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Monetary policy rules:
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Abstract

Optimal monetary policy studies typically rely on a single structural model and identification of model-specific rules that minimize the unconditional volatilities of inflation and real activity. In our proposed approach, we take a large set of structural models and look for the model-robust rules that minimize the volatilities at those frequencies that policymakers are most interested in stabilizing. Compared to the *status quo* approach, our results suggest that policymakers should be more restrained in their inflation responses when their aim is to stabilize inflation and output growth at specific frequencies. Additional caution is called for due to model uncertainty.

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

Which interest rate rule should a central bank follow? The common way to answer this question is to take a structural macroeconomic model, choose a loss function that approximates the central bank's preferences (a weighted average of the unconditional variances of inflation and real activity), and find the interest-rate (Taylor) rule coefficients that minimize the loss function.

This approach has two drawbacks. First, monetary policy through interest-rate setting should not be used as an instrument to fine-tune high-frequency fluctuations of inflation and real activity or promote long-term economic growth, but rather to smooth cyclical fluctuations. Policymakers should thus aim at stabilizing specific frequencies – not the unconditional volatility – of inflation and real activity. Second, while policymakers have a large number of models at their disposal, none of them is the true model of the economy. Furthermore, a policy rule that is optimal in one model may perform poorly in another. Thus, the choice of model(s) matters.

In this paper, we analyze the performance of monetary policy rules in the presence of model uncertainty and with respect to the frequency-specific behavior of inflation and output growth. This allows us to address both of the above-mentioned drawbacks simultaneously. Compared to the *status quo* of using a single structural model and minimizing the unconditional variances of inflation and real activity, we find that policymakers should react less strongly to inflation if they aim at stabilizing only specific frequencies of inflation and output growth. Rules robust to model uncertainty prescribe even more cautious responses by the central bank.

The paper is organized as follows. In Section 2, we review the two strands of literature on which this work builds. We present the Dynamic Stochastic General Equilibrium (DSGE) models, the central bank loss functions, the policy rules, the data, and frequency decomposition in Section 3. In Section 4, we examine how well DSGE models match inflation and output volatilities observed in the data. We move to the analysis of optimized model-specific and model-robust monetary policy rules in Section 5 and conduct various policy experiments and robustness checks in Section 6. Section 7 concludes.

2 Motivation and our contribution

This paper builds on two strands of literature: one on design limits and frequency-specific effects of monetary policy, and one on DSGE model-robust monetary policy rules. In this section, we position our paper in these two literatures.

2.1 Design limits and frequency-specific effects of monetary policy

The common way to compare the performance of monetary policy rules has been to consider a weighted average of the unconditional variances of the variables of interest (inflation and output). Such calculations, however, ignore the different high-, business cycle- and low-frequency (HF, BCF and LF, respectively) effects of monetary policy on those variables.

The presence of frequency-specific effects of monetary policy choices has already been emphasized by Onatski and Williams (2003), Brock, Durlauf, Nason and Rondina (2007), Brock, Durlauf and Rondina (2008), and Brock, Durlauf and Rondina (2013). These studies, which are based on the theory of design limits, 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. Policymakers have to be aware and informed of this trade-off when evaluating and deciding on policies, as they should act to reduce volatility at frequencies they are most interested in stabilizing.[1]

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

[1] Otrok (2001) extends and develops the theory of spectral utility functions that measure utility frequency by frequency. He shows that the weights on different frequencies can differ by more than nine to one. Thus, analyzing frequency-specific losses is important when evaluating policy rules.

	$\text{var}(\pi)$	$\text{var}(\pi^{HF})$	$\text{var}(\pi^{BCF})$	$\text{var}(\pi^{LF})$
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 the variables (inflation and its frequency components), while the remaining rows the percentage differences with respect to the values in the first row. Model used: EA_NK_BGEU10. HF stands for fluctuations shorter than 2 years, BCF for fluctuations between 2 and 8 years, and LF for cycles longer than 8 years.

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). The existing literature on design limits in monetary policy mainly relies on a single simple two-equation New Keynesian (NK) class of inflation and output model. We contribute to this literature by considering the frequency-specific effects of monetary policy rules across a large number of DSGE models, many of which are extensively used in academia and policy institutions.

2.2 Monetary policy rules robust to model uncertainty

DSGE models are widely used for monetary policy analyses. While many (DSGE) models are available, none of them is the true model of the economy and none may be ideal for answering a specific policy question. Model uncertainty itself is therefore a source of uncertainty facing policymakers.[2]

Model uncertainty has played a prominent role in monetary policy analyses (see e.g. Brock, Durlauf and West, 2003). The literature on robust policy design identifies monetary policy rules that perform well across a variety of models, i.e. identifies rules that are robust to model uncertainty. Adalid, Coenen, McAdam and Siviero (2005), Kuester and Wieland (2010), and Orphanides and Wieland (2013) focus on robust rules for the Euro Area (EA), while Levin and Williams (2003), Levin, Wieland and Williams (2003), Taylor and Wieland (2012), and Schmidt and Wieland (2013) focus on robust rules for the United States (US) economy. We contribute to this literature by designing aggregate and frequency-based model-

[2] In this paper we do not consider other uncertainty-causing factors such as poor data quality, unpredictable shocks hitting the economy, econometric errors in estimation, or parameter uncertainty.

robust (and model-specific) policy rules. We also consider a wider set of models for the US economy (29 models against at most seven models used by Schmidt and Wieland, 2013) and run our analysis separately for the EA and the US.

3 The setup

3.1 DSGE models

We take several DSGE models from the *Macroeconomic Model Data Base*.[3] These models share antecedents 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). We end up using a total of nine models for the EA (eight estimated and one calibrated) and 29 models for the US (21 estimated and eight calibrated). Some of these models are currently used in policy institutions for forecasting and policy simulations (e.g. del Negro, Giannoni and Schorfheide, 2015 is in use at the New York Fed).

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, 2003). 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). 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, small-scale NK 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.

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

With the exception of two EA models, all other models feature nominal price rigidity à la Calvo (1983) or Rotemberg (1982). More than half of the models also integrate nominal wage rigidities following Calvo (1983). The two models without price frictions include wage frictions using Taylor (1980) or Fuhrer and Moore (1995) contracts.

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 modeling 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 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 Appendix A.

3.2 Central bank preferences

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

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. Likewise, as long-term inflation is ultimately a monetary phenomenon under the control of the central bank, policy-makers may be reluctant to make interest-rate decisions that may potentially destabilize low-frequency fluctuations in inflation.[4]

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.

Given these clear frequency-specific preferences, in this paper, we consider several loss functions for the central bank so that monetary policymakers can understand how losses occur for a policy at different frequencies and how they should act according to their preferences with respect to fluctuations at different cycles.

As a starting point, we choose the traditional loss function that considers the unconditional variances (var) of inflation (π) and output growth (Δy). The literature often refers to the output gap rather than output growth in the central bank's loss function (and in the Taylor rule). The use of output gap, however, is problematic for two reasons. First, its estimations from the data depend on the empirical method used to compute potential output. Second, models use different definitions of potential output. In contrast, output growth is easy to compute from the data and consistently defined across models.

We then consider several loss functions (reported in Table 2) that include only some frequencies of the relevant variables. In particular, given the discussion above, we ignore HF fluctuations of inflation and output growth, as well as 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, $\lambda_y = 0$ more closely characterizes the ECB's strict inflation target regime, while $\lambda_y > 0$ seems to be

[4] 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.

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

Table 2: Central bank loss 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.

more in line with the Fed's dual mandate of price stability and maximum employment. Furthermore, in all loss 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 (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 violate the zero lower bound constraint on nominal interest rates.

3.3 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 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). 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.[5]

3.4 Data

We use EA and US data from 1990Q1 to 2017Q4 for two variables: year-on-year inflation rate and quarter-on-quarter real output growth. We stop at 2017Q4 as none of the models used here has been estimated using data after 2017Q4. Furthermore, we also avoid the large drop and sharp rebound in GDP growth associated with the Covid Recession. EA data is obtained from the New Area Wide Model dataset and US data is taken from FRED2. EA inflation is the Harmonised Index of Consumer Prices (HICP) inflation, and US inflation is based on the Personal Consumption Expenditures (PCE) price index. A brief description of the data is provided in Appendix B.

The first row in Figure 1 reports the time series of the EA and US variables, as well as the business-cycle recessions (depicted as gray shaded areas). Both economies experienced three recessions over the sample period, with negative GDP growth around those recessions. HICP inflation in the EA declines from the beginning of the sample until the late-1990s, then it stabilizes at around 2 % until the global financial crisis (GFC) of 2007–2008. Larger swings characterize the most recent part of the sample period. PCE inflation in the US is somehow less volatile and mostly fluctuates around 2 %.

3.5 Frequency decomposition

To extract the different frequency components from the data, we use the Maximal Overlap Discrete Wavelet Transform (MODWT). This approach permits 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.[6]

[5] Because policymakers should primarily stabilize some frequencies of inflation and output growth (as discussed in Section 3.2), one could also use a Taylor rule responding to the frequencies of interest (i.e. the BCF and/or LF fluctuations of inflation and the BCF of output growth) instead of the aggregate variables. We leave this issue for future work.

[6] Verona (2020) describe the advantages of wavelets filters over standard econometric techniques.

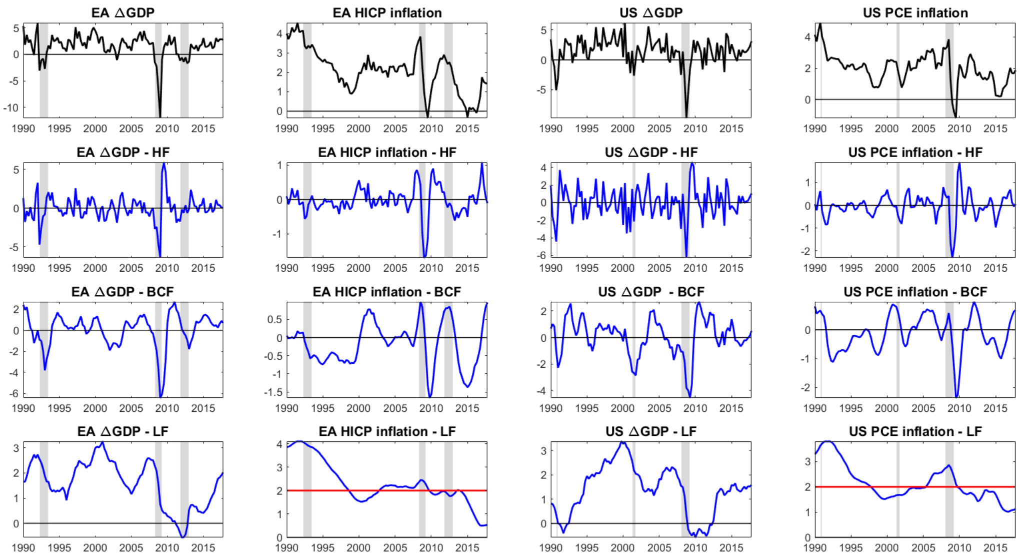


Figure 1: Time series of EA and US data

Notes. Sample period: 1990Q1–2017Q4. Shaded horizontal bars are the EA and US recessions as defined by the CEPR and NBER business cycle dating committees. HF stands for fluctuations shorter than 2 years, BCF for fluctuations between 2 and 8 years, and LF for cycles longer than 8 years.

By using the MODWT with the Haar filter,[7] any variable X_t can be decomposed as:

$$X_t = \sum_{j=1}^{J} D_{j,t} + S_{J,t} \ , \tag{1}$$

where $D_{j,t}$ are the wavelet coefficients at scale j, and $S_{J,t}$ is the scaling coefficient. These coefficients are given by

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

and

$$S_{J,t} = \frac{1}{2^j} \sum_{i=0}^{2^j-1} X_{t-i} \ . \tag{3}$$

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

[7] The Haar filter is widely used in macro and finance applications (see e.g. Faria and Verona, 2018, 2020, 2021, Lubik, Matthes and Verona, 2019, Kilponen and Verona, 2022, and Martins and Verona, 2023).

representing the fluctuation of the original time series in a specific frequency band. The coefficients $D_{j,t}$ can then be viewed as components with different levels of persistence operating at different frequencies, whereas the scaling coefficient S_J corresponds to the LF trend of the series.

We compute a J=4 level decomposition of our time series. As we use quarterly data and models, the first component (D_1) captures fluctuations with a period between 2 and 4 quarters, while the components D_2, D_3 and D_4 capture fluctuations with periods of 1–2, 2–4, and 4–8 years, respectively. Finally, the scale component S_4 captures fluctuations with a period longer than 8 years.[8]

Subsequently, we follow the norm in the business-cycle literature (e.g. Brock et al., 2013) and 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.

The second to fourth rows in Figure 1 report the time series of these frequency components for each of the EA and US variables.

In the EA, most of the volatility of GDP growth during the GFC is due to its HF and BCF fluctuations, whereas the LF component seems to have shifted to a lower level after the GFC (from 2 % to 1 %). The large swings of HICP inflation during and after the GFC are mainly due to its BCF component. The LF component of inflation (often interpreted as the inflation target or the perception thereof) has been remarkably anchored to the (by then asymmetric) 2 % target of the ECB from the late-1990s until the mid-2010s, after which it has fallen and stabilized below 1 %.

Looking at the frequency decomposition of US data, there are several similarities among the LF components of the variables. In fact, GDP growth seems to have stabilized at a lower level after the GFC, and inflation has fallen after the GFC and has remained below the 2 % FED's target until the end of the period.

[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).

4 How well do DSGE models capture heterogeneity in fluctuations?

DSGE models are intended to replicate aggregate economic behavior mainly over the business cycle and, potentially, over the long run if some features like endogenous growth or demographic changes are introduced in the model (as done by e.g. Comin and Gertler, 2006, Aksoy, Basso, Smith and Grasl, 2019, Elfsbacka Schmöller and Spitzer, 2021, and Niemeläinen, 2021). The common way to check the model fit with the data is to compare second-order moments implied by the model (volatilities, correlations, persistences) against corresponding moments from the data.

Our frequency decomposition allows us to check the models' fit from a different perspective. In particular, using the wavelet variance decomposition we can analyze how the overall volatility of a time series is split across frequency bands in the data and in the models, so that we can check how well DSGE models capture the volatilities of inflation and output growth across different frequency bands.

Figure 2 reports the variance decomposition of inflation and output growth by frequency. Each boxplot displays the distribution across models, where the red crosses represent the mean across models and the black crosses depict the value in the data. Tables 7 and 8 in Appendix C display the variance decomposition for each EA and US model, respectively.

What emerges from the variance decomposition is a multifaceted picture of macroeconomic fluctuations as they occur heterogeneously across both frequency bands and economies, yet there are some similarities.

For both regions, the data suggests that most of inflation fluctuations are due to LF movements (two-third for the EA and $\sim$40 % for the US), while HF movements only account for a small share of overall volatility (10-20 %). The remaining 30-40 % is attributed to BCF movements. The behavior of EA inflation arguably conforms to the conventional wisdom that most EA inflation is slow-moving and trend-driven by the ECB's inflation target. On the other hand, inflation in the US seems to be a less long-term phenomenon than in the EA as its fluctuations are roughly equally divided between the BCF and the LF.

Models are not very successful at matching inflation volatility. While EA (US) models match quite well the volatility of inflation at HF (BCF), they fail at matching the importance of the other frequency components. In particular, EA (US) models underestimate (overestimate) the volatility at LF by giving more (less) importance to BCF (HF). US models display larger ranges (also for output growth) due to the fact that a larger set of models is included.

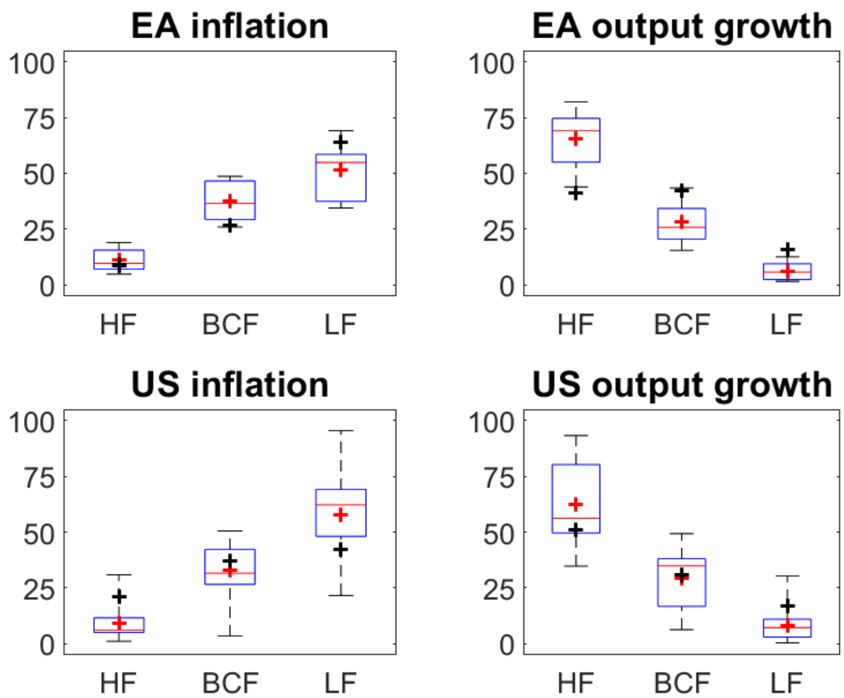


Figure 2: Wavelet variance decomposition - data and DSGE models

Notes. Sample period: 1990Q1–2017Q4. HF stands for fluctuations lasting shorter than 2 years, BCF for fluctuations between 2 and 8 years, and LF for cycles longer than 8 years. 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 the box mark the entire range of the distribution. The red (black) crosses represent the mean across models (data values).

Output growth fluctuations display a different pattern. In the EA, there is an equal split between HF and BCF (∼40%), while the remaining fluctuations are attributable to the LF component. In the US more than 50 % of output growth volatility is explained by HF fluctuations, roughly one-third by the BCF component, with the rest (17 %) by the LF component.

EA models do not match output growth volatility as the data points are outside (or close to) the range implied by the models. In particular, EA models give too much importance to HF fluctuations of output growth at the expense of the volatilities at other frequencies. US models perform better in this regard. They match BCF volatility well and, to a less extent, also HF fluctuations.[9]

5 Optimized frequency-based monetary policy rules

In this section, we first analyze the optimized monetary policy rule for each DSGE model separately, and then we evaluate the implications of model uncertainty for the design of robust monetary policy rules.

5.1 Model-specific rules

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

$$\begin{aligned} \min_{\{\rho,\alpha_\pi,\alpha_y\}} \quad & Var_m\left(\pi^{freq}\right) + \lambda_y Var_m\left(\Delta y^{freq}\right) \quad freq = BCF, LF, all \\ s.t.\ \ & r_t = \rho r_{t-1} + \alpha_\pi \pi_t + \alpha_y \Delta y_t \\ & E_t\left[f_m\left(x_t^m, x_{t+1}^m, x_{t-1}^m, z_t, \Theta^m\right)\right] = 0 \end{aligned}$$

and there exists a unique and stable equilibrium for that model, 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. For the optimized model-specific (and model-robust) rules, we set the limits for each policy parameter ($\rho \in [0, 0.9]$, $\alpha_\pi \in [0.1, 5]$, 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 loss 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 loss function. In the baseline case, we consider $\lambda_y = 0$ and $\lambda_y = 1$. In the first three columns in

[9] For future work, it would be of interest to use models that offer better modeling of long-run trends (such as models with demographic changes or endogenous growth). These models should have a better fit (compared to the models used here) with the wavelet variance decomposition of the data, as they should give more weight to BCF and LF fluctuations.

Panel A: EA						
Loss functions	Individual models			Robust rule		
	$\overline{\rho}$	$\overline{\alpha_\pi}$	$\overline{\alpha_y}$	ρ	α_π	α_y
$\text{var}(\pi)$	0.9	1.6	0.7	0.9	0.8	0.1
$\text{var}(\pi^{BCF})$	0.9	1.3	0.8	0.9	0.7	0.1
$\text{var}(\pi^{LF})$	0.9	1.3	0.9	0.9	0.7	0.2
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF})$	0.9	1.5	0.7	0.9	0.8	0.1
$\text{var}(\pi) + \text{var}(\Delta y)$	0.9	1.5	1.3	0.9	0.9	1.6
$\text{var}(\pi^{BCF}) + \text{var}(\Delta y^{BCF})$	0.9	1.3	1.2	0.9	0.6	1.2
$\text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	1.3	1.3	0.9	0.7	1.2
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	1.5	1.0	0.9	0.8	1.2
Panel B: US						
$\text{var}(\pi)$	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

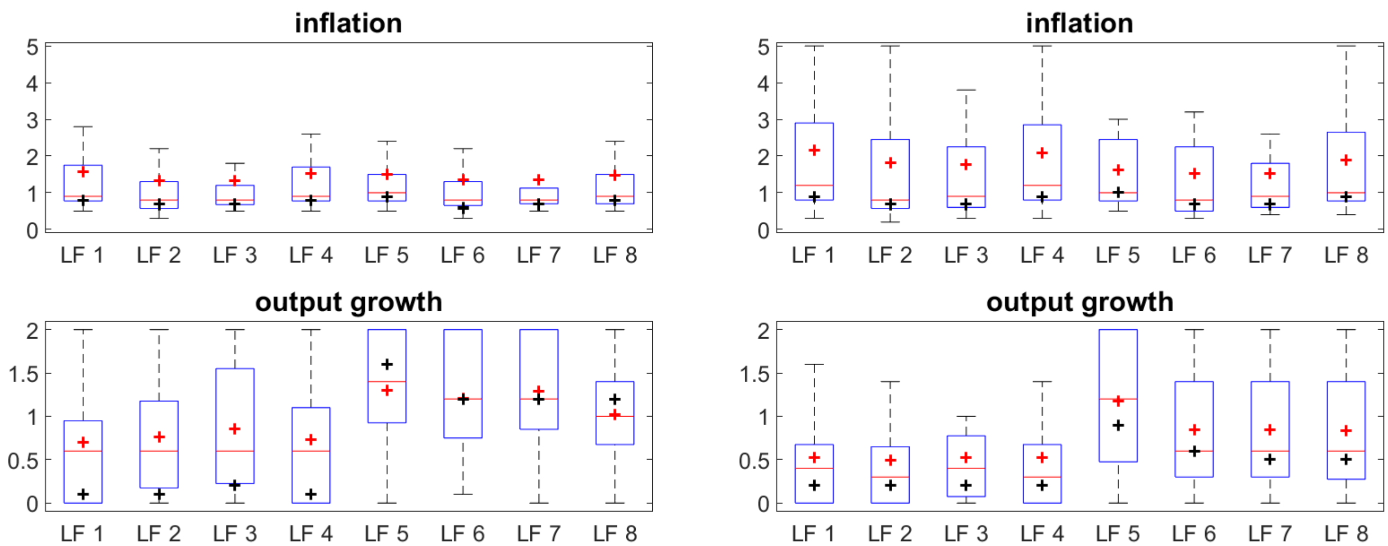
Notes. All loss functions include the term $0.5\,\text{var}(\Delta r)$. HF stands for fluctuations shorter than 2 years, BCF for fluctuations between 2 and 8 years, and LF for cycles longer than 8 years.

Table 3 we report the averages of the optimized model-specific coefficients. Panel A reports the results for the EA, while panel B shows the results using US models.

Certain results hold for both the EA and the US. First, the average coefficient on the lagged nominal interest rate is 0.9 regardless of the loss 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 average response coefficients to inflation. However, stabilizing both frequencies of inflation leads to an average inflation response similar to that of stabilizing aggregate inflation. These results hold regardless of the central bank's preference for stabilizing output growth or its BCF. Third, if the central bank is concerned about output growth stabilization, the average responses to output growth are larger (as one would expect), while the responses to inflation are unchanged (EA) or smaller (US).

Finally, when comparing EA and US results, US rules feature a stronger average reaction to inflation and smaller average response coefficients to output growth.

In Figure 3 we plot the distribution of optimized model-specific coefficients. It is clear that not only the average coefficients across models (red crosses) are lower when the policymaker aims at stabilizing only some frequencies of inflation and output growth, but the entire distribution of the optimized model-specific coefficients shifts downwards (with the exception of the output growth coefficient of EA models).



(a) EA models

(b) US models

Figure 3: Boxplot of optimized Taylor-rule coefficients

Notes. The black cross depicts the coefficients of the model-robust rule, and the red cross is the average of model-specific rules. 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. LF1 to LF8 refer to the central bank loss functions as reported in Table 2.

5.2 Model-robust rules

To identify model-robust monetary policy rules, we follow Kuester and Wieland (2010) and apply model averaging. Formally, the model-robust rule is obtained by choosing the parameters of the monetary policy rule that solve the following optimization problem:

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

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

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

and there exists a unique and stable equilibrium $\forall m \in M$. Following Kuester and Wieland (2010), we use equal weights ($\omega_m = 1/M$) on the considered models. To avoid that model-robust policy rules are driven by a single model, we check that, for each model, the unconditional variances of inflation and output growth are non-distortive for the model-specific optimized policy rule. Figure 4 in Appendix D reports the distribution of model variances, as well as for the EA and US data.

Columns 4 to 6 in Table 3 report the optimized model-robust coefficients for each loss function. We emphasize the following results, which hold for both the EA (panel A) and the US (panel B). 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 loss function, model-robust rules prescribe a much smaller response to inflation and usually a smaller reaction to output growth (except for the EA when the central bank wants to stabilize output growth). That is, a rule robust to model uncertainty generally implies a less aggressive response of central banks. Third, similar to the model-specific results, if the policymaker cares about stabilizing a subset of inflation frequencies, then the robust response to inflation should be reduced.

Finally, model-robust rules are quite similar for the EA and the US, thus implying the same robust reaction by the Fed and the ECB.

Looking at Figure 3, the model-robust coefficients (black crosses) are on the lower side of the boxes, thus implying much smaller than average responses by the central bank.

Overall, these findings suggest policymakers to be more cautious than what the *status quo* of using a single model to stabilize the overall volatility of inflation (and real activity) implies if they aim at stabilizing specific frequencies of inflation and output growth. Rules robust to model uncertainty prescribe an even more cautious response by the central bank. Furthermore, if the central bank also cares about stabilizing real activity and faces model uncertainty, its response should be much more aggressive with respect to output growth while keeping its inflation response broadly unchanged.

Besides model averaging, other methods of computing model-robust monetary policy rules have been proposed in the literature (see Onatski and Williams, 2003, Brock et al., 2007, Kuester and Wieland, 2010). Table 9 in Appendix E shows the results of model-robust monetary policy rules computed with minimax and minimax regret methods.

6 Monetary policy experiments

In this section, we present the results of two monetary policy experiments. In the first one, we split the models according to their features and compute model-robust rules for each group of models separately. In the second experiment, we check how different model-robust rules are if policymakers use the models with the best or worst fit with the data. In the final sub-section, we report the results of additional robustness tests.

6.1 Model-robust monetary policy rules and model features

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

In Table 4 we report the model-robust coefficients for models i) which are calibrated or estimated, ii) with and without financial frictions, and iii) with and without wage rigidity. Due to the small number of EA models, we run this analysis only for the US. Regardless of how the models are divided, robust

Loss functions	Robust rule			Calibrated models			Estimated models			Models with financial frictions			Models without financial frictions			Models with wage frictions			Models without wage frictions		
	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	ρ	α_π	α_y	ρ	α_π	α_y
$\text{var}(\pi)$	0.9	0.9	0.2	0.9	1.2	0.2	0.9	0.9	0.2	0.9	1	0.3	0.9	0.9	0.2	0.9	0.8	0.1	0.9	1.2	0.5
$\text{var}(\pi^{BCF})$	0.9	0.7	0.2	0.9	1	0.3	0.9	0.7	0.2	0.9	0.8	0.3	0.9	0.7	0.2	0.9	0.6	0.1	0.9	0.9	0.5
$\text{var}(\pi^{LF})$	0.9	0.7	0.2	0.9	0.9	0.3	0.9	0.7	0.2	0.9	0.7	0.3	0.9	0.8	0.2	0.9	0.6	0.2	0.9	0.9	0.4
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF})$	0.9	0.9	0.2	0.9	1.2	0.2	0.9	0.9	0.2	0.9	0.9	0.3	0.9	0.9	0.2	0.9	0.7	0.1	0.9	1	0.5
$\text{var}(\pi) + \text{var}(\Delta y)$	0.9	1	0.9	0.9	1.4	1.8	0.9	0.9	0.7	0.9	1	1	0.9	0.9	0.9	0.9	0.8	0.7	0.9	1.2	1.4
$\text{var}(\pi^{BCF}) + \text{var}(\Delta y^{BCF})$	0.9	0.7	0.6	0.9	1	1	0.9	0.7	0.5	0.9	0.8	0.6	0.9	0.7	0.6	0.9	0.5	0.4	0.9	0.9	0.8
$\text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.7	0.5	0.9	0.9	1	0.9	0.7	0.5	0.9	0.8	0.6	0.9	0.7	0.5	0.9	0.6	0.4	0.9	0.9	0.8
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.9	0.5	0.9	1.2	0.9	0.9	0.9	0.5	0.9	0.9	0.5	0.9	0.9	0.5	0.9	0.7	0.4	0.9	1	0.7

Table 4: Model-robust monetary policy rules of models with different features

Notes. This simulation is only performed using US models. The features are: calibrated and estimated models, models with and without financial friction, and models with and without wage friction. All loss functions include the term $0.5\,\text{var}(\Delta r)$. HF stands for fluctuations lasting shorter than 2 years, BCF for fluctuations between 2 and 8 years, and LF for cycles longer than 8 years.

inflation coefficients are smaller when the central bank is concerned about stabilizing specific frequencies of inflation, and robust output growth coefficients are larger when policymakers want to stabilize real activity. These results are in line with the main findings of the paper.

When compared with the baseline model-robust results, 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, financial frictions do not seem to matter too much for the design of optimal policy rules as the robust response coefficients are similar whether or not these frictions are included in the model. On the other hand, wage frictions matter as models with such frictions lead to weaker responses by policymakers, while models without them prescribe a stronger response.

Notably, we observe that the optimized model-robust coefficients usually increase as the variance of the variable of interest decreases. For instance, calibrated models and models without wage frictions generate lower volatilities than estimated models and models with wage frictions. Hence, such models would call for a stronger response by the central bank to stabilize the economy.

6.2 Model-robust monetary policy rules and model fit with the data

Some models are better than others at matching the wavelet variance decomposition of inflation and output growth (see Tables 7 and 8 in Appendix C). In this sub-section, we analyze whether using the models with the best or worst fit with the data matters for the design of robust policy rules. Since there are more models available for the US, we choose the three (five) best-fitting and worst-fitting models of the EA (US) and compare their optimal robust rules against the baseline including all models. To compute the best and worst models, we use the simple Euclidean distance between model moments and data moments. Results are displayed in Table 5 (best fit: columns 4 to 6; worst fit: columns 7 to 9).

Most of the previous findings still hold (for both regions) regardless of the model fit with the data. In particular, considering only one frequency of inflation reduces the reaction to inflation (with a few exceptions for the best-fitting models). Furthermore, including output growth in the loss functions increases

Loss functions	Robust rule								
	All models			Models with best fit			Models with worst fit		
	ρ	α_π	α_y	ρ	α_π	α_y	ρ	α_π	α_y
Panel A: EA									
$\text{var}(\pi)$	0.9	0.8	0.1	0.9	1	0	0.9	0.7	0.3
$\text{var}(\pi^{BCF})$	0.9	0.7	0.1	0.9	0.8	0	0.9	0.5	0.3
$\text{var}(\pi^{LF})$	0.9	0.7	0.2	0.9	0.8	0	0.9	0.6	0.5
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF})$	0.9	0.8	0.1	0.9	1	0	0.9	0.7	0.4
$\text{var}(\pi) + \text{var}(\Delta y)$	0.9	0.9	1.6	0.9	1	2	0.9	0.7	0.8
$\text{var}(\pi^{BCF}) + \text{var}(\Delta y^{BCF})$	0.9	0.6	1.2	0.9	0.8	2	0.9	0.5	0.6
$\text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.7	1.2	0.9	1	2	0.9	0.6	0.8
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.8	1.2	0.9	1.2	2	0.9	0.7	0.6
Panel B: US									
$\text{var}(\pi)$	0.9	0.9	0.2	0.9	1.8	0.2	0.9	0.8	0.7
$\text{var}(\pi^{BCF})$	0.9	0.7	0.2	0.9	1.2	0.3	0.9	0.6	0.8
$\text{var}(\pi^{LF})$	0.9	0.7	0.2	0.9	1.6	0.3	0.9	0.7	0.5
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF})$	0.9	0.9	0.2	0.9	1.8	0.2	0.9	0.8	0.7
$\text{var}(\pi) + \text{var}(\Delta y)$	0.9	1	0.9	0.9	1.6	2	0.9	0.8	1
$\text{var}(\pi^{BCF}) + \text{var}(\Delta y^{BCF})$	0.9	0.7	0.6	0.9	1.4	2	0.9	0.6	0.9
$\text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.7	0.5	0.9	1.6	2	0.9	0.7	0.8
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.9	0.5	0.9	2	2	0.9	0.8	0.9

Table 5: Model-robust monetary policy rules of models with best and worst data fit

Notes. The best and worst three (five) models are chosen for the EA (US), respectively. All loss functions include the term $0.5\,\text{var}(\Delta r)$. HF stands for fluctuations lasting shorter than 2 years, BCF for fluctuations between 2 and 8 years, and LF for cycles longer than 8 years.

the coefficient for output growth without having a (large) impact on the inflation coefficient.

The main differences concern the magnitude of the coefficients. For both regions, compared to the baseline model-robust results, the models with the best (worst) fit with the data would always prescribe a stronger (smaller) response to inflation. The response is actually much stronger in the case of the US for the best-fitting models.

As regards the output growth response, using the models with the best fit with the data leads to a smaller or similar response if output stabilization is not a concern for the central bank. However, the response should be much larger if policymakers seek to stabilize output fluctuations. Models with the worst fit with the data call for larger responses to output growth unless the ECB is pursuing output stabilization.

6.3 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 10 (columns 4 to 6) in Appendix F. For both regions, 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, we follow Levin et al. (2003) and Orphanides and Wieland (2013) and 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 10 (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 loss 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 as BCF fluctuations as these are arguably the most relevant frequencies for monetary policymakers, as well as between 1 and 8 years. Model-robust coefficients, reported in columns 10 to 15 of Table 10, 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 loss function) ranging from 0.1 to 1.

7 Policy conclusions

In this paper, we address a rather "old" question – which interest rate rule should a central bank follow? – using a framework that differs from and improves upon existing literature in two ways. First, motivated by the observation that stabilizing some frequencies of inflation and real activity seems to be more important for policymakers than stabilizing other frequencies, we analyze the frequency-specific effects of monetary policy rules instead of choosing the rules that minimize a weighted average of the unconditional variances of inflation and output. Second, as none of the many structural macroeconomic models available to policymakers can be considered to be the true model of the economy, we run the analysis using a large number of models to identify monetary policy rules that are robust to model uncertainty.

The policy recommendation of this paper is clear: policymakers having preferences for stabilizing specific frequencies of inflation and output growth should react less strongly to these variables. Additional caution is needed for those policymakers who are uncertain about which model(s) to use. This recommendation holds regardless of the models' features or their fit with the data.

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Appendix A Models (acronyms) and their key features

Model acronyms	Estimation period	Wage friction	Financial friction	Phillips curve
EA_ALSV06	1980Q1 – 1994Q4	No	No	hybrid
EA_CKL09	1984Q1 – 2006Q3	Yes	No	hybrid
EA_CW05fm	1974Q1 – 1998Q4	Yes	No	hybrid
EA_CW05ta	1974Q1 – 1998Q4	Yes	No	hybrid
EA_NK_BGEU10	calibrated	Yes	No	forward
EA_PV15	1999Q1 – 2013Q3	Yes	Yes	hybrid
EA_SW03	1970Q1 – 1999Q4	Yes	No	hybrid
EA_SWW14	1985Q1 – 2009Q4	Yes	No	hybrid
EA_VI16bgg	1983Q1 – 2008Q3	Yes	Yes	hybrid
US_ACELm	1959Q2 – 2001Q4	Yes	Yes	hybrid
US_ACELswm	1959Q2 – 2001Q4	Yes	Yes	forward
US_BKM12	1990M1 – 2009M10	Yes	No	hybrid
US_CD08	1979Q3 – 2004Q3	No	Yes	forward
US_CFOP14	1972Q1 – 2008Q4	Yes	Yes	hybrid
US_CPS10	1960Q1–1979Q3 / 1982Q4–2006Q4	No	No	hybrid
US_DG08	1954Q1 – 2004Q4	Yes	Yes	hybrid
US_DNGS15_SWpi	1964Q1 – 2008Q3	Yes	No	hybrid
US_FMS13	1960Q1 – 2007Q4	Yes	No	hybrid
US_FU19	1984Q1 – 2015Q4	Yes	No	hybrid
US_HL16	1982Q1 – 2015Q1	No	Yes	hybrid
US_IAC05	1974Q1 – 2003Q2	No	Yes	forward
US_IR04	1980Q1 – 2001Q3	No	No	forward
US_JPT11	1954Q3 – 2009Q1	Yes	No	hybrid
US_KS15	1964Q1 – 2008Q2	No	No	forward
US_LWY13	1984Q1 – 2007Q4	Yes	No	hybrid
US_NK_BGUS10	calibrated	Yes	No	forward
US_NK_CFP10	calibrated	No	Yes	forward
US_NK_CK08	calibrated	Yes	No	hybrid
US_NK_GK09lin	calibrated	No	Yes	backward
US_NK_KRS12	calibrated	No	Yes	hybrid
US_NK_PP17	calibrated	No	Yes	forward
US_NK_RA16	calibrated	No	Yes	hybrid
US_NK_RW97	calibrated	No	No	forward
US_PM08	1994Q1 – 2008Q1	No	No	hybrid
US_PM08fl	1994Q1 – 2008Q1	No	Yes	hybrid
US_SW07	1966Q1 – 2004Q4	Yes	No	hybrid
US_VI16bgg	1983Q1 – 2008Q3	Yes	Yes	hybrid
US_YR13	1954Q1 – 2008Q3	Yes	Yes	hybrid

Table 6: Key features of models used

Notes. All the models, except EA_CW05fm and EA_CW05ta, feature nominal price stickiness. The reference for each model acronym can be found at https://www.macromodelbase.com/files/documentation_source/mmb-model-list.pdf.

Appendix B   List of variables used

For the EA, we use the following series from the NAWM database:

- YER (Gross Domestic Product (GDP) at market prices, Million Euro, Chain linked volume, Calendar and seasonally adjusted data, Reference year: 1995) to compute quarter-over-quarter GDP growth rate;
- HICP (Overall Index, Index, Neither seasonally nor working day adjusted data, Index base year 1996 (1996 = 100)) to compute year-over-year HICP inflation rate.

For the US, we use the following series from FRED2:

- Real gross domestic product per capita, Chained 2012 Dollars, Quarterly, Seasonally Adjusted Annual Rate (Mnemonic: A939RX0Q048SBEA) to compute quarter-over-quarter GDP growth rate;
- Personal Consumption Expenditures, Chain-type Price Index, Index 2012=100, Quarterly, Seasonally Adjusted (Mnemonic: PCEPI) to compute year-over-year PCE inflation rate.

Appendix C Wavelet variance decomposition - tables

Model	Inflation			Output growth		
	HF	BCF	LF	HF	BCF	LF
EA_ALSV06	16	29	55	73	21	6
EA_CKL09	15	47	38	79	19	2
EA_CW05fm	7	40	53	64	30	7
EA_CW05ta	19	46	35	69	26	5
EA_NK_BGEU10	5	26	69	82	16	3
EA_PV15	16	49	36	72	26	2
EA_SW03	10	33	57	57	32	11
EA_SWW14	8	29	63	48	43	9
EA_VI16bgg	7	37	56	44	44	13
EA data	9	27	64	41	42	16

Table 7: Wavelet variance decomposition (EA data vs. DSGE models)

Notes. Sample period: 1990Q1–2017Q4. Percentages may not add up to 100 due to rounding. HF stands for fluctuations shorter than 2 years, BCF for fluctuations between 2 and 8 years, and LF for cycles longer than 8 years. The wavelet variance decomposition for each model is computed using the model with the original monetary policy rule.

Model	Inflation			Output growth		
	HF	BCF	LF	HF	BCF	LF
US_ACELm	5	42	53	45	47	9
US_ACELswm	6	43	52	43	49	8
US_BKM12	4	27	69	53	38	9
US_CD08	11	32	58	87	12	1
US_CFOP14	10	37	53	54	36	10
US_CPS10	1	3	95	74	23	3
US_DG08	3	17	80	50	37	14
US_DNGS15_SWpi	6	31	64	74	21	5
US_FMS13	6	28	67	56	29	16
US_FU19	5	30	65	45	41	14
US_HL16	6	27	67	38	41	21
US_IAC05	17	37	46	87	12	1
US_IR04	4	16	79	88	11	2
US_JPT11	4	22	74	35	35	30
US_KS15	18	32	51	80	16	4
US_LWY13	9	40	51	68	27	5
US_NK_BGUS10	5	26	69	80	17	3
US_NK_CFP10	4	24	71	81	16	3
US_NK_CK08	28	51	22	51	40	9
US_NK_GK09lin	13	50	38	49	42	9
US_NK_KRS12	11	40	49	67	26	7
US_NK_PP17	7	21	72	86	12	1
US_NK_RA16	17	50	33	75	22	4
US_NK_RW97	31	46	24	93	6	1
US_PM08	12	46	42	56	37	7
US_PM08fl	12	45	43	60	36	4
US_SW07	6	31	63	53	37	11
US_VI16bgg	7	29	65	52	36	12
US_YR13	5	33	62	36	48	16
US data	21	37	42	51	31	17

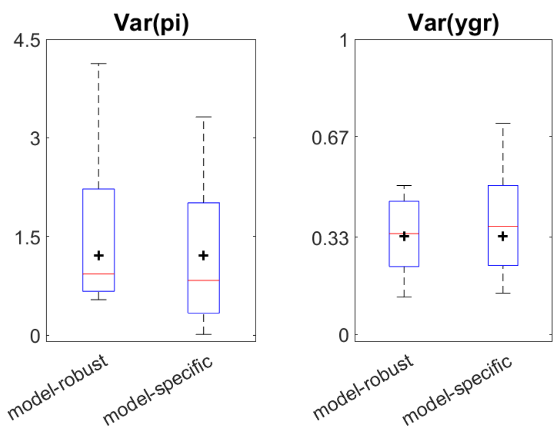
Table 8: Wavelet variance decomposition (US data vs. DSGE models)

Notes. Sample period: 1990Q1–2017Q4. Percentages may not add up to 100 due to rounding. HF stands for fluctuations shorter than 2 years, BCF for fluctuations between 2 and 8 years, and LF for cycles longer than 8 years. The wavelet variance decomposition for each model is computed using the model with the original monetary policy rule.

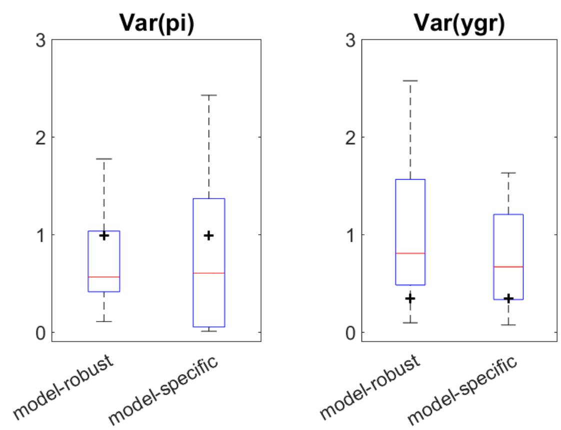
Appendix D Unconditional variances - data and DSGE model fit

We report the unconditional variances of inflation and output growth in the models and in the data in Figure 4. We report the model volatilities under two different Taylor rules. The first one is the optimized Taylor rule for the specific model, and the second one is the optimized model-robust rule which is common across models.

EA and US data are similarly volatile. EA models imply a larger variance of inflation and a smaller variance of output growth compared to US models. Models match the unconditional variances of the data quite well, except in the case for output growth in the US. Furthermore, implementing an optimized model-robust monetary policy rule does not distort the variances of single models. Consequently, the costs of a model-robust rule are rather small.



(a) EA models



(b) US models

Figure 4: Boxplot of unconditional variances

Notes. The policy rules are optimized for loss function 6. The black cross depicts the data. 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 99.7 % range of the distribution.

Appendix E Alternative approaches to computing robust rules

Besides model averaging, other alternative ways of computing model-robust monetary policy rules have been proposed in the literature. A prominent approach is minimax (see Onatski and Williams, 2003, Brock et al., 2007, Kuester and Wieland, 2010), which minimizes the maximum loss of all models. Formally, the minimax rule is obtained by choosing the parameters of the monetary policy rule (ρ, α_π, and α_y) such that they solve the following optimization problem:

$$\begin{aligned}
\min_{\{\rho,\alpha_\pi,\alpha_y\}} \ \max_{m\in M} \ & Var_m\left(\pi^{freq}\right)+\lambda_y Var_m\left(\Delta y^{freq}\right) \quad freq=BCF,LF,all \\
s.t. \ \ & r_t=\rho r_{t-1}+\alpha_\pi \pi_t+\alpha_y \Delta y_t \\
& E_t\left[f_m\left(x_t^m,x_{t+1}^m,x_{t-1}^m,z_t,\Theta^m\right)\right]=0 \ \forall m\in M
\end{aligned}$$

and there exists a unique and stable equilibrium $\forall m \in M$. Results are displayed in columns 4 to 6 of Table 9. For the EA, results are broadly in line with the model average case, but the interest-rate smoothing coefficient is smaller (0.8) in some rules. For the US, however, the minimax rule would usually prescribe a much stronger reaction to both inflation and output growth. Finally, the last three columns in Table 9 show the results using minimax regret (see Brock et al., 2007).

Panel A: EA									
Loss functions	Model average rule			Minimax rule			Minimax regret rule		
	ρ	α_π	α_y	ρ	α_π	α_y	ρ	α_π	α_y
$\text{var}(\pi)$	0.9	0.8	0.1	0.8	0.9	0	0.8	0.9	0
$\text{var}(\pi^{BCF})$	0.9	0.7	0.1	0.8	0.8	0.2	0.8	0.7	0
$\text{var}(\pi^{LF})$	0.9	0.7	0.2	0.9	0.7	0.3	0.9	0.6	0.1
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF})$	0.9	0.8	0.1	0.8	0.9	0	0.8	0.9	0
$\text{var}(\pi) + \text{var}(\Delta y)$	0.9	0.9	1.6	0.9	0.8	2	0.9	0.7	1.8
$\text{var}(\pi^{BCF}) + \text{var}(\Delta y^{BCF})$	0.9	0.6	1.2	0.8	0.7	1	0.8	0.7	1
$\text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.7	1.2	0.9	0.8	1.8	0.9	0.5	1.2
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.8	1.2	0.9	0.8	1	0.9	0.8	1
Panel B: US									
$\text{var}(\pi)$	0.9	0.9	0.2	0.9	1.6	1	0.9	1.6	1
$\text{var}(\pi^{BCF})$	0.9	0.7	0.2	0.9	0.8	0.6	0.9	0.6	0.5
$\text{var}(\pi^{LF})$	0.9	0.7	0.2	0.9	1.8	1	0.9	1.8	1
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF})$	0.9	0.9	0.2	0.9	1.8	1	0.9	1.8	1
$\text{var}(\pi) + \text{var}(\Delta y)$	0.9	1	0.9	0.9	0.8	0.4	0.9	0.8	0.4
$\text{var}(\pi^{BCF}) + \text{var}(\Delta y^{BCF})$	0.9	0.7	0.6	0.9	0.6	0.3	0.9	0.5	0.3
$\text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.7	0.5	0.9	1.6	0.9	0.9	1.6	0.9
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.9	0.5	0.9	1.4	0.6	0.9	1.4	0.6

Table 9: Model average, minimax, and minimax regret optimal monetary policy rules

Notes. All loss functions include the term $0.5\,\text{var}(\Delta r)$. HF stands for fluctuations lasting shorter than 2 years, BCF for fluctuations between 2 and 8 years, and LF for cycles longer than 8 years.

Appendix F Robustness tests - table

Loss functions	$\lambda_y = 1; h = 0$			$\lambda_y = 0.5; h = 0$			$\lambda_y = 1; h = 4$			BCF: 1-4y			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
Panel A: EA															
$\text{var}(\pi)$	0.9	0.8	0.1	0.9	0.8	0.1	0.9	1.4	2	0.9	0.8	0.1	0.9	0.8	0.1
$\text{var}(\pi^{BCF})$	0.9	0.7	0.1	0.9	0.7	0.1	0.9	0.9	0.8	0.9	0.5	0.7	0.9	0.7	0.1
$\text{var}(\pi^{LF})$	0.9	0.7	0.2	0.9	0.7	0.2	0.9	0.9	0.8	0.9	0.8	0.1	0.9	0.7	0.2
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF})$	0.9	0.8	0.1	0.9	0.8	0.1	0.9	1.2	1.6	0.9	0.8	0.1	0.9	0.8	0.1
$\text{var}(\pi) + \text{var}(\Delta y)$	0.9	0.9	1.6	0.9	0.9	1.4	0.9	1.4	2	0.9	0.9	1.6	0.9	0.9	1.6
$\text{var}(\pi^{BCF}) + \text{var}(\Delta y^{BCF})$	0.9	0.6	1.2	0.9	0.7	1.2	0.9	1.2	1.6	0.9	0.5	1.2	0.9	0.7	1.4
$\text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.7	1.2	0.9	0.7	1	0.9	1.2	1.6	0.9	0.8	1.2	0.9	0.7	1.4
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	0.9	0.8	1.2	0.9	0.8	0.9	0.9	1.4	2	0.9	0.9	1.2	0.9	0.9	1.4
Panel B: US															
$\text{var}(\pi)$	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
$\text{var}(\pi) + \text{var}(\Delta y)$	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
$\text{var}(\pi^{BCF}) + \text{var}(\Delta y^{BCF})$	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
$\text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	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
$\text{var}(\pi^{BCF}) + \text{var}(\pi^{LF}) + \text{var}(\Delta y^{BCF})$	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 10: Model-robust monetary policy rules - robustness tests

Notes. Importance of output growth in loss function (λ_y) is set to 0.5. h=4 depicts the forward horizon of inflation in the monetary policy rule. The rightmost columns with the term "BCF" depict the time horizon of BCF definition in the loss function. All loss functions include the term $0.5\,\text{var}(\Delta r)$.

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