii) models with and without financial frictions (15 and 14 models, respectively), iii) models with and without wage rigidities (15 and 14 models, respectively), and iv) models with a hybrid / backward-looking Phillips curve and with a forward-looking Phillips curve (20 and 9 models, respectively).

Regardless of how the models are divided, the results are qualitatively in line with the main findings of the paper. That is, robust inflation and output growth responses are smaller or similar when the central bank is concerned about stabilizing specific frequencies of inflation and output growth, and robust output growth responses are also larger when policymakers are concerned about stabilizing real activity.

Quantitatively, calibrated models prescribe a stronger reaction (both to inflation and output growth) by policymakers, while the response coefficients of estimated models are similar to the baseline ones. On the one hand, wage frictions play an important role as models without such frictions prescribe stronger responses (to both inflation and output growth), while models including wage frictions lead to weaker responses by policymakers. On the other hand, financial frictions do not seem to matter too much for the design of robust monetary policy rules as the response coefficients are similar whether or not these frictions are included in the model. Finally, the specification of the Phillips curve significantly shapes the results: models with a forward-looking Phillips curve prescribe much more aggressive responses than those of models with a hybrid Phillips curve, which are similar to the baseline results.

We track these quantitative differences across sub-samples of models by observing that the optimized model-robust coefficients usually increase as the variance of the variable of interest decreases. For instance, estimated models, models with wage frictions, and models with a hybrid Phillips curve generate higher volatilities of inflation and output growth than calibrated models, models without wage frictions, and models with a forward-looking Phillips curve, respectively. In the former set of models, the monetary policy response thus need not be as pronounced as in the latter set of models, as monetary policy becomes, on average, more effective in such volatile economies. Hence, the former set of models would call for a less aggressive response by the central bank to stabilize the economy and, ultimately, to avoid excessive macro fluctuations. Interestingly, models with or without financial frictions generate about the same volatility of inflation and output growth. If anything, we find that models with financial frictions generate slightly less volatility, which is at odds with the conventional "financial accelerator" view of business cycle fluctuations (Bernanke et al., 1999). This can be due to the fact that the models included in our exercise were estimated using data pre-GFC, and financial frictions might have played a negligible role during that sample period (see e.g. Drautzburg and Uhlig, 2015).

3.5 Robustness tests

In the first robustness check, we relax the assumption that the central bank equally values the variances of inflation and output growth by assigning different values for the relative weight of the latter variable. Results for $\lambda_y = 0.5$ are displayed in Table 9 (columns 4 to 6) in Appendix C. The benchmark results are reported in the first three columns in that table. A reduction of the relative weight of output growth does not influence the reaction to inflation, while, as one would expect, it usually moderately decreases the reaction to output growth (when compared to the $\lambda_y = 1$ case).

Next, following Levin et al. (2003) and Orphanides and Wieland (2013), we consider forecast-based monetary policy rules of the type:

$$r_t = \rho r_{t-1} + \alpha_\pi E_t \pi_{t+4} + \alpha_y \Delta y_t \ , \tag{4}$$

where $E_t \pi_{t+4}$ corresponds to inflation expectation 4-quarter ahead. Results are reported in Table 9 (columns 7 to 9). The responses to inflation and output growth are larger if the central bank reacts to one-year ahead expected inflation instead of current inflation. However, the main findings still hold, i.e. considering one frequency in the objective function decreases the reaction to inflation, and including output growth typically increases the response to it.

We then consider fluctuations between 1 and 4 years and between 1 and 8 years as BCF fluctuations. Model-robust coefficients, reported in columns 10 to 15 of Table 9, are not too sensitive to the definition of BCF fluctuations.

Finally, we find that results are quantitatively robust for preference parameter for restraining the variability of changes to nominal interest rates (in the objective function) ranging from 0.1 to 1, which is the typical range used in the literature (e.g. Brock, Durlauf and West, 2003 and Levin and Williams, 2003).

4 Policy conclusions

What policy rule should a central bank follow? In this paper, we address this classic question by departing from the canonical approach in two ways. First, instead of relying on one single structural macroeconomic model, we run the analysis using a large number of DSGE models to identify monetary policy rules that are robust to model uncertainty. Second, instead of choosing the rules that minimize a weighted average of the unconditional variances of inflation and output, we search for the rules that minimize fluctuations at specific frequencies, which are arguably more relevant for policymakers.

The policy recommendations of this paper are clear. Model uncertainty calls for much less aggressive responses by monetary policymakers. Frequency-specific stabilization preferences further dampen their optimal policy responses.

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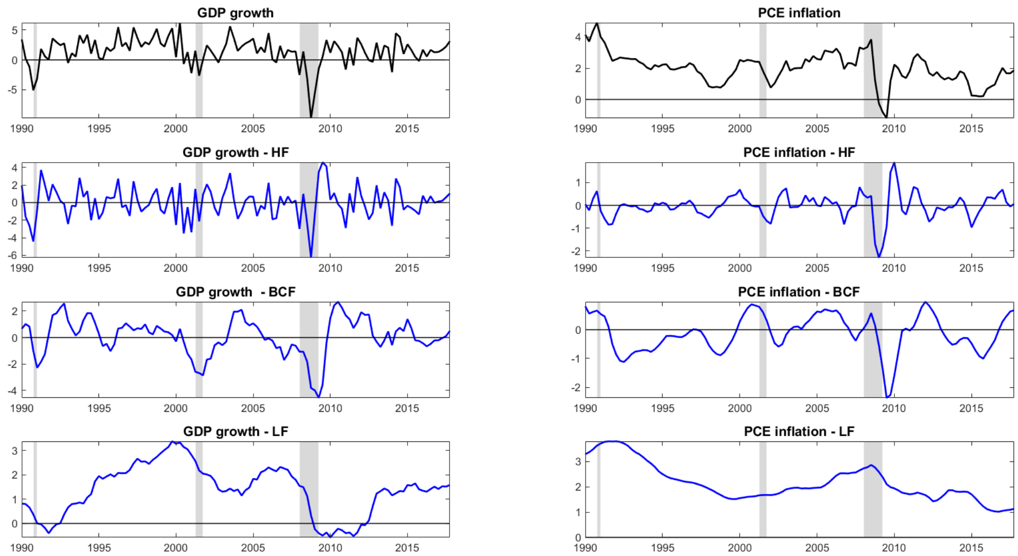

Figure 1: Frequency decomposition of inflation and output growth

Notes. Sample period: 1990Q1–2017Q4. Shaded horizontal bars are NBER recessions. HF stands for fluctuations shorter than 2 years, BCF for fluctuations between 2 and 8 years, and LF for cycles longer than 8 years. Quarterly GDP growth is computed from Real GDP per capita, and year-over-year PCE inflation rate is computed from the PCE price index. Source: FRED2 data base.

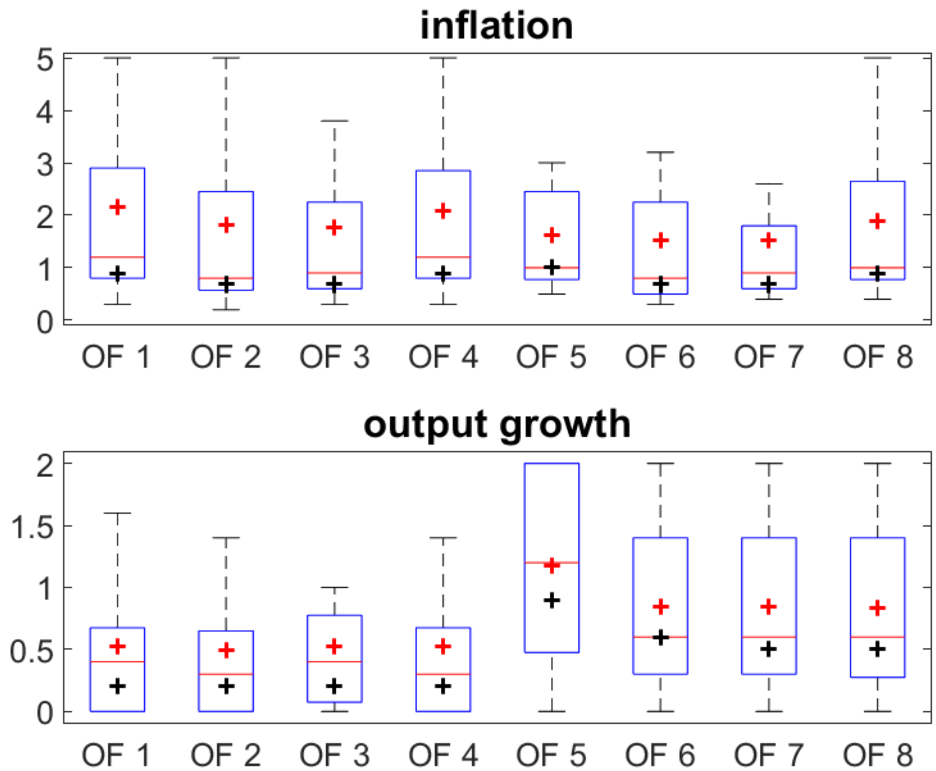

Figure 2: Boxplot of optimized Taylor-rule coefficients

Notes. In the box, the red line displays the median across models. The boundaries of the box depict the 25 % and 75 % percentiles. The whiskers outside of the box mark the entire range of the distribution. The black cross depicts the coefficients of the model-robust rule, and the red cross is the average of model-specific rules. OF 1 to OF 8 refer to the central bank objective functions as reported in Table 2.

	$\text{var}(\pi)$	$\text{var}(\pi^{HF})$	$\text{var}(\pi^{BCF})$	$\text{var}(\pi^{LF})$
Taylor rule that $\min \text{var}(\pi)$	0.12	0.03	0.06	0.03
Taylor rule that $\min \text{var}(\pi^{BCF})$	11	-10	-2	60
Taylor rule that $\min \text{var}(\pi^{LF})$	10	40	7	-19

Table 1: Frequency-specific effects and trade-offs of monetary policy choices

Notes. The first row reports the unconditional variances (*var*) of inflation and its frequency components, while the remaining rows report the percentage differences with respect to the values in the first row. Model used: Blanchard and Gali (2010). HF stands for fluctuations shorter than 2 years, BCF for fluctuations between 2 and 8 years, and LF for cycles longer than 8 years.

Objective Function 1	$\text{var}(\pi)$
Objective Function 2	$\text{var}(\pi^{BCF})$
Objective Function 3	$\text{var}(\pi^{LF})$
Objective Function 4	$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF})$
Objective Function 5	$\text{var}(\pi) + \lambda_y \text{ var}(\Delta y)$
Objective Function 6	$\text{var}(\pi^{BCF}) + \lambda_y \text{ var}(\Delta y^{BCF})$
Objective Function 7	$\text{var}(\pi^{LF}) + \lambda_y \text{ var}(\Delta y^{BCF})$
Objective Function 8	$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF}) + \lambda_y \text{ var}(\Delta y^{BCF})$

Table 2: Central bank objective functions

Notes. HF stands for fluctuations shorter than 2 years, BCF for fluctuations between 2 and 8 years, and LF for cycles longer than 8 years. All objective functions include a term for restraining the variability of changes to nominal interest rates (Δr) with a weight of 0.5.

Objective functions	Individual models			Robust rule		
	$\overline{\rho}$	$\overline{\alpha_\pi}$	$\overline{\alpha_y}$	ρ	α_π	α_y
$\text{var}(\pi)$	0.9	2.2	0.5	0.9	0.9	0.2
$\text{var}(\pi^{BCF})$	0.9	1.8	0.5	0.9	0.7	0.2
$\text{var}(\pi^{LF})$	0.9	1.8	0.5	0.9	0.7	0.2
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF})$	0.9	2.1	0.5	0.9	0.9	0.2
$\text{var}(\pi) + \text{var}(\Delta y)$	0.9	1.6	1.2	0.9	1	0.9
$\text{var}(\pi^{BCF}) + \text{var}(\Delta y^{BCF})$	0.9	1.5	0.8	0.9	0.7	0.6
$\text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	1.5	0.9	0.9	0.7	0.5
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	1.9	0.8	0.9	0.9	0.5

Table 3: Model-specific and model-robust monetary policy rules

Notes. HF stands for fluctuations shorter than 2 years, BCF for fluctuations between 2 and 8 years, and LF for cycles longer than 8 years. All objective functions include a term for restraining the variability of changes to nominal interest rates (Δr) with a weight of 0.5.

Optimized rule for ↓	used in model ↓																												
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18	M19	M20	M21	M22	M23	M24	M25	M26	M27	M28	M29
M1	0	0	15	0	9	16	13	6	3	8	4	6	1	5	1	9	0	1	64	1	4	13	0	13	29	13	6	13	7
M2	0	0	14	0	11	14	14	7	3	8	3	6	2	5	2	9	0	1	64	1	5	12	0	12	27	12	6	12	7
M3	82	82	0	82	22	15	7	22	16	2	11	6	152	23	152	5	82	167	20	69	105	69	73	69	4	3	16	0	11
M4	0	0	31	0	44	30	40	32	8	17	7	14	5	24	5	22	0	4	158	2	11	26	0	26	55	31	22	26	22
M5	564	564	48	564	0	337	7	4	66	46	104	38	1601	11	1601	19	564	1629	54	691	1484	1335	484	1335	116	18	11	54	13
M6	87	87	66	87	126	0	120	97	33	39	20	41	209	77	209	67	87	226	445	79	144	74	74	74	94	88	73	50	70
M7	356	356	21	356	9	155	0	12	36	17	47	15	892	18	892	5	356	944	30	369	717	573	304	573	66	4	11	23	7
M8	212	212	265	212	0	1110	32	0	28	122	75	57	605	2	605	54	212	610	115	260	693	1368	181	1368	772	86	3	262	13
M9	147	147	138	147	39	368	42	25	0	49	9	18	253	17	253	31	147	286	164	102	191	367	125	367	379	59	10	125	11
M10	160	160	4	160	15	19	6	15	12	0	8	1	271	16	271	1	160	310	47	118	156	82	138	82	20	3	9	2	5
M11	78	78	77	78	76	47	84	47	1	19	0	11	194	28	194	35	78	200	465	87	166	135	65	135	247	64	28	54	29
M12	114	114	14	114	33	37	19	23	6	1	6	0	208	18	208	4	114	224	158	101	155	109	99	109	46	10	11	10	6
M13	7	7	36	7	51	17	45	41	17	21	12	20	0	34	0	28	7	0	163	3	2	9	8	9	78	36	31	29	30
M14	289	289	437	289	12	543	114	3	37	169	86	87	923	0	923	114	289	933	585	375	896	946	243	946	1264	203	10	372	34
M15	3	3	45	3	65	13	65	49	18	27	13	25	0	38	0	38	3	0	249	2	0	2	4	2	82	50	38	36	38
M16	0	353	18	353	11	76	5	11	26	3	29	4	704	15	704	0	353	767	83	324	476	267	305	267	83	4	7	14	3
M17	0	0	87	0	52	102	54	40	16	53	30	36	62	31	62	45	0	47	153	29	127	175	0	175	166	61	27	79	30
M18	7	7	0	7	54	48	53	43	13	34	12	23	0	35	0	36	7	0	253	2	2	10	7	10	245	57	28	71	27
M19	494	494	21	0	16	204	10	23	77	42	103	45	1400	33	1400	24	494	1429	0	599	1269	1050	426	1050	17	15	30	29	28
M20	1	1	38	1	62	22	47	45	11	18	7	16	1	34	1	26	1	1	194	0	2	8	1	8	97	35	30	31	27
M21	9	9	88	9	71	38	86	54	23	43	19	36	2	43	2	54	9	3	389	5	0	8	10	8	217	77	45	70	47
M22	11	11	19	11	46	3	36	39	17	15	12	17	3	34	3	23	11	4	103	6	1	0	12	0	27	26	30	15	27
M23	0	0	51	0	49	88	49	34	9	26	11	19	10	25	10	29	0	8	222	5	25	80	0	80	110	41	24	44	25
M24	50	50	19	50	58	3	34	49	14	12	7	12	24	44	24	19	50	33	151	15	5	0	47	0	23	25	29	15	22
M25	1307	1307	16	1307	243	424	113	193	163	59	183	83	3902	174	3902	64	1307	4216	637	1407	3077	2605	1099	2605	0	52	135	25	105
M26	594	594	7	594	8	365	3	6	55	24	92	23	2060	10	2060	4	594	2081	82	779	1997	2027	501	2027	19	0	8	15	6
M27	188	188	42	188	4	111	13	1	10	13	17	5	487	1	487	7	188	512	113	200	395	319	160	319	140	17	0	35	1
M28	241	241	1	241	51	21	21	42	29	4	25	11	479	39	479	9	241	527	86	213	310	149	209	149	13	7	28	0	20
M29	211	211	18	211	7	154	8	2	13	9	27	5	693	1	693	2	211	701	129	269	663	651	177	651	65	6	0	17	0

Table 4: Robustness of model-specific rules

Notes. The values display the increase of inflation volatility (in %), relative to the first-best simple rule for each model.

	Optimized model-robust rule for							
	OF 1	OF 2	OF 3	OF 4	OF 5	OF 6	OF 7	OF 8
M1	5	4	5	5	11	9	9	8
M2	5	4	4	5	11	8	8	8
M3	12	14	11	12	14	11	12	12
M4	16	12	5	12	20	15	7	14
M5	23	18	21	26	39	21	20	26
M6	55	6	82	55	55	9	93	61
M7	12	11	5	13	11	6	3	10
M8	15	14	12	15	132	81	50	55
M9	5	1	3	3	27	12	6	6
M10	6	5	5	6	21	12	16	17
M11	16	6	7	10	27	12	8	15
M12	4	4	4	4	54	2	4	3
M13	25	20	19	22	26	16	16	20
M14	30	26	14	27	72	17	20	34
M15	30	25	16	23	26	26	15	24
M16	6	4	7	8	7	1	4	5
M17	25	12	10	21	155	37	52	26
M18	22	17	11	18	68	35	35	33
M19	38	29	22	39	31	19	14	30
M20	21	17	10	17	15	15	11	16
M21	38	35	21	32	44	45	22	38
M22	24	21	19	21	25	16	17	19
M23	19	15	9	15	16	20	12	18
M24	19	14	11	16	91	38	45	41
M25	108	93	25	99	56	49	22	72
M26	14	9	6	14	28	9	7	14
M27	1	0	0	1	5	2	0	1
M28	20	15	21	21	22	17	23	23
M29	1	1	0	1	10	3	1	2
Average	21	16	13	19	39	19	19	23

Table 5: The cost of insurance against model uncertainty

Notes. The values display the increase of each objective function (in %) when using the optimized model-robust rule relative to the first-best simple rule for each model.

	Optimized rule for											
	OF 1 → OF 2		OF 1 → OF 3		OF 1 → OF 4		OF 5 → OF 6		OF 5 → OF 7		OF 5 → OF 8	
	m-s	m-r	m-s	m-r	m-s	m-r	m-s	m-r	m-s	m-r	m-s	m-r
M1	0	-2	0	-2	0	0	0	-1	0	-1	0	2
M2	0	-2	0	-2	0	0	0	-1	0	-1	0	2
M3	2	2	0	2	0	0	3	-4	2	-8	2	-9
M4	0	-6	1	-3	0	0	14	-3	15	1	14	2
M5	8	24	11	27	1	0	5	45	7	50	0	27
M6	18	2	0	-32	0	0	11	-5	0	-53	0	-18
M7	5	13	0	11	0	0	10	15	7	11	7	2
M8	4	7	3	7	0	0	13	132	11	161	11	157
M9	8	0	6	-3	0	0	6	37	3	36	10	31
M10	2	4	1	3	0	0	4	-4	2	-11	3	-14
M11	10	-5	17	-5	1	0	10	-4	17	-5	1	10
M12	2	1	5	4	0	0	15	0	11	0	15	-3
M13	0	-5	0	-5	0	0	5	-8	3	-9	8	-3
M14	9	5	1	2	0	0	5	32	4	65	18	125
M15	0	-9	0	-5	0	0	1	-11	1	-7	1	-2
M16	4	11	6	14	0	0	8	11	7	11	8	1
M17	0	-4	0	-4	0	0	2	2	0	-12	10	-18
M18	0	-6	0	-4	0	0	1	-18	0	-22	7	-2
M19	3	20	0	20	0	0	6	25	3	23	2	5
M20	0	-8	1	-5	0	0	1	-8	1	-8	2	-2
M21	0	-12	0	-6	0	0	0	-15	0	-6	0	7
M22	0	-4	0	-3	0	0	0	-8	0	-10	0	-7
M23	0	-7	1	-4	0	0	4	3	4	7	4	11
M24	0	-3	0	-2	0	0	0	-23	1	-30	2	-22
M25	8	15	13	24	1	0	9	22	9	33	0	-21
M26	8	20	9	21	0	0	9	37	9	41	0	14
M27	3	4	4	5	0	0	2	11	2	12	2	13
M28	2	5	1	3	0	0	2	-3	1	-11	2	-16
M29	3	6	1	5	0	0	3	16	1	15	0	11
Average	3	2	3	2	0	0	5	9	4	9	5	10

Table 6: The cost of ignoring frequency-specific fluctuations

Notes. The values display the increase of each objective function (in %) when using the optimized rule of objective function X in objective function Y, relative to its own optimized rule (OF X → OF Y). The terms m-s / m-r refer to the model-specific / model-robust rule, respectively.

Objective functions	Calibrated			Estimated			Financial frictions			No financial frictions		
	ρ	α_π	α_y	ρ	α_π	α_y	ρ	α_π	α_y	ρ	α_π	α_y
$\text{var}(\pi)$	0.9	1.2	0.2	0.9	0.9	0.2	0.9	1	0.3	0.9	0.9	0.2
$\text{var}(\pi^{BCF})$	0.9	1	0.3	0.9	0.7	0.2	0.9	0.8	0.3	0.9	0.7	0.2
$\text{var}(\pi^{LF})$	0.9	0.9	0.3	0.9	0.7	0.2	0.9	0.7	0.3	0.9	0.8	0.2
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF})$	0.9	1.2	0.2	0.9	0.9	0.2	0.9	0.9	0.3	0.9	0.9	0.2
$\text{var}(\pi) + \text{var}(\Delta y)$	0.9	1.4	1.8	0.9	0.9	0.7	0.9	1	1	0.9	0.9	0.9
$\text{var}(\pi^{BCF}) + \text{var}(\Delta y^{BCF})$	0.9	1	1	0.9	0.7	0.5	0.9	0.8	0.6	0.9	0.7	0.6
$\text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.9	1	0.9	0.7	0.5	0.9	0.8	0.6	0.9	0.7	0.5
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	1.2	0.9	0.9	0.9	0.5	0.9	0.9	0.5	0.9	0.9	0.5

Objective functions	Wage frictions			No wage frictions			Hybrid Phillips curve			Forward-looking Phillips curve		
	ρ	α_π	α_y	ρ	α_π	α_y	ρ	α_π	α_y	ρ	α_π	α_y
$\text{var}(\pi)$	0.9	0.8	0.1	0.9	1.2	0.5	0.9	0.9	0.2	0.9	1.6	0.3
$\text{var}(\pi^{BCF})$	0.9	0.6	0.1	0.9	0.9	0.5	0.9	0.7	0.2	0.9	1.4	0.3
$\text{var}(\pi^{LF})$	0.9	0.6	0.2	0.9	0.9	0.4	0.9	0.7	0.2	0.9	1.2	0.4
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF})$	0.9	0.7	0.1	0.9	1	0.5	0.9	0.9	0.2	0.9	1.6	0.3
$\text{var}(\pi) + \text{var}(\Delta y)$	0.9	0.8	0.7	0.9	1.2	1.4	0.9	0.9	0.7	0.9	1.6	2
$\text{var}(\pi^{BCF}) + \text{var}(\Delta y^{BCF})$	0.9	0.5	0.4	0.9	0.9	0.8	0.9	0.7	0.5	0.9	1.2	1.4
$\text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.6	0.4	0.9	0.9	0.8	0.9	0.7	0.4	0.9	1.2	1.6
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.7	0.4	0.9	1	0.7	0.9	0.8	0.4	0.9	1.4	1.2

Table 7: Model-robust monetary policy rules of models with different features

Notes. The features are: calibrated and estimated models, models with and without financial friction, models with and without wage friction, and models with a hybrid and forward-looking Philips curve. HF stands for fluctuations shorter than 2 years, BCF for fluctuations between 2 and 8 years, and LF for cycles longer than 8 years. All objective functions include a term for restraining the variability of changes to nominal interest rates (Δr) with a weight of 0.5.

Appendix A Models (acronyms) and their key features

Model acronyms		Paper	Estimation period	Wage frictions	Financial frictions	Phillips curve
US_ACELm	M1	Altig, Christiano, Eichenbaum and Linde (2011)	1959Q2-2001Q4	Yes	Yes	hybrid
US_ACELswm	M2	Altig et al. (2011)	1959Q2-2001Q4	Yes	Yes	forward
US_BKM12	M3	Bils, Klenow and Malin (2012)	1990M1-2009M10	Yes	No	hybrid
US_CD08	M4	Christensen and Dib (2008)	1979Q3-2004Q3	No	Yes	forward
US_CFOP14	M5	Carlstrom, Fuerst, Ortiz and Paustian (2014)	1972Q1-2008Q4	Yes	Yes	hybrid
US_CPS10	M6	Cogley, Primiceri and Sargent (2010)	1982Q4-2006Q4	No	No	hybrid
US_DG08	M7	de Graeve (2008)	1954Q1-2004Q4	Yes	Yes	hybrid
US_DNGS15_SWpi	M8	del Negro et al. (2015)	1964Q1-2008Q3	Yes	No	hybrid
US_FMS13	M9	Feve, Matheron and Sahuc (2013)	1960Q1-2007Q4	Yes	No	hybrid
US_FU19	M10	Fratto and Uhlig (2020)	1984Q1-2015Q4	Yes	No	hybrid
US_HL16	M11	Hollander and Liu (2016)	1982Q1-2015Q1	No	Yes	hybrid
US_IAC05	M12	Iacoviello (2005)	1974Q1-2003Q2	No	Yes	forward
US_IR04	M13	Ireland (2004)	1980Q1-2001Q3	No	No	forward
US_JPT11	M14	Justiniano, Primiceri and Tambalotti (2011)	1954Q3-2009Q1	Yes	No	hybrid
US_KS15	M15	Kriwoluzky and Stoltenberg (2015)	1964Q1-2008Q2	No	No	forward
US_LWY13	M16	Leeper, Walker and Yang (2013)	1984Q1-2007Q4	Yes	No	hybrid
NK_BGUS10	M17	Blanchard and Gali (2010)	calibrated	Yes	No	forward
NK_CFP10	M18	Carlstrom, Fuerst and Paustian (2010)	calibrated	No	Yes	forward
NK_CK08	M19	Christoffel and Kuester (2008)	calibrated	Yes	No	hybrid
NK_GK09lin	M20	Gertler and Karadi (2011)	calibrated	No	Yes	backward
NK_KRS12	M21	Kannan, Rabanal and Scott (2012)	calibrated	No	Yes	hybrid
NK_PP17	M22	De Paoli and Paustian (2017)	calibrated	No	Yes	forward
NK_RA16	M23	Rannenberg (2016)	calibrated	No	Yes	hybrid
NK_RW97	M24	Rotemberg and Woodford (1997)	calibrated	No	No	forward
US_PM08	M25	Carabenciov, Ermolaev, Freedman, Juillard, Kamenik, Korshunov and Laxton (2008)	1994Q1-2008Q1	No	No	hybrid
US_PM08fl	M26	Carabenciov et al. (2008)	1994Q1-2008Q1	No	Yes	hybrid
US_SW07	M27	Smets and Wouters (2007)	1966Q1-2004Q4	Yes	No	hybrid
US_VI16bgg	M28	Villa (2016)	1983Q1-2008Q3	Yes	Yes	hybrid
US_YR13	M29	Rychalovska (2016)	1954Q1-2008Q3	Yes	Yes	hybrid

Table 8: Key features of models used

Notes. All models feature nominal price stickiness.

Appendix B Maximal Overlap Discrete Wavelet Transform with the Haar filter when *J*=4

By using the Maximal Overlap Discrete Wavelet Transform (MODWT) with the Haar filter, a variable X_t can be decomposed as in equations (1)-(3) in the paper. In our analysis we compute a *J*=4 level decomposition. The corresponding time series components are thus given by:

$$X_t^{D_1} = \frac{X_t - X_{t-1}}{2}$$

$$X_t^{D_2} = \frac{X_t + X_{t-1} - (X_{t-2} + X_{t-3})}{4}$$

$$X_t^{D_3} = \frac{X_t + X_{t-1} + X_{t-2} + X_{t-3} - (X_{t-4} + X_{t-5} + X_{t-6} + X_{t-7})}{8}$$

$$X_t^{D_4} = \frac{X_t + \ldots + X_{t-7} - (X_{t-8} + \ldots + X_{t-15})}{16}$$

$$X_t^{S_4} = \frac{X_t + \ldots + X_{t-15}}{16} \ .$$

The sum of $X_t^{D_1}$ and $X_t^{D_2}$ gives the HF component of the series (which captures fluctuations with a period less than 2 year), the sum of $X_t^{D_3}$ and $X_t^{D_4}$ gives the BCF component (which captures fluctuations between 2 and 8 years), whereas the LF component corresponds to $X_t^{S_4}$.

Appendix C Robustness tests

Objective functions	$\lambda_y = 1$			$\lambda_y = 0.5$			$\lambda_y = 1; h = 4$			$\lambda_y = 1$; BCF: 1-4y			$\lambda_y = 1$; BCF: 1-8y		
	ρ	α_π	α_y	ρ	α_π	α_y	ρ	α_π	α_y	ρ	α_π	α_y	ρ	α_π	α_y
$\text{var}(\pi)$	0.9	0.9	0.2	0.9	0.9	0.2	0.9	1	1.2	0.9	0.9	0.2	0.9	0.9	0.2
$\text{var}(\pi^{BCF})$	0.9	0.7	0.2	0.9	0.7	0.2	0.9	0.8	0.7	0.9	0.6	0.2	0.9	0.8	0.2
$\text{var}(\pi^{LF})$	0.9	0.7	0.2	0.9	0.7	0.2	0.9	0.8	0.7	0.9	0.8	0.2	0.9	0.7	0.2
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF})$	0.9	0.9	0.2	0.9	0.9	0.2	0.9	1	1.2	0.9	0.9	0.2	0.9	0.9	0.2
$\text{var}(\pi) + \lambda_y\ \text{var}(\Delta y)$	0.9	1	0.9	0.9	1	0.7	0.9	1.2	1.6	0.9	1	0.9	0.9	1	0.9
$\text{var}(\pi^{BCF}) + \lambda_y\ \text{var}(\Delta y^{BCF})$	0.9	0.7	0.6	0.9	0.7	0.4	0.9	1	1.2	0.9	0.6	0.7	0.9	0.8	0.7
$\text{var}(\pi^{LF}) + \lambda_y\ \text{var}(\Delta y^{BCF})$	0.9	0.7	0.5	0.9	0.7	0.4	0.9	0.9	1	0.9	0.9	0.6	0.9	0.8	0.7
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF}) + \lambda_y\ \text{var}(\Delta y^{BCF})$	0.9	0.9	0.5	0.9	0.9	0.4	0.9	1	1.2	0.9	1	0.6	0.9	0.9	0.7

Table 9: Model-robust monetary policy rules - robustness tests

Notes. Importance of output growth in objective function (λ_y) is set to 0.5. h=4 depicts the forward horizon of inflation in the monetary policy rule (equation 4). The rightmost columns with the term "BCF" depict the time horizon of BCF definition in the objective function. All objective functions include a term for restraining the variability of changes to nominal interest rates (Δr) with a weight of 0.5.

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