Bank of Finland Research Discussion Papers
2 • 2025

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Bank of Finland
Research

Bank of Finland Research Discussion Papers
Editor-in-Chief Esa Jokivuolle

Bank of Finland Research Discussion Papers 2/2025
8 January 2025

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ISSN 1456-6184, online

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Beyond one-size-fits-all: designing monetary policy for diverse models and frequencies*

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Abstract

We offer a contribution to the analysis of optimal monetary policy. The standard 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 propose monetary policy rules that perform robustly across a broad range of structural models, focusing on minimizing volatility at the frequencies most relevant for policymakers' stabilization goals. Our findings indicate that robust rules, which account for model uncertainty, advocate significantly less aggressive policy responses. Moreover, incorporating frequency-specific stabilization preferences further moderates the optimal policy actions. Ignoring model uncertainty imposes significant costs, while the cost of insuring against this uncertainty is relatively low. This cost-benefit analysis strongly supports adopting a robust-model approach to monetary policy.

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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* This is a revised version of a paper previously circulated as "Monetary policy rules: model uncertainty meets design limits". We are grateful for the useful comments of Fabio Canova, Beatriz de Blas, Ester Faia, Michalis Haliassos, Esa Jokivuolle, Alexander Meyer-Gohde, Volker Wieland, as well as of participants at several conferences and seminars. Alexander Dück acknowledges the support of the International Association for Applied Econometrics through a travel grant. The views expressed are those of the authors and do not necessarily reflect those of the Bank of Finland or zeb.

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1 Introduction

We propose a novel approach to designing optimal monetary policy rules. The traditional method involves selecting a structural macroeconomic model and determining the interest rate (Taylor) rule coefficients that minimize the central bank's objective function, typically a weighted average of the unconditional variances of inflation and real activity. In this paper, we challenge this approach for two key reasons.

First, policymakers have access to numerous structural models, yet none represents the true economy, nor are they ideal for all policy questions. As Levin, Wieland and Williams (2003) demonstrate, a policy rule optimized for one model can lead to poor or even disastrous outcomes in others, highlighting the critical importance of model selection. The lack of robustness in model-specific rules is a recurring issue in the literature. Relying solely on a single structural model risks an overly narrow perspective, underscoring the need to account for model uncertainty when designing policy rules. To address this, the literature on model-robust monetary policy identifies rules with stabilization properties that perform well across a range of models. A consistent finding is that simple model averaging improves robustness.[1]

Second, monetary policy, through interest-rate setting, should focus on smoothing cyclical fluctuations rather than fine-tuning high-frequency movements in inflation and real activity or promoting long-term economic growth. Policymakers should aim to stabilize specific frequencies of inflation and real activity, rather than targeting their unconditional volatilities, as commonly done in the literature. By focusing on unconditional variances, researchers and policymakers overlook the distinct high-, business-cycle-, and low-frequency (HF, BCF, and LF) effects of monetary policy. Studies such as Onatski and Williams (2003), Brock, Durlauf, Nason and Rondina (2007), and Brock, Durlauf and Rondina (2008, 2013) emphasize the frequency-specific nature of these effects. They show that choosing a policy rule involves a frequency-by-frequency variance trade-off: reducing variance at certain frequencies may increase it at

[1] For example, Levin and Williams (2003), Levin et al. (2003), Taylor and Wieland (2012), Schmidt and Wieland (2013), and Wieland, Afanasyeva, Kuete and Yoo (2016) develop model-robust policy rules using structural models of the US economy. Côte, Kuszczak, Lam, Liu and St-Amant (2004) analyze monetary policy rule robustness in Canadian models, while Adalid, Coenen, McAdam and Siviero (2005), Kuester and Wieland (2010), and Orphanides and Wieland (2013) conduct similar analyses for the Euro area (EA).

others.

Table 1 illustrates well this trade-off. The first row reports the volatility of inflation and its frequency components (HF, BCF, LF) under a Taylor rule that minimizes overall inflation volatility. The second and third rows show percentage differences in these volatilities when the Taylor rule is optimized to minimize BCF or LF volatility specifically. A rule targeting BCF volatility increases LF volatility, while a rule targeting LF volatility raises HF and BCF volatilities. Policymakers must consider these trade-offs and prioritize the frequency components most relevant to their stabilization goals.

Building on this context, in this study we depart from the traditional approach and evaluate monetary policy rules considering both model uncertainty and frequency-specific effects in a unified framework. Our contribution is twofold.

First, we advance the literature on model-robust monetary policy rules (see references in footnote 1) by developing frequency-based rules tailored to both model-specific and model-robust settings. This analysis uses an extensive array of Dynamic Stochastic General Equilibrium (DSGE) models for the US economy, including the latest vintages.[2] Unlike much of the existing literature, which typically dichotomizes models into backward- and forward-looking categories, our analysis considers a variety of model groupings based on their key characteristics.[3]

Second, we contribute to the literature on design limits in monetary policy by developing optimal frequency-specific responses across a broad range of DSGE models. Prior research in this area has largely relied on simple two-equation New Keynesian models of inflation and output (see e.g., Brock et al., 2007, and Brock et al., 2008, 2013). Furthermore, it has typically focused on the sensitivity of policy rules to frequency-specific preferences rather than addressing the design of optimal responses as we do here.

Our findings highlight several key insights. Compared to conventional approaches that rely on a single

[2] Our analysis considers the policymaker's uncertainty to be about identifying the reference model of the economy. It excludes other sources of uncertainty, such as parameter uncertainty, shock processes, or data quality concerns. For a comprehensive discussion of these additional uncertainties, see, for example, Onatski and Williams (2003).

[3] Binder, Lieberknecht, Quintana and Wieland (2019) offers a notable exception by distinguishing models with and without financial frictions, but our approach significantly expands this scope.

structural model and minimize unconditional variances of inflation and real activity, we demonstrate that both model uncertainty and frequency-specific preferences advocate for less aggressive policy responses. Quantitatively, model uncertainty exerts a much larger influence, reducing optimal policy responses by over half, while frequency-specific preferences have a comparatively modest dampening effect. Moreover, we find that ignoring model uncertainty imposes significant costs, while the cost of insuring against this uncertainty is relatively low. This cost-benefit analysis strongly supports adopting a robust-model approach to monetary policy.

The paper is organized as follows. Section 2 introduces the DSGE models, central bank objective functions, monetary policy rules, and frequency decomposition methods. Section 3 examines optimized model-specific and model-robust policy rules, alongside various experiments and robustness checks. Section 4 concludes.

2 The setup

2.1 DSGE models

DSGE models are fundamental tools in monetary policy analysis, widely employed by both academics and policymakers. For this study, we selected several DSGE models from the *Macroeconomic Model Data Base*,[4] ensuring they represent a broad spectrum of economic transmission mechanisms, frictions, and shocks. The initial selection was refined by excluding models that exhibited excessive macroeconomic volatility, instability, or significant redundancy with other models. This process culminated in a final set of 29 US-focused DSGE models. Notably, some of these are actively used in policy institutions, such as the model by del Negro, Giannoni and Schorfheide (2015), employed at the Federal Reserve Bank of New York.[5]

[4] 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.

[5] In an earlier version of the paper, we conducted the analysis separately for the Euro area using nine DSGE models calibrated or estimated on Euro area data. The results were similar and are available upon request.

The models span various sizes and complexities. About half are small- to medium-scale New Keynesian (NK) models, including simple three-equation frameworks and medium-sized DSGE models, such as the influential Smets and Wouters (2007) model. We include these small-scale NK models to render policy recommendations more robust to model uncertainty. Furthermore, as demonstrated by del Negro, Hasegawa and Schorfheide (2016), their forecasting performances are usually better than those of larger models with financial frictions during stable economic periods. The remaining models incorporate advanced features, such as financial frictions, using mechanisms like the Bernanke, Gertler and Gilchrist (1999) financial accelerator or Gertler and Karadi's (2011) framework for financial intermediation.

All models include nominal price rigidity, as proposed by Calvo (1983) or Rotemberg (1982), with over half also incorporating nominal wage rigidity à la Calvo. Additionally, one model employs an entirely backward-looking accelerationist Phillips curve, while others balance backward- and forward-looking inflation dynamics to create hybrid Phillips curves. Real rigidities, such as habit formation in consumption and investment or capital adjustment costs, are common across the models.

Some models offer detailed sectoral dynamics. For example, labor market frictions are modeled using the search-and-matching framework of Mortensen and Pissarides (1994), while housing markets are modeled through Two-Agent New Keynesian (TANK) frameworks, inspired by Iacoviello (2005), which incorporate heterogeneity among households.[6]

The models differ in their estimation methods and data samples. For consistency, we utilized the authors' provided estimations or calibration values. Table A1 in Appendix A lists the models and summarizes their key features. All models were solved using log-linear approximations around their respective steady states.

[6] The *Macroeconomic Model Data Base* does not include the latest generation of macro DSGE models that incorporate fully developed heterogeneity, specifically Heterogeneous Agent New Keynesian (HANK) models.

2.2 Central bank preferences and objective functions

Inflation and output (or unemployment) are central to monetary policy decisions, but policymakers often prioritize specific frequencies of fluctuations in these variables. For example, Lagarde (2021) and Powell (2021) emphasize that monetary policy should avoid reacting to temporary, high-frequency fluctuations in inflation, as these changes often dissipate before policy interventions take effect. Similarly, since long-term inflation trends are predominantly driven by monetary factors, central banks may refrain from actions that could destabilize low-frequency inflation fluctuations. Practical examples include the Federal Reserve's 2020 revision of its price-stability mandate, which de-emphasized short-term inflation deviations in favor of ensuring that inflation averages 2 % over the long run. This highlights a clear focus on low-frequency inflation management.[7]

In the same vein, central banks avoid using monetary policy to influence the economy's long-term growth rate (Mester, 2023) and to fine-tune high-frequency variations in real economic activity. As Kažimír (2024) argues, acting on short-term surprises without a clear medium-term perspective is inherently risky.

To reflect these frequency-specific preferences, we evaluate several central bank objective functions (detailed in Table 2). These allow policymakers to target specific frequency bands of fluctuations in inflation and output growth.

As a starting point, we adopt the traditional objective function (OF), which minimizes the unconditional variances (*var*) of inflation (π) and output growth (Δy). Although many studies employ the output gap (the deviation of output from its potential level) in central bank objective functions and Taylor rules, its use is not without challenges. As Plosser (2010) notes, output gap measurements depend heavily on the empirical method used to estimate potential output, and different economic models may adopt varying theoretical definitions of this gap. By contrast, output growth is straightforward to calculate and consistently defined across models, making it a more practical alternative.

[7] As reported in Verona, Martins and Drumond (2013, Table 1), the Federal Reserve 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.

Building on this, we explore objective functions that prioritize certain frequency components. For instance, we exclude high-frequency fluctuations in inflation and output growth, as well as low-frequency output growth fluctuations. Instead, we focus on combinations of business-cycle frequency (BCF) and low-frequency (LF) volatilities for inflation, alongside BCF fluctuations for output growth.

Following standard practice in business-cycle literature (e.g., Brock et al., 2013), we define BCF fluctuations as cycles with periods of two to eight years. High-frequency (HF) components are those with periods below two years, while LF components correspond to periods longer than eight years. Robustness tests, detailed later, explore alternative ways of computing BCF fluctuations.

We introduce a relative weight (λ_y) to output growth in the objective function, reflecting varying central bank mandates. For instance, $\lambda_y > 0$ aligns with the Federal Reserve's dual mandate of price stability and maximum employment, while $\lambda_y = 0$ mirrors the European Central Bank's stricter focus on inflation targeting. Additionally, all objective functions incorporate a penalty term to limit the variability of changes in nominal interest rates (Δr), following common practice (e.g., Smets, 2003 and Kuester and Wieland, 2010). This term reflects central banks' preference for interest rate smoothing and prevents excessively volatile optimized policy responses that may violate constraints like the zero lower bound on nominal interest rates.

In this study, we use an ad hoc loss function as the performance criterion, inspired by Tinbergen (1952). This approach closely aligns with standard central bank mandates and policy practices and has been widely adopted in the literature (e.g., Lippi and Neri, 2007, Sala, Soderstrom and Trigari, 2008, Adolfson, Laseen, Linde and Svensson, 2011, Gelain, Lansing and Mendicino, 2013, and Verona, Martins and Drumond, 2017). This method contrasts with studies such as Faia and Monacelli (2007), Schmitt-Grohe and Uribe (2007), and Curdia and Woodford (2010), which evaluate policies by directly incorporating households' utility. While utility-based approaches provide theoretically consistent Ramsey policies and enable analytical social welfare analysis, they present several significant challenges. First, these methods are highly sensitive to model-specific distortions, leading to performance criteria that vary across models and complicating comparisons under model uncertainty. Second, utility-based loss functions are often unsuitable for real-world application, making it difficult for central banks to design effective policy rules for achieving macroeconomic stability. Furthermore, no central bank's mandate explicitly includes maximizing social welfare. Given these limitations, we adopt a more pragmatic approach. By focusing on minimizing a loss function, we ensure better alignment with central bank mandates and the operational realities of policymaking.

2.3 Taylor rules

Policymakers aim to achieve their macroeconomic targets by setting nominal interest rates according to simple, implementable feedback rules (e.g., Faia and Monacelli, 2007 and Schmitt-Grohe and Uribe, 2007). In this paper, we assume the nominal interest rate (r_t) is determined by a Taylor rule of the form:

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

where r_t is the quarterly annualized nominal interest rate, π_t represents the quarterly annualized inflation rate, and Δy_t denotes quarter-on-quarter output growth. The coefficients α_π and α_y measure the central bank's responsiveness to inflation and output growth, respectively, while ρ captures the degree of interest rate smoothing.

This framework aligns with the class of simple Taylor rules widely used in monetary policy literature (e.g., Gilchrist and Zakrajsek, 2011 and Carrillo and Poilly, 2013). Such rules rely solely on observable macroeconomic indicators, making them both practical and transparent. By focusing on inflation and output growth, central banks can formulate effective policies without requiring unobservable variables like the natural rate of interest or potential output.

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 method decomposes time series into a trend and several cyclical components, capturing fluctuations across distinct frequency bands. The approach is comparable to the traditional Beveridge and Nelson (1981) trend-cycle decomposition but offers greater flexibility, as it applies to variables with diverse time series properties.[8]

Using the Haar filter, the MODWT allows us to decompose any variable X_t into:

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

where $X_t^{D_j}$ represents wavelet coefficients capturing cyclical fluctuations at scale j, and $X_t^{S_J}$ is the scaling coefficient. The wavelet coefficients are calculated as:

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

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. Importantly, the Haar filter's one-sided structure ensures that it can be implemented in real time, making it suitable for operational use

[8] See Crowley (2007) for a comprehensive review of the theory and applications of the MODWT. Applications of the MODWT in DSGE models include Caraiani (2015), Gallegati, Giri and Palestrini (2019), Lubik, Matthes and Verona (2019), and Caraiani and Gupta (2020).

in policy analysis.[9]

In this paper we compute a J=4 level decomposition of our time series. The time period in the models is 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.[10] 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.

For illustrative purposes, we decomposed US data (1990Q1-2017Q4) on Personal Consumption Expenditures (PCE) inflation 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 Federal Reserve since the late-1990s.

[9] The Haar filter is widely used in macro and finance applications (see e.g. Faria and Verona, 2018, 2020, 2021, 2025, Bandi, Perron, Tamoni and Tebaldi, 2019, Kilponen and Verona, 2022, Martins and Verona, 2023, 2024, Stein, 2024, and Canova, 2025). 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.

[10] 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.

3 Optimized monetary policy rules

In this section, we begin by analyzing the optimized monetary policy rule for each DSGE model individually (Sub-section 3.1). We then explore the implications of model uncertainty for the design of robust monetary policy rules (Sub-section 3.2). In Sub-section 3.3, we quantify the costs associated with model uncertainty and the neglect of frequency-specific preferences, measured in terms of the increase in the central bank's objective functions. Next, in Sub-section 3.4, we categorize the models based on their key features and compute model-robust rules for each group separately. Finally, in Sub-section 3.5, we present the results of various robustness tests.

3.1 Model-specific rules

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

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

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

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

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 variables and parameters, while z are common 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 conduct the analysis by considering both the unconditional volatilities of the variables of interest (denoted as "*all*", since all frequencies are implicitly included in this case) and various frequency combinations in the objective function, as detailed in Table 2. In the baseline case, we examine $\lambda_y = 0$ and $\lambda_y = 1$.

The first three columns of Table 3 display the averages of the optimized model-specific coefficients. We highlight four key results. First, the average smoothing coefficient for the nominal interest rate is 0.9, regardless of the objective function. Second, if the central bank focuses on stabilizing only one frequency of inflation fluctuations (either the BCF or the LF), the optimized model-specific rules suggest smaller or comparable average response coefficients to inflation. However, when both frequencies of inflation are stabilized, the average inflation response is either higher or similar to that of stabilizing aggregate inflation. Third, if the central bank prioritizes stabilizing output growth, the average response to output growth is larger (as expected), while the response to inflation is smaller. Fourth, when the central bank aims to stabilize the BCF of GDP growth, its average response to GDP growth is lower compared to when it focuses on stabilizing the volatility of aggregate GDP growth.

In Figure 2, we plot the distribution of optimized model-specific coefficients. It is evident that not only are the average model-robust coefficients (marked by red crosses) lower when the policymaker focuses on stabilizing specific frequencies of inflation and output growth, but the entire distribution of optimized model-specific coefficients shifts downward. Frequency-specific preferences, therefore, lead to more restrained responses by policymakers.

Next, we assess the robustness of the optimized model-specific rules to model uncertainty, or, in other words, the cost of disregarding model uncertainty. We evaluate the performance of rules optimized for one model when applied to other models. Table 4 reports the percentage increase in objective function 1 (% L) when using a rule optimized for model X in model Y, compared to using the rule optimized for model Y.[11] To interpret the economic significance of this metric, Levin and Williams (2003) suggest that a rule yielding up to a 50 % increase in % L may still be considered satisfactory, while a rule that causes a % L increase greater than 100 % would imply that insurance against model uncertainty is prohibitively costly.

[11] These results hold for all objective functions of the central bank.

This analysis shows that rules optimized for specific models lead to significant losses (though never explosiveness, indeterminacy, or multiple equilibria) when applied to other models. This finding is consistent with earlier literature. Specifically, the majority of optimized model-specific rules (as shown in Table 4) result in large increases in % L in several other models, making them unsuitable in the face 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 %. Additionally, four other rules (M_3, M_13, M_22, and M_24) perform reasonably well across all models. On the other hand, as seen in the columns of Table 4, only a few models (notably M_12) are relatively insensitive to other optimized model-specific rules, while most models exhibit high % L increases when applying rules optimized for other models.

3.2 Model-robust rules

Given the lack of robustness in the optimized model-specific rules discussed in the previous sub-section, we now seek rules that perform well across all models. To achieve this, we follow the approach of Levin et al. (2003), Taylor and Wieland (2012), and Orphanides and Wieland (2013), applying simple model averaging.[12]

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)

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

and $\omega_m = 1/M$.

Columns 4 to 6 in Table 3 present the optimized model-robust coefficients for each objective function. We highlight the following key results. First, all model-robust rules exhibit the same degree of interest rate smoothing, which aligns with the optimized average model-specific coefficient. Second, compared to the average model-specific coefficients, model-robust rules prescribe significantly smaller responses to inflation and more subdued reactions to output growth, regardless of the objective function. In other words, rules robust to model uncertainty generally imply much less aggressive central bank responses. Third, similar to the model-specific rules, if the policymaker prioritizes stabilizing only a subset of inflation and output growth frequencies, the robust responses to both inflation and output growth are further reduced.

Figure 2 illustrates that the model-robust coefficients (represented by black crosses) are positioned on the lower end of the boxes, indicating much smaller than average (and smaller than median) responses by the central bank when facing model uncertainty.

Overall, policymakers facing uncertainty about which model(s) to use must adopt much more cautious policy responses than those prescribed by the *status quo* of using a single model. Policymakers with preferences for stabilizing specific frequencies of inflation and output growth should exercise even greater caution.

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

3.3.1 The cost of insuring against model uncertainty

The model-robust rule is designed to perform well across all models, but it is rarely the best rule for any single model. To assess the relative performance of the model-robust policy rule in a particular model, we compute the percentage increase in each objective function (% L) when using the optimized model-robust rule, relative to the optimal outcome achievable in that model (i.e., the optimized model-specific rule for that model).

Results are presented in Table 5. Although some individual % L values exceed the 50 % threshold considered acceptable (as discussed in Sub-section 3.1), the average losses remain well below this threshold. Moreover, when the policymaker focuses on stabilizing specific frequencies of inflation and output growth (objective functions 2-4 and 6-8), the cost of insuring against model uncertainty is significantly lower, both on average and for nearly all models individually. For example, comparing the costs implied by objective function 5 with those of objective functions 6 to 8 shows that the average cost of insuring against model uncertainty is halved.

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

3.3.2 The cost of ignoring frequency-specific fluctuations

What if policymakers ignore, or are unaware of, the frequency-specific trade-offs discussed in the introduction and instead base their policies on the aggregate volatilities of the variables of interest?

We present the cost of this approach in Table 6. Each value in the table shows the percentage increase in each objective function when using the optimized model-specific (m-s) or model-robust (m-r) rule from objective function 1 (5) in objective functions 2 to 4 (6 to 8), relative to its own optimized rule. As reported in the last row of the table, the average percentage increases in objective functions are not substantially higher (at most 10 %). Only two models (M_8 and M_14) show greater sensitivity when the stabilization of real activity is a priority (objective functions 5 to 8).

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

3.4 Model-robust monetary policy rules and and the features of the models

The DSGE models used in this paper feature various frictions and transmission mechanisms. In this subsection, we explore whether and how specific model features affect the size of the model-robust policy responses.

Table 7 reports 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 versus a forward-looking Phillips curve (20 and 9 models, respectively).

Regardless of how the models are grouped, the results are qualitatively consistent with the main findings of the paper. Specifically, robust inflation and output growth responses tend to be smaller or similar when the central bank is concerned with stabilizing specific frequencies of inflation and output growth. Moreover, robust output growth responses are larger when policymakers prioritize stabilizing real activity.

Quantitatively, calibrated models suggest a stronger response (both to inflation and output growth) by policymakers, while the response coefficients of estimated models are closer to the baseline ones. Wage frictions also play a significant role: models without wage frictions prescribe stronger responses to both inflation and output growth, whereas models with wage frictions result in weaker policy responses. Financial frictions, however, do not appear to substantially affect the design of robust monetary policy rules, as the response coefficients are similar in models with or without these frictions. Finally, the specification of the Phillips curve significantly shapes the results: models with a forward-looking Phillips curve prescribe more aggressive responses compared to models with a hybrid Phillips curve, which yield results closer to the baseline.

We track these quantitative differences across model sub-samples by observing that the optimized model-robust coefficients typically increase as the variance of the variable of interest decreases. For example, estimated models, models with wage frictions, and models with a hybrid Phillips curve tend to exhibit 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 group, the monetary policy response does not need to be as pronounced, as monetary policy is more effective in volatile economies. As a result, these models would call for a less aggressive central bank response to stabilize the economy and avoid excessive macroeconomic fluctuations. Interestingly, models with or without financial frictions generate similar levels of inflation and output growth volatility. In fact, models with financial frictions produce slightly less volatility, which contrasts with the conventional "financial accelerator" view of business cycle fluctuations (Bernanke et al., 1999). This could be due to the fact that the models used in our analysis were estimated using data from before the GFC, during which financial frictions might have played a less significant role (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 weights to output growth. Results for $\lambda_y = 0.5$ are displayed in Table C1 (columns 4 to 6) in Appendix C, with the benchmark results shown in the first three columns of the table. Reducing the relative weight on output growth does not affect the central bank's response to inflation. However, as expected, it generally leads to a moderate decrease in the response to output growth compared to the case where $\lambda_y = 1$.

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

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

where $E_t \pi_{t+4}$ represents the inflation expectation 4-quarter ahead. Results are reported in Table C1 (columns 7 to 9). We find that the responses to inflation and output growth are larger when the central bank reacts to one-year-ahead expected inflation rather than current inflation. Nevertheless, the main findings remain consistent: considering one specific frequency in the objective function reduces the response to inflation, while including output growth typically increases the response to inflation.

Next, we consider fluctuations between 1 and 4 years, and between 1 and 8 years, as BCF fluctuations. The model-robust coefficients, reported in columns 10 to 15 of Table C1, show that the results are not highly sensitive to the definition of BCF fluctuations.

Finally, we find that the results are quantitatively robust to variations in the preference parameter for restraining the variability of changes to nominal interest rates (in the objective function). This preference parameter, which typically ranges from 0.1 to 1 in the literature (e.g., Brock, Durlauf and West, 2003 and Levin and Williams, 2003), does not significantly alter the outcomes.

4 Conclusions

What policy rule should a central bank follow? This paper tackles this classic question with a novel approach, departing from the traditional framework in two key ways.

First, instead of relying on a single structural macroeconomic model, we conduct our analysis using a wide range of DSGE models. This allows us to identify monetary policy rules that remain robust despite model uncertainty. Second, rather than focusing on rules that minimize a weighted average of the unconditional variances of inflation and output, we search for the rules that reduce fluctuations at specific frequencies – those most relevant to policymakers.

Our findings offer clear policy guidance. Central banks facing model uncertainty should adopt less aggressive policy responses. Moreover, stabilization preferences tied to specific frequencies further dampen these responses. Ignoring model uncertainty proves costly, while the measures required to mitigate its effects come at a relatively low expense. This cost-benefit analysis thus strongly supports a robust-model approach to monetary policy.

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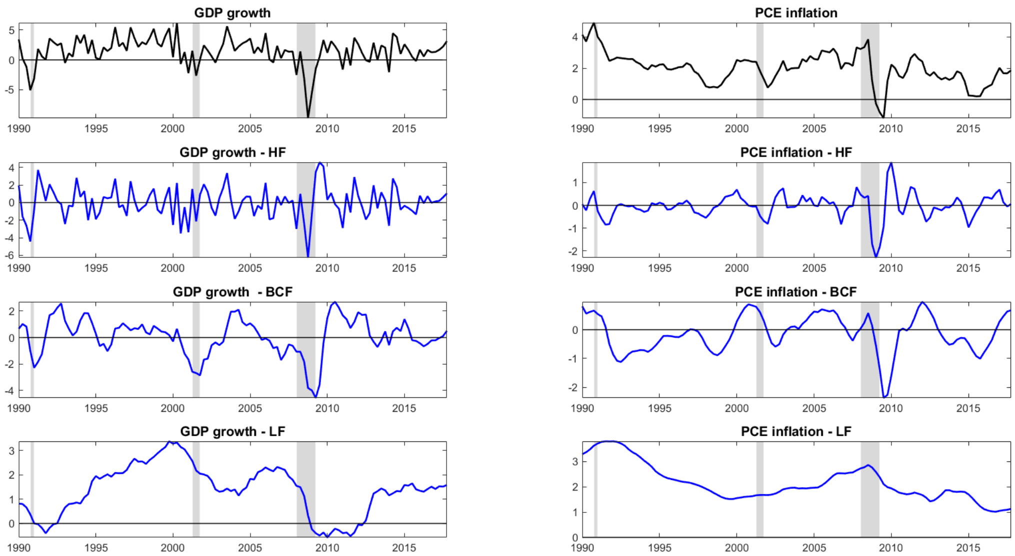

Figure 1: Frequency decomposition of inflation and output growth

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.

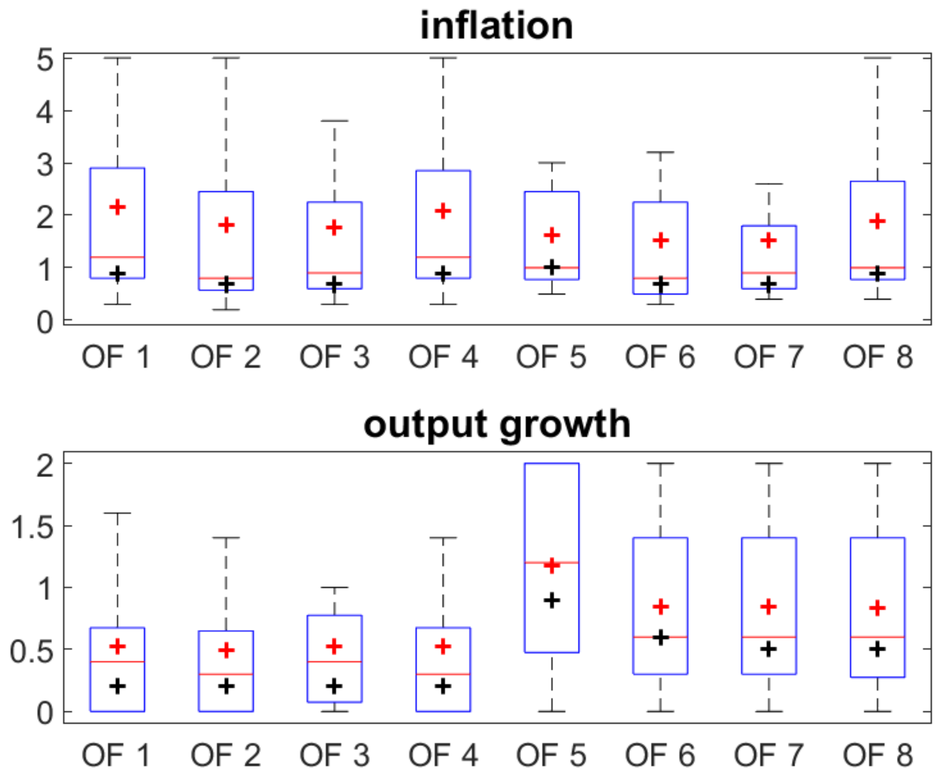

Figure 2: Boxplot of optimized Taylor-rule coefficients

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.

	$\mathrm{var}(\pi)$	$\mathrm{var}(\pi^{HF})$	$\mathrm{var}(\pi^{BCF})$	$\mathrm{var}(\pi^{LF})$
Taylor rule that $\min \mathrm{var}(\pi)$	0.12	0.03	0.06	0.03
Taylor rule that $\min \mathrm{var}(\pi^{BCF})$	11	-10	-2	60
Taylor rule that $\min \mathrm{var}(\pi^{LF})$	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	$\mathrm{var}(\pi)$
Objective Function 2	$\mathrm{var}(\pi^{BCF})$
Objective Function 3	$\mathrm{var}(\pi^{LF})$
Objective Function 4	$\mathrm{var}(\pi^{BCF}) + \mathrm{var}(\pi^{LF})$
Objective Function 5	$\mathrm{var}(\pi) + \lambda_y \ \mathrm{var}(\Delta y)$
Objective Function 6	$\mathrm{var}(\pi^{BCF}) + \lambda_y \ \mathrm{var}(\Delta y^{BCF})$
Objective Function 7	$\mathrm{var}(\pi^{LF}) + \lambda_y \ \mathrm{var}(\Delta y^{BCF})$
Objective Function 8	$\mathrm{var}(\pi^{BCF}) + \mathrm{var}(\pi^{LF}) + \lambda_y \ \mathrm{var}(\Delta y^{BCF})$

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
$\mathrm{var}(\pi)$	0.9	2.2	0.5	0.9	0.9	0.2
$\mathrm{var}(\pi^{BCF})$	0.9	1.8	0.5	0.9	0.7	0.2
$\mathrm{var}(\pi^{LF})$	0.9	1.8	0.5	0.9	0.7	0.2
$\mathrm{var}(\pi^{BCF}) + \mathrm{var}(\pi^{LF})$	0.9	2.1	0.5	0.9	0.9	0.2
$\mathrm{var}(\pi) + \mathrm{var}(\Delta y)$	0.9	1.6	1.2	0.9	1	0.9
$\mathrm{var}(\pi^{BCF}) + \mathrm{var}(\Delta y^{BCF})$	0.9	1.5	0.8	0.9	0.7	0.6
$\mathrm{var}(\pi^{LF}) + \mathrm{var}(\Delta y^{BCF})$	0.9	1.5	0.9	0.9	0.7	0.5
$\mathrm{var}(\pi^{BCF}) + \mathrm{var}(\pi^{LF}) + \mathrm{var}(\Delta y^{BCF})$	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
$\mathrm{var}(\pi)$	0.9	1.2	0.2	0.9	0.9	0.2	0.9	1	0.3	0.9	0.9	0.2
$\mathrm{var}(\pi^{BCF})$	0.9	1	0.3	0.9	0.7	0.2	0.9	0.8	0.3	0.9	0.7	0.2
$\mathrm{var}(\pi^{LF})$	0.9	0.9	0.3	0.9	0.7	0.2	0.9	0.7	0.3	0.9	0.8	0.2
$\mathrm{var}(\pi^{BCF}) + \mathrm{var}(\pi^{LF})$	0.9	1.2	0.2	0.9	0.9	0.2	0.9	0.9	0.3	0.9	0.9	0.2
$\mathrm{var}(\pi) + \mathrm{var}(\Delta y)$	0.9	1.4	1.8	0.9	0.9	0.7	0.9	1	1	0.9	0.9	0.9
$\mathrm{var}(\pi^{BCF}) + \mathrm{var}(\Delta y^{BCF})$	0.9	1	1	0.9	0.7	0.5	0.9	0.8	0.6	0.9	0.7	0.6
$\mathrm{var}(\pi^{LF}) + \mathrm{var}(\Delta y^{BCF})$	0.9	0.9	1	0.9	0.7	0.5	0.9	0.8	0.6	0.9	0.7	0.5
$\mathrm{var}(\pi^{BCF}) + \mathrm{var}(\pi^{LF}) + \mathrm{var}(\Delta y^{BCF})$	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
$\mathrm{var}(\pi)$	0.9	0.8	0.1	0.9	1.2	0.5	0.9	0.9	0.2	0.9	1.6	0.3
$\mathrm{var}(\pi^{BCF})$	0.9	0.6	0.1	0.9	0.9	0.5	0.9	0.7	0.2	0.9	1.4	0.3
$\mathrm{var}(\pi^{LF})$	0.9	0.6	0.2	0.9	0.9	0.4	0.9	0.7	0.2	0.9	1.2	0.4
$\mathrm{var}(\pi^{BCF}) + \mathrm{var}(\pi^{LF})$	0.9	0.7	0.1	0.9	1	0.5	0.9	0.9	0.2	0.9	1.6	0.3
$\mathrm{var}(\pi) + \mathrm{var}(\Delta y)$	0.9	0.8	0.7	0.9	1.2	1.4	0.9	0.9	0.7	0.9	1.6	2
$\mathrm{var}(\pi^{BCF}) + \mathrm{var}(\Delta y^{BCF})$	0.9	0.5	0.4	0.9	0.9	0.8	0.9	0.7	0.5	0.9	1.2	1.4
$\mathrm{var}(\pi^{LF}) + \mathrm{var}(\Delta y^{BCF})$	0.9	0.6	0.4	0.9	0.9	0.8	0.9	0.7	0.4	0.9	1.2	1.6
$\mathrm{var}(\pi^{BCF}) + \mathrm{var}(\pi^{LF}) + \mathrm{var}(\Delta y^{BCF})$	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, Giannoni and Schorfheide (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 A1: 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
$\mathrm{var}(\pi)$	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
$\mathrm{var}(\pi^{BCF})$	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
$\mathrm{var}(\pi^{LF})$	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
$\mathrm{var}(\pi^{BCF}) + \mathrm{var}(\pi^{LF})$	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
$\mathrm{var}(\pi) + \lambda_y\ \mathrm{var}(\Delta y)$	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
$\mathrm{var}(\pi^{BCF}) + \lambda_y\ \mathrm{var}(\Delta y^{BCF})$	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
$\mathrm{var}(\pi^{LF}) + \lambda_y\ \mathrm{var}(\Delta y^{BCF})$	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
$\mathrm{var}(\pi^{BCF}) + \mathrm{var}(\pi^{LF}) + \lambda_y\ \mathrm{var}(\Delta y^{BCF})$	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 C1: 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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