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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

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1 Introduction

Which interest rate rule should a central bank follow? The common approach is to select a (Dynamic Stochastic General Equilibrium, DSGE) 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 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 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 provide a true model of the economy. 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 DSGE 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, and even less because of model uncertainty. Furthermore, the Federal Reserve (Fed) should be more hawkish in its responses than the European Central Bank (ECB).

The paper is organized as follows. In Section 2, we review the two strands of literature on which this work builds. We present the 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 optimal (frequency-based) 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

The motivation for this study emerges from the strands of literature dealing with design limits and DSGE model-robust monetary policy rules. This section highlights current issues in these fields.

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 of interest.

The presence of frequency-specific effects of monetary policy choices has 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 design limit studies 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 their variance at other frequencies. Policymakers thus need to consider 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 (using the EA_NK_BGEU10 model). 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 respectively the percentage differences in the volatility of inflation and its frequency components compared to the first row when the central bank follows a Taylor rule that minimizes the volatility of the BCF or LF inflation components. The example shows that a Taylor rule that minimizes the variance of inflation at BCF and HF does

[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 9 to 1. Thus, analyzing frequency-specific losses is important when evaluating policy rules.

so at the expense of increasing the variance of inflation at LF. A similar trade-off exists when using a policy rule that minimizes the variance of the LF inflation component.

The existing literature largely relies on a single simplistic model belonging to the two-equation New-Keynesian class of inflation and output models. We contribute to this literature by considering the frequency-specific effects of monetary policy rules across a large number of DSGE models.

2.2 Model-robust monetary policy rules

DSGE models are widely used in academia and by policymakers in monetary policy analysis. While a large number of (DSGE) models is available, none provides a true model of the economy. Model uncertainty itself is therefore a source of uncertainty facing policymakers.[2]

The large body of literature on robust policy design identifies monetary policy rules that perform well across a variety of models, i.e. identify 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 addressing the question of designing aggregate and frequency-based optimal model-robust (and model-specific) policy rules. We also consider a wide set of models for the US economy and run our analysis separately for the EA and the US.[3]

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

[3] For the US we consider 29 structural models against at most seven models used by Schmidt and Wieland (2013).

3 The setup

3.1 DSGE models

For the purposes of this study, we take several DSGE models from the *Macroeconomic Model Data Base*.[4] These models share antecedents and the same methodological core, but each emphasizes different transmission channels, frictions, and shocks.

We use a total of nine models for the EA (eight estimated and one calibrated) and 29 models for the US (21 estimated and eight calibrated). 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.

Next, we provide a brief overview of the models' features. With the exception of two EA models, all other models have nominal price rigidity. Most incorporate nominal price rigidity using the Calvo (1983) price stickiness, but several use Rotemberg (1982) price adjustment costs. More than half of the models feature Calvo (1983) wage stickiness. The two models without price frictions include wage frictions using Taylor (1980) or Fuhrer and Moore (1995) contracts.

About half of the models are either small-scale New-Keynesian 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).

One model features the 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

[4] `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.

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).

3.2 Central bank preferences

Inflation and output (or unemployment) are the key variables central banks look at when making their 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. HF) fluctuations in inflation. Likewise, as long-term inflation is ultimately a monetary phenomenon under the control of the central bank, policymakers may be reluctant to make interest-rate decisions that may potentially destabilize LF fluctuations in inflation.[5]

Regarding real activity, implementation of monetary policy by interest-rate setting should not be used to promote long-term economic growth (above potential) or fine tune HF fluctuations in the real economy as other policies (e.g. fiscal policy) are thought to be better suited for addressing these issues.

In this paper we consider several loss functions for the central bank so that our findings may be used by policymakers according to their preferences.

As a starting point, we choose the traditional loss function that considers the unconditional variances of inflation (π) and output growth (Δy):

$$Var(\pi) + \lambda_y Var(\Delta y) \quad .$$

[5] Forward guidance has been extensively used to shape inflation expectations and, ultimately, inflation in the long run.

The literature often refers to the output gap rather than output growth in the central bank's loss function (and in the Taylor rule). Use of the 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 attach a relative weight λ_y to the real activity term 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 more in line with the Fed's dual mandate of maximum employment and price stability.

We then consider several loss functions 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 the LF fluctuations of output growth. Instead, we consider different combinations of volatilities of inflation at BCF and LF, as well as the BCF component 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.

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 regularly violate the zero lower bound constraint on nominal interest rates.

3.3 Taylor rules

As a baseline Taylor rule, we follow the literature (e.g. Rubio and Carrasco-Gallego, 2016 and Bekiros, Nilavongse and Uddin, 2018) and use the following 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 solely in response to observable variables.

As a robustness test, we follow Levin et al. (2003) and Orphanides and Wieland (2013) and also consider forecast-based monetary policy rules of the type

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

where $E_t \pi_{t+h}$ corresponds to inflation expectation h-quarter ahead.

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. Due to data availability, we stop at 2017Q4 for the EA. We also stop at the same quarter for the US in order to have the same sample period as for the EA. Moreover, none of the US DSGE models used here has been estimated using data after 2017Q4, and we also avoid the large drop and sharp rebound in GDP growth associated with the Covid Recession during the first wave of the pandemic. The EA data is obtained from the New Area Wide Model dataset and EA inflation is the Harmonised Index of Consumer Prices (HICP) inflation. The US data is taken from FRED2. US inflation is based on the Personal Consumption Expenditures (PCE) price index.[6] The first row in Figure 1 reports the time series of the EA and US variables, as well as with 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 less volatile and mostly fluctuates around 2 %.

3.5 Frequency decomposition

To extract the different frequency components from the data, we use wavelet multiresolution analysis. This approach permits decomposition of any variable regardless of its time series properties into a trend, a cycle, and a HF component in a manner similar to the traditional Beveridge and Nelson (1981) time series trend-cycle decomposition approach. We employ the version of wavelet transform knows as the Maximal Overlap Discrete Wavelet Transform (MODWT).

By using MODWT multiresolution analysis with the Haar (wavelet) filter,[7] any variable X_t can be decomposed as:

$$X_t = \sum_{j=1}^{J} D_{j,t} + S_{J,t} \ , \tag{2}$$

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

[6] A brief description of the data used is provided in Appendix B.

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

given by

$$D_{j,t} = \frac{1}{2^j}\left[\sum_{i=0}^{2^{(j-1)}-1} X_{t-i} - \sum_{i=2^{(j-1)}}^{2^j-1} X_{t-i}\right] \tag{3}$$

and

$$S_{J,t} = \frac{1}{2^j}\sum_{i=0}^{2^j-1} X_{t-i} \ . \tag{4}$$

Equations (2)-(4) show that the original series X_t, exclusively defined in the time domain, can be decomposed (by means of an appropriate sequence of wavelet 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 wavelet 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 can be seen as the LF trend of the time 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 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 ($\pi_t^{BCF}$) is computed as $\pi_t^{BCF} = \pi_t^{D_3} + \pi_t^{D_4}$, whereas its LF components correspond to $\pi_t^{S_4}$. We augment each model with the frequency decomposition of the relevant variables as defined by equations (2)-(4), and define output growth and the change in the interest rate in terms of model-specific variables.

The second to fourth rows in Figure 1 report the time series of these frequency components for each of the EA and US variables, along with business-cycle recessions (depicted as gray shaded areas).

In the EA, most of the volatility of GDP growth during the GFC is due to its HF and BCF fluctuations,

[8] In the MODWT, each wavelet component at frequency j approximates an ideal high-pass filter with passband $f \in [1/2^{j+1}, 1/2^j]$. Hence, they are associated with periodicity fluctuations $[2^j, 2^{j+1}]$ (quarters, in our case). Regarding the choice of J, the number of observations dictates the maximum number of frequency bands that can be used. Here, the sample period contains $N = 112$ observations, so J is such that $J \leq \log_2 N \simeq 6.8$.

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. GDP growth seems to have stabilized at a lower level after the GFC. Inflation falls after the GFC and remains below the 2 % FED's target to the end of the observation period.

4 How well do DSGE models capture heterogeneity in fluctuations?

DSGE models are intended to replicate aggregate economic behavior over the business cycle and the long run. 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 go deeper and check how well DSGE models capture the volatility across different frequency bands, as we can compute the variance decomposition of inflation and output growth by frequency in the models and compare it with the one in the data. This ANalysis Of VAriance (ANOVA) allows us to uncover which frequency bands contribute relatively more or less to the overall volatility of a time series, and how DSGE models perform in this dimension.

The last rows of panels A and B in Table 2 report the variance decomposition of each variable by frequency for the EA and the US data. What emerges from the ANOVA decomposition is a multifaceted picture of macroeconomic fluctuations as they occur heterogeneously across both frequency bands and economies.

About two-third of inflation fluctuations in the EA are due to LF movements and 27 % to the BCF component. HF movements only account for a small share of overall volatility (9 %). 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. Only 16 % of GDP growth fluctuations are attributable to the LF component, while the remaining share is evenly split between the HF (41 %) and BCF (42 %) components.

Inflation fluctuations in the US are roughly equally divided between the BCF (37 %) and the LF (42 %), with HF fluctuations accounting for 21 % of the volatility of inflation. Inflation in the US seems to be a less long-term phenomenon than in the EA. More than 50 % of output growth is explained by HF fluctuations, roughly one-third by the BCF component, with the rest (17 %) by the LF component, which is quite similar to the EA.

We now check if DSGE models considered in this analysis are consistent with this heterogeneity in fluctuations. The first to third rows of panels A and B in Table 2 report the minimum, the average, and the maximum of the volatilities across frequencies for the EA and US models, respectively.

The means across models of the frequency decomposition of inflation and output growth volatility are very similar across regions.

In the EA, the importance of the HF component of inflation is matched quite well. However, EA models underrate its LF component by giving more importance to BCF fluctuations. In contrast, US models replicate the volatility of inflation at BCF quite well, while they underestimate (overestimate) the importance of its HF (LF) component.

Regarding output growth, the importance of the HF component is amplified by the models for the EA, while the other frequencies are less important. In contrast, the BCF for the US matches quite well, while the share of the HF (LF) is slightly overestimated (underestimated).

Overall, looking at the ranges of values, the US models seem to match the volatilities at BCF and LF better than the EA models.[9]

[9] US results display larger ranges due to the fact that a larger set of models is included.

5 Optimal frequency-based monetary policy rules

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

5.1 Model-specific rules

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

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

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

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

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 optimal 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 the frequencies are implicitly included in that analysis), as well as for different frequency combinations in the loss function (L_m). In the baseline case, we consider $\lambda_y = 0$ and $\lambda_y = 1$.

In the first three columns in Table 3 we report the averages of the optimal model-specific ρ, α_π, and α_y 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 optimal model-specific rules imply a 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 no matter if the central bank aims at stabilizing output growth or its BCF. Third, if the central bank is concerned about output growth stabilization, then 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 reaction to inflation and smaller response coefficients to output growth.[10]

5.2 Model-robust rules

To identify model-robust monetary policy rules, we follow Kuester and Wieland (2010) and apply Bayesian model averaging in designing monetary policies. Formally, the model-robust 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:[11]

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

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

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

and there exists a unique and stable equilibrium $\forall m \in M$. As in Kuester and Wieland (2010), we use equal weights ($\omega_m = 1/M$) on the considered models.

Columns 4 to 6 in Table 3 report the optimal 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

[10] Figure 2 in Appendix C shows the distribution of optimal model-specific coefficients for two different loss functions.

[11] To avoid that model-robust policy rules are driven by a single model, we check for each model that the unconditional variances of inflation and output growth are non-distortive for the model-specific optimal policy rule. Tables 8 and 9 in Appendix D report these variances for each model, as well as for the EA and US data.

Bayes rules feature the same degree of interest rate smoothing, which also coincides with the optimal average model-specific coefficient. Second, compared to the average optimal model-specific coefficients and regardless of the loss function, Bayes 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, by taking model uncertainty into consideration, Bayes rules generally imply 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 response to inflation should be reduced. Finally, Bayes rules also suggest that the Fed should be more hawkish than the ECB in pursuing its policy goals.

Therefore, policymakers should 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 their goal is to stabilize specific frequencies of inflation and output growth, and even more caution because of model uncertainty. 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.[12]

6 Monetary policy experiments

In this section, we present the results of two experiments. In the first monetary policy 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 second experiment, we split the models according to their features and compute model-robust rules for each group of models separately. In the final sub-section, we report the results of additional robustness tests.

[12] Besides Bayesian model averaging, other alternative methods of computing model-robust monetary policy rules have been proposed in the literature. In Appendix E, we show the results of model-robust monetary policy rules computed with minimax and minimax regret methods.

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

Tables 11 and 12 in Appendix F report the results of the ANOVA decomposition of each model for the EA and the US, respectively. It is evident that some models are better than others at matching the ANOVA decomposition of inflation and output growth. In this sub-section, we analyze whether using the models with the best or worst fit with the data matters for the design of optimal policy rules.

In particular, we check how robust the monetary policy rules are when the policymaker only uses models that have a good or bad fit with the ANOVA decomposition. 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 Bayes rules against the baseline including all models. Results are displayed in Table 4 (best fit: columns 4 to 6; worst fit: columns 7 to 9).[13]

The results confirming most of the previous findings and hold for both regions regardless of the model fit. In particular, considering only one frequency of inflation reduces the reaction to inflation (with a few exceptions for the models with the best ANOVA data fit). Furthermore, including output growth in the loss functions increases the coefficient for output growth without having a (large) impact on the inflation coefficient. Again, the Fed should be more hawkish than the ECB, regardless of the model fit with the data.

The main differences concern the magnitude of the coefficients. For both regions, compared to the baseline Bayes results, the models with the best (worst) fit with the data would always prescribe a stronger (smaller) response to inflation.

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.

[13] To compute the best and worst models, we use the simple Euclidean distance between model moments and data moments.

6.2 Model-robust monetary policy rules and model features

The DSGE models used in this analysis feature different frictions and transmission mechanisms. In this experiment we investigate if specific features of the models affect the optimal model-robust policy coefficients. In Table 5 we show the Bayes rules for models i) which are calibrated or estimated, ii) with and without financial frictions, and iii) with and without wage rigidity.[14]

Regardless of how the models are divided, inflation coefficients are smaller when the central bank is concerned about stabilizing specific frequencies of inflation. Output growth coefficients are larger when policymakers want to stabilize real activity. These results are in line with the main findings of this paper.

When compared with the baseline Bayes results, calibrated models would 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 matter for the design of optimal policy rules as the 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.

6.3 Robustness tests

We first check the robustness of our results if we relax the assumption that the central bank equally values variance 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 6 (columns 4 to 6). 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 moderately decreases the reaction to output growth in most cases.

We then use forecast-based monetary policy rules with respect to inflation by setting the forecast horizon to h=4 quarters in Equation (1). Results are reported in Table 6 (columns 7 to 9). The responses to

[14] Due to the small number of EA models, we run this analysis only for the US.

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. Differently from the baseline case, the ECB should be more hawkish than the Fed using a forecast-based Taylor rule.

We also 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. Results, reported in columns 10 to 15 of Table 6, are not overly 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 Concluding remarks

In this paper we address an "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 models available to policymakers provides a perfect model of the economy, we run the analysis using a large number of DSGE models to identify optimal model-robust policy rules with respect to policymaker goals.

We find that policymakers seeking to stabilize specific frequencies of inflation and output growth should react less strongly to inflation and output growth. Additional caution is called for due to model uncertainty. Furthermore, the Fed should be more hawkish in its responses than the ECB. These findings are robust as optimal policy coefficients do not (or only slightly) depend on models' features and fit with the data, the definition of business-cycle frequency, the relative weight on output growth and changes in nominal interest rate in the loss function, and the use of forecasts-based interest-rate rules.

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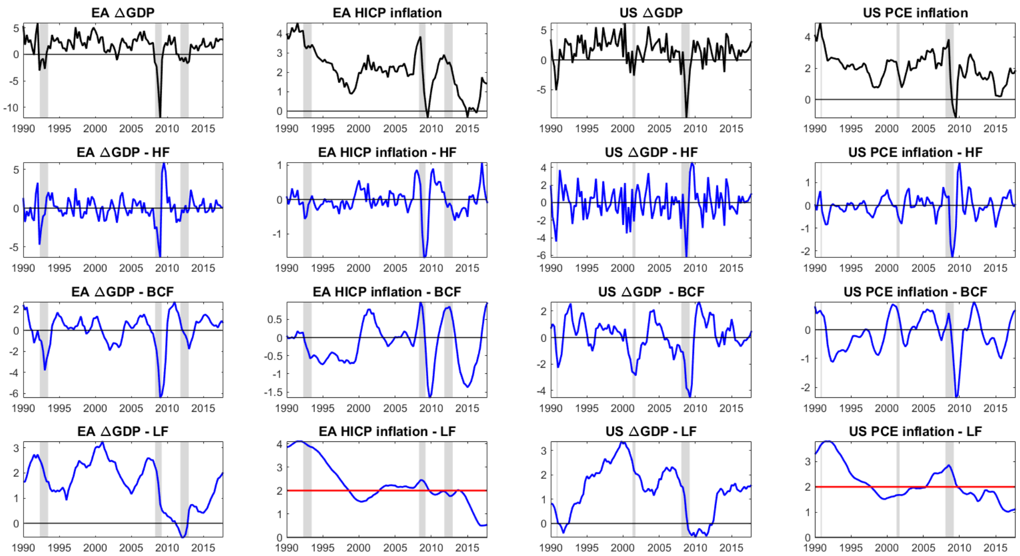

Figure 1: Time series, EA and US data, sample period 1990Q1–2017Q4

Notes. 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.

	$\text{var}(\pi)$	$\text{var}(\pi^{HF})$	$\text{var}(\pi^{BCF})$	$\text{var}(\pi^{LF})$
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. Model used: EA_NK_BGEU10. The first row reports the unconditional variances of the variables, while the remaining rows the percentage differences with respect to the values in the first row.

	Inflation			Output growth		
	HF	BCF	LF	HF	BCF	LF
Panel A: Euro Area						
Min	5	26	35	44	16	2
Mean	11	37	51	65	28	6
Max	19	49	69	82	44	13
Data	9	27	64	41	42	16
Panel B: United States						
Min	1	3	22	35	6	1
Mean	9	33	58	63	29	8
Max	31	51	95	93	49	30
Data	21	37	42	51	31	17

Table 2: ANOVA - data and DSGE models
Notes. Sample period: 1990Q1–2017Q4. Percentages may not add up to 100 due to rounding. 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.

Loss functions	Individual models			Bayes rule		
	$\overline{\rho}$	$\overline{\alpha_\pi}$	$\overline{\alpha_y}$	ρ	α_π	α_y
Panel A: EA						
$\text{var}(\pi)$	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 $0.5\,\text{var}(\Delta r)$.

Panel A: EA									
Loss functions	Bayes rule			Best data fit			Worst data fit		
	ρ	α_π	α_y	ρ	α_π	α_y	ρ	α_π	α_y
$\text{var}(\pi)$	0.9	0.8	0.1	0.9	1	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 4: 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 $0.5\,\text{var}(\Delta r)$.

Loss functions	Bayes 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
$\mathrm{var}(\pi)$	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
$\mathrm{var}(\pi^{BCF})$	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
$\mathrm{var}(\pi^{LF})$	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
$\mathrm{var}(\pi^{BCF})+\mathrm{var}(\pi^{LF})$	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
$\mathrm{var}(\pi)+\mathrm{var}(\Delta y)$	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
$\mathrm{var}(\pi^{BCF})+\mathrm{var}(\Delta y^{BCF})$	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
$\mathrm{var}(\pi^{LF})+\mathrm{var}(\Delta y^{BCF})$	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
$\mathrm{var}(\pi^{BCF})+\mathrm{var}(\pi^{LF})+\mathrm{var}(\Delta y^{BCF})$	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 5: Model-robust monetary policy rules of models with different features

Notes. This simulation is only performed for the US. 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 $0.5\,\mathrm{var}(\Delta r)$.

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 6: Model-robust monetary policy rules, robustness

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. All loss functions include the term $0.5\,\text{var}(\Delta r)$.

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 7: Key features of models used

Note. 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. Distribution of optimal model-specific coefficients

Figure 2 shows the distribution of optimal model-specific coefficients for the EA and US. A similar pattern can be observed for both regions. If the policymaker wants to stabilize aggregate inflation and output growth in the loss function (left panel), the median of optimal inflation coefficient is approximately 1 with a narrow lower quantile, while the upper quantile is larger, especially for the US. There are also outliers at the upper bound. Although (in line with Bayes results) the average of the optimal inflation coefficient decreases if the policymaker considers only the BCF fluctuations of inflation and output growth in the loss function (right panel), this is only barely visible in the boxplot with the upper and lower quantile slightly decreasing (and, for the US, the upper tail even increases).

Optimal output growth coefficients have a median between 1 and 1.5 (left panel) and are distributed across the whole range of the grid with a larger focus on the upper bound. Considering only the BCF fluctuations in the loss function (right panel), output growth parameters behaves in accordance with average coefficients. In particular, for the EA the median and lower quantile decrease, while for the US the whole distribution shifts downwards, such that the cluster at the upper bound vanishes.

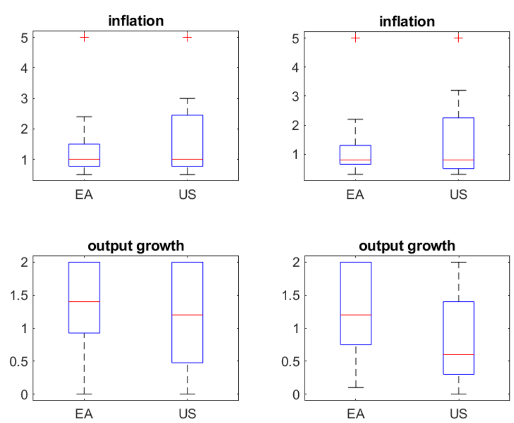

Figure 2: Boxplot of optimal model-specific coefficients
Notes. The left panel depicts the distribution of the coefficients for loss function var(π) +var(Δy) and the right panel for loss function var(π^{BCF}) +var(Δy^{BCF}).

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 (see Tables 8 and 9 for the EA and US). We report the model volatilities under the three different Taylor rules. The first one is the original Taylor rule of the respective model, the second one is the optimal Taylor rule for that model, and the third one is the optimal model-robust rule which is common across models.

For both regions, the original Taylor rules imply substantial heterogeneous inflation volatilities. There are some models with small and some with slightly higher volatilities, but for both regions some volatilities are large (up to 105 for inflation and 20 for output growth). In general, volatilities based on the original Taylor rules are significantly larger than for the optimal (model-specific and model-robust) rules and data. In other words, optimizing the Taylor rule coefficients significantly reduces these volatilities. Furthermore, implementing an optimal model-robust monetary policy rule does not distort variances of single models. Consequently, the costs of a model-robust rule are rather small. When the original variances are large, optimized rules typically improve the data fit. On the other hand, if variances are already small for the original Taylor rule, the data fit of the optimized rules usually gets worse (e.g. EA_CW05ta).

Model	Model-specific Taylor rule		Optimal model-specific Taylor rule		Optimal model-robust Taylor rule	
	var(π)	var(Δy)	var(π)	var(Δy)	var(π)	var(Δy)
EA_ALSV06	5.9	0.3	0.0	0.3	0.3	0.2
EA_CKL09	4.9	2.8	0.2	0.2	0.3	0.2
EA_CW05fm	7.4	0.3	1.3	0.7	2.4	0.5
EA_CW05ta	1.3	0.3	0.8	0.4	0.9	0.4
EA_NK_BGEU10	10	3.0	4.1	1.7	3.0	3.2
EA_PV15	58	2.3	0.0	0.2	0.2	0.1
EA_SW03	1.4	0.4	0.5	0.3	0.5	0.3
EA_SWW14	2.3	6.6	0.6	0.4	0.6	0.4
EA_VI16bgg	19	7.5	0.9	0.9	1.2	0.6
EA data	1.2	0.3	1.2	0.3	1.2	0.3

Table 8: Variances, EA models and data

Notes. Sample period: 1990Q1–2017Q4. Unconditional variances of the target variables in the EA models when the policymaker commits to using either the original,the optimal model-specific or the optimal model-robust rule for a loss function including aggregate inflation and output growth.

Model	Model-specific Taylor rule		Optimal model-specific Taylor rule		Optimal model-robust Taylor rule	
	var(π)	var(Δy)	var(π)	var(Δy)	var(π)	var(Δy)
US_ACELm	2.1	0.4	0.0	0.0	0.0	0.1
US_ACELswm	2.0	0.5	0.0	0.0	0.0	0.0
US_BKM12	1.4	18	0.1	0.2	0.1	0.3
US_CD08	1.4	0.8	0.0	0.4	0.1	0.4
US_CFOP14	5.9	1.3	0.8	0.8	1.0	0.7
US_CPS10	5.1	0.4	4.2	0.3	4.3	0.3
US_DG08	11	3.5	0.4	0.7	0.4	0.8
US_DNGS15_SWpi	7.1	8.9	0.6	5.4	0.6	5.4
US_FMS13	8.3	4.0	2.1	2.6	1.6	3.4
US_FU19	4.8	12	0.4	0.3	0.3	0.6
US_HL16	16	1.2	0.2	1.4	1.1	1.2
US_IAC05	4.8	20	0.5	0.7	0.3	1.3
US_IR04	7.7	6.1	0.1	0.5	0.1	0.4
US_JPT11	73	3.7	1.7	5.7	3.4	4.6
US_KS15	0.7	0.6	0.0	0.4	0.1	0.4
US_LWY13	8.4	4.0	1.1	1.0	0.8	1.4
US_NK_BGUS10	5.3	5.6	1.4	1.3	0.8	2.4
US_NK_CFP10	13	8.8	0.5	1.1	0.5	1.1
US_NK_CK08	0.6	1.0	0.4	0.2	0.4	0.2
US_NK_GK09lin	105	13	0.1	0.6	0.2	0.5
US_NK_KRS12	13	1.3	0.1	0.5	0.3	0.4
US_NK_PP17	1.7	2.6	0.0	0.2	0.1	0.2
US_NK_RA16	24	4.4	0.1	0.8	0.1	0.7
US_NK_RW97	0.1	5.0	0.1	0.3	0.1	0.5
US_PM08	2.3	0.3	0.7	0.4	0.6	0.7
US_PM08fl	1.9	0.3	0.5	0.4	0.5	0.4
US_SW07	8.6	1.8	0.6	1.0	0.6	1.0
US_VI16bgg	3.7	5.0	0.6	0.4	0.4	0.7
US_YR13	46	3.2	0.3	0.6	0.3	0.5
US data	1.0	0.4	1.0	0.4	1.0	0.4

Table 9: Variances, US models and data

Notes. Sample period: 1990Q1–2017Q4. Unconditional variances of the target variables in the US models when the policymaker commits to using either the original, the optimal model-specific or the optimal model-robust rule for a loss function including aggregate inflation and output growth.

Appendix E. Alternative approaches to computing robust rules

Besides Bayesian 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:

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

and there exists a unique and stable equilibrium $\forall m \in M$. Results are displayed in columns 4 to 6 of Table 10.[15] For the EA, results are broadly in line with the Bayes 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.

[15] The last three columns in Table 10 show the results using minimax regret (see Brock et al., 2007).

Loss functions	Bayes rule			Minimax rule			Minimax regret rule		
	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	0.8	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 10: Bayes, minimax, and minimax regret optimal monetary policy rules

Notes. All loss functions include the term $0.5\,\text{var}(\Delta r)$.

Appendix F. ANOVA decomposition (data and DSGE models)

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 11: ANOVA (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.

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 12: ANOVA (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.

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