Joint Discussion Paper
Series in Economics

by the Universities of

Aachen · Gießen · Göttingen
Kassel · Marburg · Siegen

ISSN 1867-3678

No. 08-2020

Johannes Zahner and Jonas Gross

What's on the ECB's Mind?- Monetary Policy Before and After the Global Financial Crisis

This paper can be downloaded from
http://www.uni-marburg.de/fb02/makro/forschung/magkspapers

Coordination: Bernd Hayo • Philipps-University Marburg
School of Business and Economics • Universitätsstraße 24, D-35032 Marburg
Tel: +49-6421-2823091, Fax: +49-6421-2823088, e-mail: hayo@wiwi.uni-marburg.de

MACIE PAPER SERIES

Marburg Centre for Institutional Economics

MACIE

Nr. 2020/01

What's on the ECB's mind? – Monetary policy before and after the global financial crisis

Johannes Zahner
MACIE, Philipps-Universität Marburg

Jonas Gross
Universität Bayreuth

Marburg Centre for Institutional Economics • Coordination: Prof. Dr. Elisabeth Schulte
c/o Research Group Institutional Economics • Barfuessertor 2 • D-35037 Marburg

Phone: +49 (0) 6421-28-23196 • Fax: +49 (0) 6421-28-24858 •
www.uni-marburg.de/fb02/MACIE • macie@wiwi.uni-marburg.de

Philipps Universität Marburg

What's on the ECB's mind? – Monetary policy before and after the global financial crisis*

Jonas Gross[†]   Johannes Zahner[‡]

February 4, 2020

Abstract

This paper analyzes the interest rate setting of the European Central Bank (ECB) both before and after the outbreak of the global financial crisis. In the current monetary policy literature, researchers typically select *one* Taylor rule-based model in order to analyze the interest rate setting of central banks, but neglect uncertainty about the choice of this respective model. We apply a Bayesian model averaging (BMA) approach to extend the standard Taylor rule to account for model uncertainty driven by heterogeneity in the ECB decision-making body, the governing council. Our results suggest the following: First, the ECB acts according to its official mandate to maintain price stability and therefore to focus its decisions on the inflation rate. Second, economic activity measures have been in the focus of the ECB before the financial crisis broke out. Third, over the last decade, the role of economic activity for ECB monetary policy has decreased so that inflation seems to be the main driver of monetary policy decisions. Fourth, central bankers appear to consider more than one model when they decide about monetary policy measures.

Keywords: European Central Bank, Taylor Rule, Bayesian Model Averaging, Model Uncertainty
JEL Codes: C11, E43, D81, E52, E58

[*]We would like to thank Jesús Crespo-Cuaresma and Florian Huber for raising our interest in the topic of Bayesian model averaging. Furthermore, we are very grateful for the helpful comments by Elisabeth Schulte, Bernhard Herz, Bernd Hayo and Tim Friehe.

[†]University of Bayreuth. Email: `jonas.gross@uni-bayreuth.de`.

[‡]Corresponding author. Marburg Centre for Institutional Economics (MACIE), Philipps-University Marburg. Email: `johannes.zahner@wiwi.uni-marburg.de`. Address: Barfüßertor 2 D-35037 Marburg, Germany.

1 Introduction

"The challenge for monetary policy in practice is to retain the virtues of rule-based policy-making, while taking into account the complex, uncertain and constantly evolving environment facing monetary policy-makers." ECB (2001, p. 38)

Due to its pivotal role in monetary policy the interest rate setting of central banks is one of the most debated topics in macroeconomics. As indicated in the quote above, the European Central Bank (ECB) advocates a rule-based approach when setting interest rates – while retaining room for discretionary intervention. Researchers mainly apply the so-called Taylor rule in order to analyze the central bank's interest rate setting (see Taylor (1993)). The rule states that data for the inflation rate and economic activity can well approximate the short-term interest rate set by a central bank. Various studies suggest that this simple rule is a powerful tool to approximate central bank interest rates under special conditions (see, e.g., Sturm and Wollmershäuser (2008)).

However, there are various reasons why applying a standard Taylor rule could yield misleading policy implications. First, it seems far-fetched to restrict decision-makers to a monetary policy rule, in which only two determinants are assumed to explain the real economy. Vítor Constâncio, former vice president of the ECB, argues that "*the environment in which monetary policy-makers have to act is much more complex than what is assumed in model-based analysis of policy rules*" (see ECB (2017)). He adds that "*a simple rule that responds to one or two macroeconomic variables and ignores all other indicators of price developments is not able to account for the complexities of the real world.*"

Second, interest rate decisions are accompanied by incomplete data and uncertainties about the actual state of the economy. For example, an increase in the inflation rate per se does not indicate whether the increase is temporary or permanent. It may be due to structural factors or to temporary reasons, such as a rise in oil prices. However, this distinction is important for central bankers since it implies different monetary policy reactions. Hence, central bankers might analyze a variety of different economic variables and indicators – besides the inflation rate and economic activity – to obtain more precise information about the state of the economy and to set interest rates accordingly (see Milani (2002)).

Third, ECB central bankers can be suspected of having more than one model in mind of how the economy functions in reality. The interest setting body of the ECB, the Governing Council, consists of the presidents of the national central banks of the Euro Area countries and the Executive Board. These central bankers have different cultural backgrounds, which might affect their attitude towards the inclusion and relevance of certain variables such as inflation, economic activity, etc. Depending on the country's previous experience with inflation, these central bankers may place different weights on the importance of inflation. An extreme example could be Germany, which suffered heavily as a result of hyperinflation in the last century, leading the German central bank to adopt a policy with a strong emphasis on stable prices. Another source of heterogeneity might be the different professional backgrounds of the Governing Council members – from economists to lawyers and former politicians. Those experiences could have an effect on the perception of the respective central bankers about how the economy works. To summarize, the members of the ECB Governing Council are heterogeneous with respect to their social, political and academic backgrounds. This leads to different conceptions about the transmission of shocks and the interaction of economic agents. These differences might yield deviating policy implications and interest rate recommendations. Therefore, we argue that a standard Taylor rule should be extended to analyze the interest rate setting of central banks more precisely and to avoid misleading inferences.

In this paper, we add a wide range of variables to the standard Taylor rule that potentially impact the ECB interest rate. We analyze the interest rate setting of the ECB and estimate broad central bank reaction functions. Our goal is to enrich the monetary policy literature by accounting for two key factors: Uncertainty about the form of the central bankers' reaction functions and uncertainty about the size of the coefficients included in the specific reaction functions. Therefore, we account for heterogeneous reaction functions of central bankers' with respect to the included variables per se and also with respect to the magnitude of the included variables. In addition, we consider a potential structural change in the reaction function around the outbreak of the global financial crisis. In our analysis, we use real-time data and insights stemming from textual analysis of ECB press conference statements.

We employ an empirical Bayesian model averaging (BMA) approach, which allows us to extend the standard Taylor rule and to evaluate $2^{15} \sim 33.000$ model combinations of potential determinants. We consider a variety of possible influence factors and evaluate all model combinations with respect to the observed data to determine the most likely models and, thus, the ECB's most likely interest rate determinants. Further, we assess the economic relevance of each indicator. Applying BMA in the context of ECB's monetary policy is – to the best of our knowledge – a novel approach and addresses a gap in the current literature.

The key findings are as follows: First, ECB acts in accordance with its official mandate to maintain price stability and thus focuses its decisions mainly on the Harmonized Index of Consumer Prices (HICP) inflation rate. Second, economic activity seems to be a key priority for the central bank prior to the financial crisis. Third, the importance of economic activity in ECB monetary policy decision seems to have decreased over the past decade, so that inflation tends to be the driving force of monetary policy decisions from 2008 onwards. Fourth, central bankers tend to consider more than one model, when determining monetary-policy measures. This finding supports the necessity to use model averaging techniques when studying ECB's interest rate setting in order to take model uncertainty into account.

This paper is structured as follows: In the following section, the variables potentially influencing the ECB interest rate are discussed. The variables are identified by a literature review and a textual analysis of ECB communication. Furthermore, we describe the motivation behind considering model uncertainty in the context of a central bank reaction function. In section three, the BMA approach is explained, and different prior specifications within the Bayesian framework are discussed. In section four, the estimation results are explained in detail, and robustness checks are conducted. The last section concludes the paper.

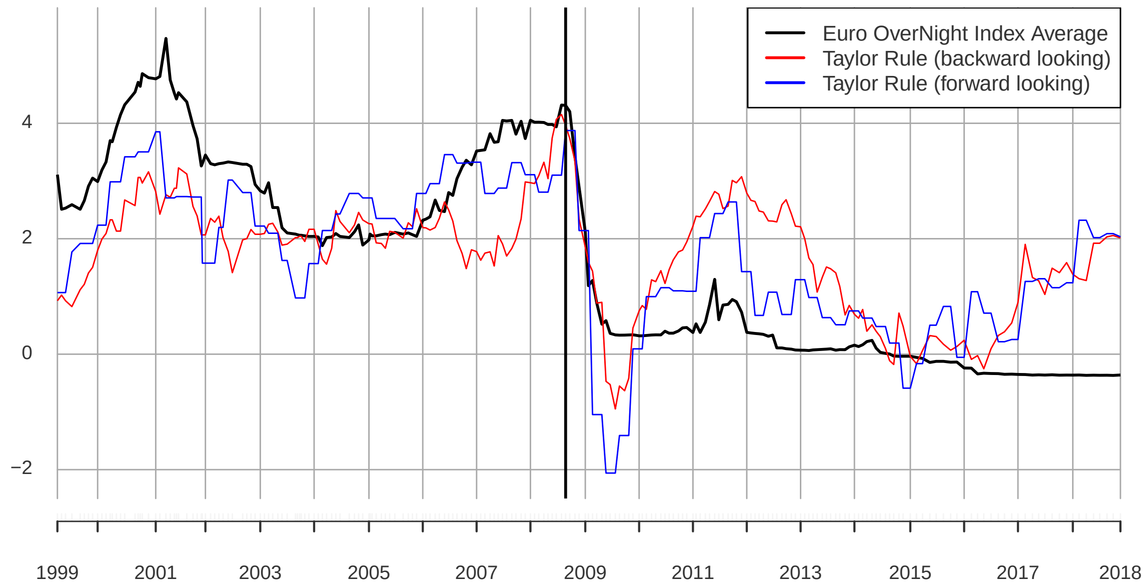
2 Monetary policy with a wide information set

In 1993, John Taylor proposed that the inflation rate and a measure of economic activity can well describe the short-term interest rates set by central banks.[1] Quite surprisingly, this standard Taylor rule has provided a relatively good fit of the actual interest rate path of the Federal Reserve (Fed) as well as of the ECB (Gerdesmeier and Roffia (2004); see Sturm and Wollmershäuser (2008)). In Figure 1, we compare the actual ECB interest rate and its Taylor rule-based approximations for the period 1999 until 2018.[2] We measure

[1]Note that the real interest rate is assumed to be constant (as in Taylor (1993)).

[2]The corresponding regression table for this in sample prediction can be found in appendix A.1.

Figure 1: Comparison of the actual and Taylor rule-approximated ECB interest rate



the ECB's interest rate by the Euro OverNight Index Average (EONIA) rate and use two Taylor rule-based interest rate approximations as comparisons: one calculated using actual inflation and output (red line) and one with expected inflation and expected output (blue line).[3] Two main conclusions can be drawn from Figure 1. First, while both Taylor rules appear to be (relatively) good at approximating the short-term interest rate until the crisis emerges, there are small variations between the actual and the approximated interest rates. Second, after the outbreak of the financial crisis in 2008, the variations have become more severe, suggesting a more restrictive monetary policy stance than actually conducted by the ECB. The divergence between the actual interest rate and the Taylor rule estimations provides evidence that a single reaction function based on the standard Taylor rule is not sufficient to precisely approximate the interest rate. Even if this simple rule of thumb has the merit of being relatively easy to apply and to evaluate it is unlikely that two variables capture the full information necessary to properly set interest rates.

In line with Milani (2002), we argue that the central bankers in charge do not seem to follow one single model when setting interest rates. Considering a variety of different models with a particular probability is equivalent to assume that each central banker has a model about the economy in mind and some probability that his model will be chosen to represent the aggregated governing council decision. Those models can be both overlapping and contradicting.

Furthermore, the figure indicates a time-variant shift in the central bankers' model choice after the outbreak of the global financial crisis in 2008, when the correlation between the suggested Taylor interest rate and the actual interest rate started to decrease. This substantial divergence raises the question which determinants actually drive the ECB's interest rate decision.

Note that two important aspects are beyond the scope of this paper: First, we do not examine whether these

[3]Note that conclusions derived from Taylor rules based on actual data (*backward-looking*) or based on expected data (*forward-looking*) can vary and, therefore, provide different policy implications (see e.g. Svensson (2003); Gerdesmeier and Roffia (2004)). The implications of forward- and backward-looking elements are further discussed in Section 2.1.

additional variables enter the ECB monetary policy framework on their own or as an instrument, by affecting other variables like inflation or economic activity. As a result, the findings should be interpreted with caution as to whether these determinants actually drive the decision of the ECB and can be seen as causal effects. Second, we do not claim to estimate the ”true” ECB reaction function, since the governing council interest rate discussions are not provided to the general public and are, therefore, not subject to this analysis. We analyze the perception of the public rather than the representation of private – ECB internal – information by estimating a possible reaction function using exclusively public information.

Textual analysis of ECB communication is used as an additional instrument to analyze the public perception of the monetary policy reaction function of the ECB. Analyzing introductory statements of the ECB press conferences – the official communication instrument of the central bank to the general public – provides evidence for the potential inclusion of more determinants in the monetary reaction function and for an alteration in the relevance of the 'traditional' Taylor rule determinants. A word cloud of the introductory statements (see Appendix A.2) shows that the ECB discusses myriads of different variables and indicators, each, at least implicitly, a potential indication for some reaction by central bankers to the respective variable. Even though the ECB mentions inflation and output in the introductory statements frequently, which can be seen as support for following the standard Taylor rule, those two variables do not encompass all of the attention. Other variables, e.g. related to financial stability or commodity prices are also mentioned frequently in ECB communication. Therefore, the introductory statements indicate that additional factors might play a role in the ECB interest rate setting. In the following sections, we will discuss insights from previous monetary policy literature and textual analyses to identify possible determinants for the ECB's interest rate setting.

2.1 Standard Taylor rule

Inflation and output According to its official mandate, the ECB's main objective is to maintain price stability (see Article 127 §1 of the Treaty on the Functioning of the European Union). Since 2003, price stability is defined as a medium-term annual growth of the HICP of below but close to two percent (see ECB (2019)). Consequently, according to its official mandate, the ECB should focus on the inflation rate when setting interest rates. Another explicit official objective of the ECB is to support general economic policies of the European Union (EU) as a second, subordinated goal (see Article 3 of the Treaty on the Functioning of the European Union). Article 127 directed to the European System of Central Banks (ESCB) states that

> *”without prejudice to the objective of price stability, the ESCB shall support the general economic policies in the Union [...] as laid down in Article 3.”*

This target is often interpreted as considering economic activity or output data when setting interest rates. Due to their pivotal role, it is not surprising that the terms ”inflation” and ”output” are heavily used in the communication of the ECB. They account for more than 1.3% of all terms in press conference statements, where ”inflation” is mentioned almost 2,000 times and economic activity 142 times. Therefore, we suspect that inflation and output is included in ECB's reaction functions.

However, the actual indicators for both measuring inflation and output are heavily discussed. While many studies use actual data for inflation and output for their Taylor rule estimates, Svensson (2003) argued that a standard Taylor rule focusing on backward-looking data would not be optimal in a reasonable macroeconomic model. According to Svensson (2003) monetary policy should focus on expectations as interest rate changes affect inflation and output with a sizable lag. As a consequence, forward-looking data has been used in Sauer and Sturm (2007) and Gerlach (2007). Further, it is ambiguous whether ECB focuses on HICP inflation, the more stable core inflation (see Gerlach (2007)) – an aggregate inflation measurement that excludes energy, food, alcohol, and tobacco – or commodity prices. Since we are interested in a wide set of information, none of the potential regressors is preliminarily excluded. In our analysis, we utilize backward-looking and forward-looking inflation and output as well as core inflation, and commodity prices.

Unemployment The ECB – in contrast to the Fed – has no direct unemployment target. However, the Treaty on the Functioning of the European Union specified an objective concerning a high level of employment. Article 3 defines full employment as one goal of the EU. This objective is one reason why a Euro Area-wide unemployment rate could be relevant for the ECB's interest rate decision. Another reason is that the state of the labor market can be interpreted as an indicator of economic activity. For example, Molodtsova and Papell (2012) use unemployment instead of the output gap as an indicator of economic activity. Textual analysis supports the importance of unemployment revealing frequent use of terms related to the labor market. Terms containing the word "employment" are mentioned more than three times as often as the terms "production" or "output" (429 times). Such a high frequency indicates a potential relevance of the labor market.

2.2 Financial stability

One of the most prominent extensions of the standard Taylor rule is with respect to financial stability (see e.g. Kaefer (2014)). ECB press conferences suggest the importance of financial stability by mentioning financial stability more than 50 times. Financial stability is often regarded as a public good (see Allen and Wood (2006)) and the ECB as a regulator might be a suitable institution to target financial stability. However, it is challenging to select one specific measure of financial stability. In this paper, we follow the approach by Kaefer (2014). Kaefer identified various channels through which financial stability could influence the ECB's interest rate setting: exchange rates, asset prices, and credit measures.

Exchange rate Exchange rate movements can impact economies and affect financial stability. In the case of an appreciation, exporters become less competitive, which in turn drives a decline in output and inflation. The appreciation yields capital inflows to domestic capital markets potentially leading to asset bubbles. Companies holding the appreciated currency are burdened, and consumers might adjust inflation expectations. The exchange rate is mentioned more than 100 times by the ECB.

Stock prices The inclusion of stock prices in our regression follows a similar argumentation as the inclusion of the exchange rate. A justified increase in asset prices can lead to a rise in output and inflation through increased consumption and investments. Moreover, asset prices can include relevant information about future inflationary pressures. An unjustified increase in asset prices, on the other hand, can result in bubbles that threaten financial stability. Stock market prices play an important role in the ECB communication as well, as the term "stock prices" has appeared more than 170 times in ECB communication.
Another question is whether central bankers consider absolute measures – e.g., the stock market price – or

volatility measures. Periods of high volatility could have an impact on growth and inflation through financial intermediaries' balance sheets. Bleich, Fendel, and Rülke (2013) propose to use an asset price volatility measure as a proxy for financial market stress. The possible influence of volatility measures led researchers to use market volatility as a measurement of financial stability (see Albulescu, Goyeau, and Pépin (2013)). Since we are interested in a wide information set, we include stock market prices as well as market volatility measures.

Credit measures Credit growth can be suspected to impact financial stability via two channels: First, asset bubbles could emerge if excessive credit is invested in asset markets. Second, credit-based consumption and investment could lead to a non-sustainable level of debt, which could negatively influence economic activity. The term ”credit” is mentioned more than 600 times in ECB's communication.

Financial stability indicator The global financial crisis has revealed that instabilities in the financial sector can have a major impact on financial stability and therefore on the real economy and monetary policy. Hollo, Kremer, and Duca (2012) have constructed an indicator for measuring systemic risk in the financial sector and contemporaneous stability in the financial system, the so-called Composite Index of Systemic Stress (CISS). It aggregates information about the current instability of the financial system, as well as the level of frictions, stress, and strain in a single indicator. The CISS can be seen as a measure to monitor the financial sector in real-time. ”Stress” is mentioned almost 30 times in ECB communication.

2.3 Further indicators

Money supply One important component of ECB's monetary policy strategy is the monetary analysis, in which the ECB assesses the developments of monetary aggregates. An expansion in the money base is expected to drive inflation in the long-run (see Friedman (1963); Belke and Klose (2010)). Therefore, it seems reasonable to include money supply as a possible determinant of ECB monetary policy and it is mentioned more than 500 times in ECB communication.

Government bond yield Opponents criticize the ECB for its expansionary monetary policy measures and argue that these policy measures have mainly been implemented to ease refinancing conditions of Euro Area countries. An interest rate cut works as a stimulus for the economy as the interest rate burden decreases due to a decline in the government bond yield. Castro (2011) argues that the relevance of government bond yields arises from their impact on financial stability.
Furthermore, Roskelley (2016) stresses the forward-looking macroeconomic information, which is contained in the government bond market. Terms such as ”government debt”, ”government deficit”, and ”government bond” are mentioned more than 100 times in the ECB press conferences. Consequently, government bond yields are included in our regression.

Political and economic uncertainty From a central bank's perspective, uncertainty is undesirable, as it can lead to ineffective monetary policy measures. In particular, political and economic uncertainty could encourage individuals to postpone investment and consumption decisions. Aastveit, Natvik, and Sola (2013) argue that individuals react more cautiously to central bank interest rate decisions when a high degree of uncertainty is present. In order to ensure an effective monetary policy, central banks have to act more aggressively to achieve their objectives. Philip Lane, the chief economist of the ECB, argues that uncertainty can affect the wage-setting of companies (see Lane (2019)). Due to its potential impact, a measure of political and economic uncertainty in the Euro Area is included as a possible determinant.

Trade deficit Recent political events have brought trade-related aspects into the focus of monetary policy. The ECB mentions trade-related phrases almost 70 times. As global imbalances are mainly reflected in the trade balance, the high trade deficit in the US indicates a high degree of global imbalances with the rest of the world. Obstfeld and Rogoff (2005) and Ferrero, Gertler, and Svensson (2008) argue that a trade deficit will yield a future real depreciation of the currency. Hence, the trade balance can be suspected to carry information about future exchange rate adjustments and can be a source of inflationary pressures.

Note that we neglect interest rate smoothing and do not consider the previous ECB interest rate as a possible determinant of the actual interest rate. The intuition behind this approach is the assumption that the central bank monitors a variety of different indicators and variables when setting interest rates. The central bank, therefore, reacts to different signals – positive or negative –, which might provide mixed policy implications indicating a smooth interest rate response. Milani (2002) argues that *"the explicit introduction of a wider information set is [...] itself a cause of interest rate smoothness"*. Therefore, interest rates are inert due to the incorporation of a wide information set and changes between two subsequent periods are mainly small.[4] In summary, we identified and discussed a high amount of potential relevant determinants for the ECB interest rate setting. An overview can be found in Appendix A.3.

3 Methodology

3.1 Overview

The primary objective of this paper is to analyze the ECB's interest rate setting under the assumption that central bankers consider a wide set of different variables. Using the empirical Bayesian model averaging (BMA) approach allows to assess and evaluate every feasible model combination that can be constructed from a predefined dataset based on the potentially relevant variables identified in Section 2. In this section, we briefly summarize the methodology of BMA.[5]

The BMA approach works as follows: First, we specified the ECB short-term interest rate as the dependent variable y.[6] Second, we chose a set of independent variables, which are suspected to influence the dependent variable, the matrix Z. The matrix Z consists of all potential regressors that have been identified and discussed in Section 2. Third, we performed the actual BMA estimation and analyzed and evaluated all possible linear

[4]This hypothesis is later supported by Figure 6 plotting the BMA-based estimated monetary policy reaction function, mainly indicating a smooth interest rate path.

[5]We refer the interested reader to more comprehensive BMA literature such as Fernandez, Ley, and Steel (2001), Milani (2002), Zeugner and Feldkircher (2015) and Moral-Benito (2010). We mainly follow the notation of Moral-Benito.

[6]Throughout the paper, the EONIA rate is used as the central bank benchmark interest rate. The results do not change remarkably if the MRO rate is applied as the respective central bank interest rate. For a discussion about the different central bank interest rates see Section 4.

combinations of these regressors.[7] As a consequence of examining all model candidates, uncertainty about the (subjective) choice of the ”true model” vanishes as not only one single model is analyzed, but rather all possible model combinations. For every model, the regression coefficients captured in the vector $\hat{\beta}$ are estimated via Bayesian techniques. As a last step, we computed an average coefficient estimate weighted by the respective likelihood of the model. This vector of average coefficients $\hat{\beta}_{BMA}$ can be expressed as

$$\hat{\beta}_{BMA} = \sum_{j=1}^{2^k} \hat{\beta}^j w^j, \tag{1}$$

where $\hat{\beta^j}$ is the coefficient estimate of model j and w^j is the weight. In the following, $\hat{\beta}$ is referred to as the posterior probability and w as the posterior model probability.

3.2 Bayesian model averaging

In this paper, the following linear model is considered:

$$y_t = Z_t'\beta + \varepsilon \tag{2}$$

$$\varepsilon \sim N(0, \sigma^2)$$

where y_t is the interest rate at time t and Z_t is a vector of k explanatory variables. β is the k-dimensional vector of regression coefficients and ε is a vector of error terms, which follows an univariate normal distribution with zero mean and variance σ^2. This distributional assumption is in line with the BMA literature (see e.g., Zeugner and Feldkircher (2015); Moral-Benito (2010)).

With k being the amount of possible regressors, we observe model space $M = \{M_j : j = 1, ..., 2^k\}$ and coefficients $\beta = \{\beta^j : j = 1, ..., 2^k\}$ with each model j having k individual beta coefficients. By applying Bayes rule, the posterior probability – the distribution of the estimated coefficient vector conditional on one specific model j and the underlying data – can be derived as follows:

$$p(\beta^j | y, M_j) = \frac{p(y|\beta^j, M_j)p(\beta^j|M_j)}{p(y|M_j)}. \tag{3}$$

Equation (3) states that the posterior probability $p(\beta^j|y, M_j)$ is calculated by multiplying the likelihood $p(y|\beta^j, M_j)$ with the probability $p(\beta^j|M_j)$ and dividing by the marginal likelihood $p(y|M_j)$.[8] Note that the marginal likelihood is constant over all models and is a multiplicative term. Thus, the marginal likelihood is not in the focus of our analysis since it does not depend on β, which we seek to examine in this paper.

The inclusion of own information – so-called priors – into the regression framework is one of the key features of Bayesian methods. In this way, a researcher defines assumptions about the distribution, e.g., of a coefficient or a model space, before observing the data. Note that the choice of priors expresses subjective beliefs and has to be set with caution. In this paper, $p(\beta^j|M_j)$ is referred to as the prior on the parameter space and expresses the belief about the probability distribution of β^j. In Section 3.3, different model prior specifications are

[7] Note that the integration of interaction terms or other non-linear parameters is still an open research topic in BMA and, therefore, excluded from our analysis.

[8] Note that $p(y|M_j) = \sum_{s=1}^{2^k} p(y|\beta^s, M_s)p(\beta^s|M_s)$.

discussed.

In the previous paragraphs, the posterior distribution for one particular model has been considered. To aggregate the posterior distributions of the whole model space as a next step, an aggregation weight w^j has to be specified. The posterior model probability $p(M_j|y)$ is used as a weight, since it indicates the degree of support for model M_j. Applying Bayes rule, yields the following posterior model probability:

$$w_h = p(M_j|y) = \frac{p(y|M_j)p(M_j)}{p(y)} = \frac{p(y|M_j)p(M_j)}{\sum_{s=1}^{2^k} p(y|M_s)p(M_s)}. \tag{4}$$

Equation (4) states that the posterior model probability – the probability of selecting a specific model j – depends on the marginal likelihood $p(y|M_j)$, the marginal probability $p(M_j)$, and the integrated likelihood $p(y)$. Note that the integrated likelihood does not vary across models and is, therefore, only a multiplicative term. To compute the posterior model probability, a second prior specification regarding the distribution of the model space $p(M_j)$ is required. It expresses the researcher's belief about the probability of choosing model M_j before observing the data.

As a next step, a weighted average of all the individual posteriors probabilities is computed to obtain one full posterior distribution. As a weight, the posterior model probability from Equation (4) is used. Hence, the full posterior distribution β_{BMA} can be expressed as follows:

$$p(\beta_{BMA}|y) = \sum_{j=1}^{2^k} p(\beta^j|y,M_j)p(M_j|y). \tag{5}$$

This full posterior distribution allows us to analyze coefficient distributions across all models. In Bayesian frameworks, one does not analyze point estimates of coefficients (marginal effects) as in frequentist econometrics but coefficient distributions.

Remember that one key objective of this paper is to analyze the economic relevance of the included variables. Economic relevance is examined by estimating the expected value $E(\beta_{BMA}|y)$ and variance $V(\beta_{BMA}|y)$. Following Moral-Benito (2010) and Koop (2003), both equations for the expected value and the variance can be derived from Equation (5):

$$E(\beta_{BMA}|y) = \sum_{j=1}^{2^k} E(\beta^j|y,M_j)p(M_j|y) \tag{6}$$

$$V(\beta_{BMA}|y) = \sum_{j=1}^{2^k} V(\beta^j|y,M_j)p(M_j|y) + [E(\beta^j|y,M_j) - E(\beta^j|y)]^2 p(M_j|y) \tag{7}$$

The second objective of this paper is to identify relevant variables for the ECB interest rate. In this context, analyzing the posterior inclusion probability (PIP) is helpful as it enables the ranking of the most relevant regressors, based on how well they fit the data. The PIP for variable h can be computed as follow:

$$PIP_h = p(\beta_h \neq 0|y) = \sum_{\beta_h \neq 0} p(M_j|y). \tag{8}$$

A variable with a high PIP indicates that the variable is included in a variety of relevant models and is thus considered robust. In our analysis, we consider variables with a PIP of > 0.15 to be robust.

3.3 Definition of priors

In this section, we specify the priors on the parameter space $p(\beta^j|M_j)$ from Equation (3) and on the model space $p(M_j)$ from Equation (4).

Prior on the parameter space In the context of Bayesian priors, it is common to specify a zero mean for the distribution of the coefficient to put as less (subjective) information on the distribution of the coefficient as possible before observing the data (see Koop (2003)). Therefore, we specify a normal distribution with zero mean. For the variance, we apply the g-prior proposed in Zellner (1986), who introduced an additional parameter g into the variance structure.[9] The vector of the estimated coefficients β of model j follows the following normal distribution[10]:

$$\beta^j|\sigma^2, M_j, g, X \sim N(0, \sigma^2 g(X_j'X_j)^{-1}) \tag{9}$$

In line with the BMA literature, the standard deviation parameter σ is assumed to be equal in all models and is set as an uninformative prior, as proposed in Fernandez, Ley, and Steel (2001) and Zeugner and Feldkircher (2015)[11]:

$$p(\sigma) \propto \frac{1}{\sigma} \tag{10}$$

The expected value of β^j of the resulting t-distribution conditional on model M_j and the g-prior specification can be expressed as follows (see Zeugner and Feldkircher (2015)):

$$E(\beta^j|M_j, g) = \frac{g}{1+g}\hat{\beta}^j_{OLS} \tag{11}$$

Equation (11) shows that using the g-prior, the expected value of the coefficients can be expressed as a convex combination of the OLS estimator $\hat{\beta}^j_{OLS}$ and the prior mean (zero). By specifying g, the researcher indicates how much importance is put on the prior belief. In other words, it can be indicated how certain the researcher is about the belief. A small g expresses a high weight of the prior mean. In the case $g \to 0$, the expected value of the coefficient converges to the prior mean (zero) and corresponds to an uninformative prior. In the case $g \to \infty$, the estimated value approaches the OLS estimator, neglecting the prior completely. In summary, this prior structure yields a likelihood $p(y|M_j, X, g)$, which is similar to R^2 from an OLS framework and includes a penalty for large models.

Now, we turn to the specification of g. In the literature, three different possibilities are primarily considered for the specification of g, namely the Unit Information Prior (UIP) proposed by Kass and Raftery (1995) ($g = t$), the Risk Inflation Criterion (RIC) by Foster and George (1994) ($g = k^2$) and the Benchmark Prior (BRIC) by Fernandez, Ley, and Steel (2001) ($g = max(t, k^2)$). We apply the BRIC prior as it combines the UIP and the RIC priors by using the maximum g of both variants and thereby putting as little importance on the prior as

[9] The popularity of the g-prior variance specification is mainly due to the facts that (1) a closed-form solution for the posterior distributions exists, which reduces computational issues, (2) the variance of the coefficient only depends on the scaling parameter g as σ is equal in all models (see Moral-Benito (2010)), and (3) a penalty for large models is included.

[10] Note that the variance of β^j is very similar to the variance of the ordinary least squares (OLS) estimator in frequentist economics with $\sigma^2(X'X)^{-1}$.

[11] Note that the prior choice p(σ) does not influence the estimation results since σ is equal in all models and, therefore, has the same implications for every model (see Koop (2003)).

possible. We will show that the difference between the different priors is marginal, indicating that our results are quite robust for the different specifications.[12]

Prior on the model space Besides a prior on the parameter space, a prior on the model space $p(M_j)$ has to be specified. It defines the expectation about the number of regressors the researcher expects to be included in the posterior model. For example, if the prior is set to five the researcher expects the dependent variable to be most accurately explained by five independent variables. Hence, the researcher can express a preference for smaller or larger models by the choice of the prior on the model space. We assume that the model size Ξ follows a binomial distribution, specified as $\Xi \sim Bin(k, \theta)$, where θ is the prior inclusion probability for each variable in the model. Model M_j with k regressors has a prior model probability of

$$p(M_j) = \theta^{k_j}(1-\theta)^{k-k_j} \tag{12}$$

In the following, we consider two approaches for implementing the prior on the model space, namely through a binomial distribution and a binomial-beta distribution. Both priors have the advantage of being easy to implement but have the disadvantage of neglecting multicollinearity issues, meaning that the probability that a regressor will be included in a model is observed separately.[13] Therefore, the inclusion or elimination of one variable does not change the probability of any other regressors being included (see e.g., Wang (2018)). Our approach to circumvent multicollinearity issues is discussed in Section 5.

(a) Binomial (uniform) model prior Using a binomial approach, the expected model size can be expressed as:

$$E(\Xi) \equiv m = k\theta \tag{13}$$

Previous BMA literature (e.g. Milani (2002)) typically sets $\theta = 1/2$, allocating the highest probability (and the expected value) to models that contain $k/2$ variables. An alternative is to set $\theta < 1/2$. This specification increases the likelihood of smaller models and could take limitations in human cognitive abilities into account. It can be suspected that central bankers tend to consider primarily small models indicated by a single-digit amount of indicators. We implement several specifications of θ decreasing the probability for larger models.[14]

(b) Binomial-beta prior Ley and Steel (2009) criticize the standard binomial prior as it does not allow enough variability around the expected model size m and is, therefore, biased due to the subjective choice of m. Ley and Steel suggested to apply a hyperprior on the inclusion probability θ, which makes θ random, in contrast to the binomial distribution, where θ is fixed. Ley and Steel suggested to use a beta distribution for the hyperprior $\theta \sim Be(a, b)$. The use of such a binomial-beta prior leads to an expected model size of

$$E(\Xi) = m = \frac{a}{a+b}k \tag{14}$$

[12] For robustness checks, see section 6.1.

[13] Multicollinearity can lead to outcomes that highly correlated variables are included in the models and, therefore, causes biased estimation results.

[14] Our results indicate a tendency towards small models, independent of the specification of θ.

Ley and Steel suggested to set $a = 1$ and $b = (k-m)/m$ expecting the researcher to specify – similar to the binomial prior – only the expected model size m. Choosing $m = k/2$ leads to $b = a = 1$, which yields the following flat model size probability distribution (see Ley and Steel (2009)):

$$p(M_j) = \frac{1}{k} \tag{15}$$

Equation (15) indicates that the selected binomial-beta distribution results in a posterior probability that is equal for each model size. Thereby, it reduces the subjective influence concerning the expected model size which minimized the impact of the prior choice by the researcher. While the probability distribution is centered around the expected model size for a binomial distribution, in the case of a binomial-beta distribution, the probability distribution of the posterior is flat for all models. In our analysis, such a binomial-beta distribution is used.

4 Data

This section discusses the data used in the BMA analysis. We focus on two key aspects: the use of real-time and high frequency data. The consideration of both aspects allows a more comprehensive understanding of the perceived central banker's reaction to macroeconomic data.

Orphanides (2001) provides evidence that monetary policy findings based on revised data are inaccurate as the data used by policy-makers and researchers does not align. Each revision constitutes new information about previous data that was not available for policy-makers at that point in time. Therefore, if an interest rate decision has been made between the revision of data, the additional information might be captured in the subsequent interest rate response. Since the ECB recognizes that macroeconomic variables have been subject to significant revisions from time to time (see ECB (2010)), it is essential to use real-time information available to policy-makers at a time when monetary policy decisions have been made.

We obtain real-time data from the ECB's own Real Time Database (RTD), which aggregates time series reported primarily in the Monthly Bulletin. The data is used in its original format, and each revision is reported individually.[15] In this way, we are able to create a high frequency, real-time macroeconomic dataset since revisions take place at a high frequency and each revision represents a new observation.

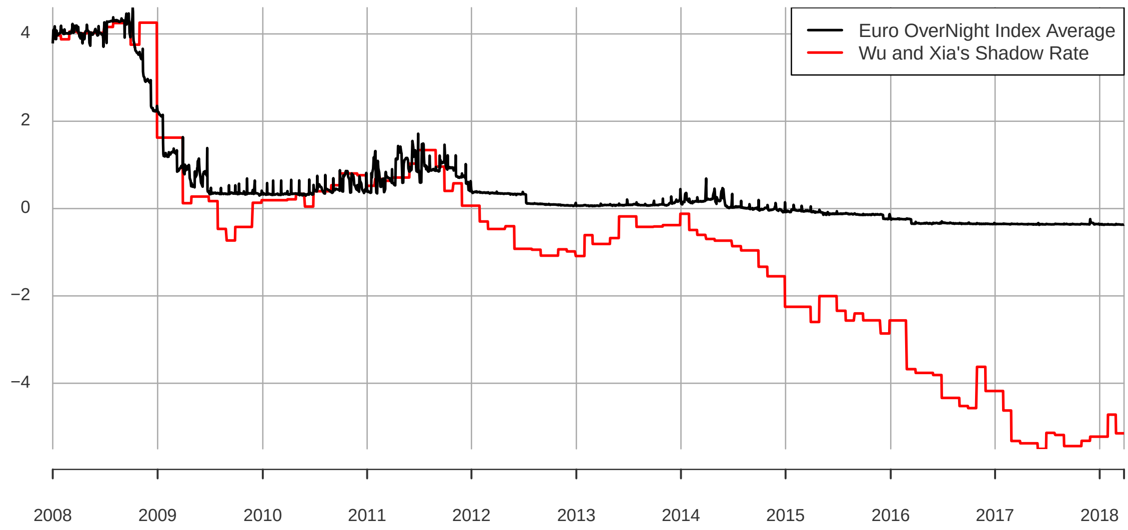
We identified three additional advantages for using the RTD dataset. First, using RTD data allows us to merge low frequency macroeconomic data such as gross domestic product (GDP) or inflation data that is only accessible on either a monthly or quarterly basis with high-frequency financial data as asset prices or exchange rate data that are accessible on very granular frequencies. Second, the fact that the information is provided by the same organization, which sets monetary policy guidelines, can be seen as an additional advantage. It seems reasonable that policy-makers primarily consider their own information. Third, the ECB usually publishes a revision of data on the day before a press conference. Therefore, the RTD contains new information for market participants on the day before the interest rate decision. Due to these three factors, we argue that RTD data represents an accurate information set for central bankers.

However, the RTD does not contain data for all the variables considered in this paper. In particular, ex-

[15] To prevent misleading information, for most data, the only transformation was to compute an annual growth to reduce stationarity. The calculation of the output gap, where a Hodrick-Prescott (HP) filter was applied, is one exception.

pectation data of macroeconomic variables, such as inflation, economic activity, or unemployment, are not accessible in the RTD. We obtain expectation data from the Survey of Professional Forecasters (SPF), which is also provided by the ECB. It aggregates unrevised expectation data about market beliefs of surveyed participants. The public availability of the release dates for the SPF information allows us to transform the expectation data into real-time data. The remaining data is obtained from various sources. The used data and their sources are shown in Appendix A.3. To decrease the extent of potential endogeneity issues, we use the information available on day $t-1$ (one day before the respective governing council meeting) in our regression on the monetary policy response on day t.

Figure 2: Comparison of the shadow rate by Wu and Xia (2016) and the EONIA rate.



After discussing data for the explanatory variables, we turn the focus on the endogenous variables used in the regression. The interest rate set by the ECB's governing council is the main refinancing operations (MRO) rate. However, the presence of the effective lower bound (ELB) and the ECB's unconventional monetary policy measures do not favor the MRO as an appropriate representation of the short-term interest rate. Instead, we – in line with the literature – propose two alternatives to circumvent this restriction. First, we consider the EONIA rate because it is the most relevant interest rate for financial institutions and has been heavily applied as a benchmark rate in Taylor rules (see, e.g. Fendel and Frenkel (2006), Castro (2011)). The EONIA has the advantage of a higher variance than the MRO and includes – to a certain extent – information about unconventional monetary policy measures. The EONIA rate is used as the endogenous variable before the outbreak of the financial crisis.

In recent years, the Wu and Xia shadow rate (see Wu and Xia (2016)) is heavily applied as an alternative to the MRO and the EONIA rate, since it captures additional information from unconventional monetary policy measures such as forward guidance or asset purchase programs. In Figure 2, both the EONIA rate and the shadow rate are plotted. The figure highlights only minor deviations between the two rates from 2008 until 2011. However, the divergence between the two rates strongly increased from 2011 onwards – with the EONIA restricted by the ELB – and reached a gap of more than five percentage points from 2017 onwards.

Table 1: Benchmark regression results

	1999 – 2018		*1999 – 2008*		*2008 – 2018*	
	PIP	Post Mean	PIP	Post Mean	PIP	Post Mean
HICP Inflation Rate	1.000	1.095 (0.169)	0.736	0.313 (0.216)	0.941	0.776 (0.273)
Unemployment (expected)	1.000	-0.666 (0.111)	0.239	-0.068 (0.136)		
Output Gap (expected)			0.986	1.708 (0.438)		
Output Gap (actual)			0.967	0.500 (0.179)		
Observations		216		114		102

Notes: Only robust variables with a PIP ≥ 0.15 *are presented.*

The shadow rate is applied as the dependent variable for the period after the outbreak of the global financial crisis when unconventional monetary policy measures have been introduced. We set the date for the outbreak of the financial crisis to September 15th, 2008. On this day, the bankruptcy of Lehman Brothers was officially declared.

5 Results

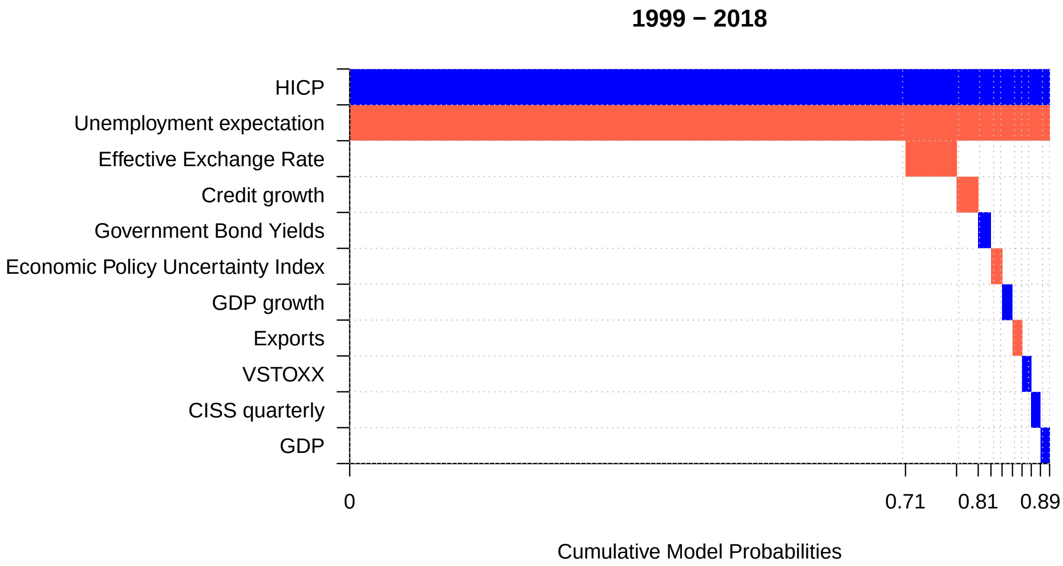
In the following section, the main results of the BMA analysis are discussed. For the estimation, we use the BRIC g-prior as the prior on the parameter space and a flat binomial-beta distribution with the parameter $a = b = 1$ for the prior on the model space. Remember that these specifications have been chosen in order to put as little (subjective) information on the prior as possible. As described in Section 4, the EONIA rate and the Wu and Xia shadow rate have been combined as the dependent variable. As we will discuss in the next chapter, our main findings are robust across different prior specifications. We run the regressions in R, utilizing the BMS package by Zeugner and Feldkircher (2015).

To account for multicollinearity, we applied a method used in Cuaresma and Slacik (2009) and neglected all regressors with a correlation higher than $|0.6|$.[16] In total, we estimated $2^k = 2^{15} \approx 33,000$ different models for the time period from April 1999 until March 2018. We aggregated the respective model-specific regression results to obtain one average effect for every regressor.

1999 – 2018 The main results of the regression are shown in Table 1. The first column states the name of the regressor, the second column shows the PIP – the aggregated probability of the models including the

[16] Actual unemployment, expected inflation, and money growth were excluded from the regression due to strong correlation. We have conducted a range of robustness checks to see if our choice has altered the outcomes. The primary findings appear to be selection independent.

Figure 3: Top ten models (Whole Period)

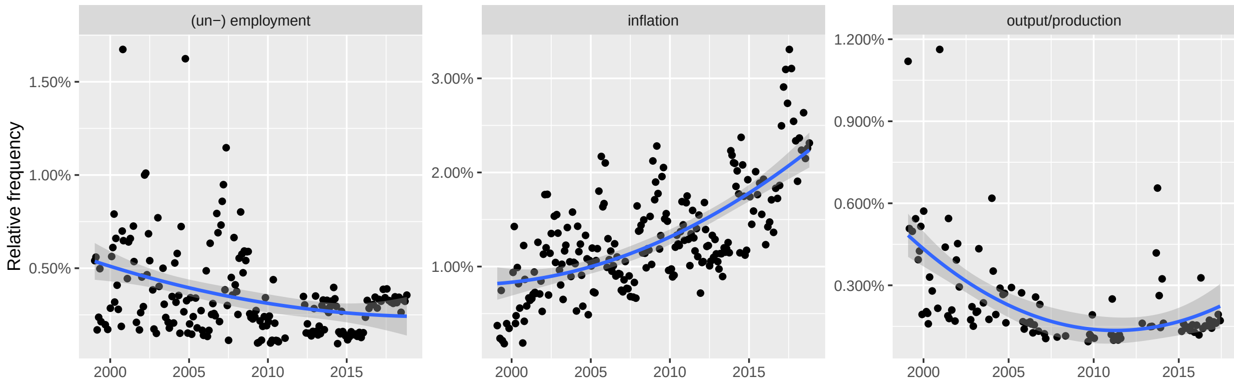


respective variable –, and the third column indicates the post mean – the average marginal effect with the standard deviations denoted in brackets. First, the whole period from 1999 until 2018 is considered, which is expressed in columns two and three. The main results are the following: First, the HICP inflation rate is included in all relevant models indicated by a PIP of 100%. This finding is not surprising since the ECB has an explicit inflation target. Therefore, the results suggest that the actual inflation rate is indeed primarily considered when the ECB sets interest rates. Put differently, the critique that the ECB does not focus enough on inflationary developments cannot be confirmed. The coefficient for the inflation rate indicates that the ECB reacts to an increase in the annual inflation rate of 1% by increasing the interest rate by 1.1%. Therefore, the result suggests that the Taylor principle is fulfilled indicating that the interest response of the central bank in nominal terms lies above one and in real terms above zero (here 0.1). Second, besides the inflation rate, unemployment expectation has a PIP of 100% as well. In line with the literature, the coefficient for the expected unemployment rate is negative which indicates that the central bank reacts to an increase in the expected unemployment rate with expansionary monetary policy. Third, no further variables are considered in the majority of the models, indicated by a PIP of $> 15\%$.

In addition to the two key variables, HICP inflation and unemployment expectations, we found variables that are not robust across all model specifications but are included in specific models with particular high model probability. Figure 3 provides an overview of the ten best-performing models ranked by their respective model inclusion probability. On the vertical axis, the relevant regressors are named, and the horizontal axis shows the cumulative model probabilities. Blue color indicates a positive sign of the respective coefficient, while red color indicates a negative sign. The model that can explain the data in the most precise manner (the "topmodel") has a model probability of 0.71, meaning that one single model out of the 2^{15} different models receives 71% of the model probability. This specific model includes only the two (robust) variables inflation with a positive sign and unemployment with a negative sign. This result indicates that model probabilities are not evenly distributed across a large number of heterogeneous models. Restricting the analysis to one single model, which is a common approach in classical model-selected Taylor rules, would neglect most of these potential model probabilities. The cumulative inclusion probability increases significantly if we allow a few more determinants and use the ten best models (0.89).

1999 – 2008 A crucial question is whether the ECB has altered its monetary policy strategy after the financial crisis broke out. During times of economic unrest, other factors might be taken into account in monetary policy decisions to maintain financial stability. One way to detect a potential systemic alteration in the perceived ECB reaction function is to observe the communication of the central bank. Figure 4 illustrates the relative frequency of the previously estimated indicators – inflation and unemployment – mentioned in ECB press conferences over the last two decades. Analyzing ECB communication over time reveals that the determinants are not equally distributed over time. The figure seems to indicate a gradual shift in priorities from the original dual mandate – inflation and output/employment – to inflation targeting.

Figure 4: Frequency of ECB's determinant communication.



To account for this potential shift, we separate the time periods during and after the crisis explicitly from the period before the financial crisis.[17] For the pre-crisis period, BMA estimates are generated from 1999 until the outbreak of the crisis in 2008 using the EONIA as the dependent variable. The main results are displayed in Table 1 in columns four and five.

The key findings for the pre-crisis period are the following. First, the output gap seems to be the main determinant of the ECB interest rate. Both the expected output gap – based on forecast data – and the actual output gap – based on actual past data – are robust and significant. Both variables are included in almost all models with a PIP of 0.99 and 0.97 respectively. The sign of the output gap coefficients is positive, which is in line with economic theory: An increase in the output gap leads on average to an increase in the interest rate. The coefficient for the expected output gap is higher than the coefficient for the actual output gap indicated by a posterior mean of 1.7 (vs. 0.5). Therefore, the ECB seems to have reacted very intensively to changes of the expected output gap. This reaction is in line with the ECB's official objective to support economic activity of the Euro Area, which is done in an anti-cyclical manner. Quite interestingly, the coefficient for the actual output gap equals 0.5, which is exactly the weight Taylor has used in his initial calibration of the Taylor rule in 1993 (see Taylor (1993)). However, he includes only one measure of economic activity, which

[17]Note that we use the term "post-crisis" for the time period after the financial crises even if it actually includes both the period of the crisis itself as well as the post-crisis period.

is a key difference to our empirical results. Note that this result is also in line with the communication of the ECB. Observing output related terms in the press conferences, one can clearly see the ECB's higher focus on output prior to the financial crisis (see Figure 4).

Second, besides the output gap measures, the HICP inflation rate is again robust indicated by a PIP of 0.74 , but with a lower coefficient. The high relevance of the inflation rate should come as no surprise due to the ECB's mandate to explicitly address inflation.

Third, the unemployment rate is included in some relevant models. However, the PIP equals 0.24 indicating that the unemployment rate is only included in a minority of the models. The analysis of the top ten models (see Appendix A.4) reveals that unemployment is only included in two out of the ten models with the highest likelihood. Therefore, our results suggest that some central bankers prior to 2008 saw unemployment as an important determinant to consider in the context of monetary policy but the majority favored the output gap as a measure for economic activity. The coefficient of the unemployment rate is negative suggesting an increase in the interest rates if the unemployment rate decreases. This relation is in line with economic theory. Note that, overall, the unemployment rate coefficient is not significant.

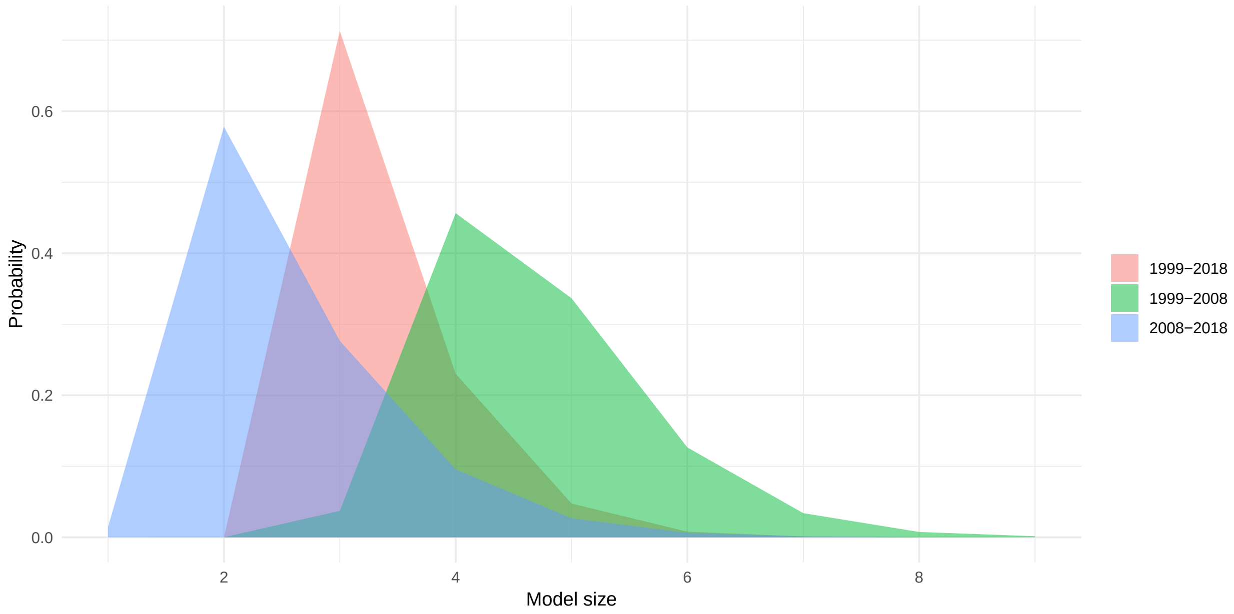
Third, further indicators, such as the exchange rate or stock market prices, only enter the minority of the models with a PIP of lower than 0.15 and are, therefore, not robust.

To summarize, the results suggest that the main determinants of ECB monetary policy for the period before the financial crisis are related to economic activity and the inflation rate. These findings are in line with the actual official mandate of the ECB to account for both the development of inflation and economic activity when setting monetary policy. However, the Treaty on the Functioning of the European Union specifies that the two objectives are hierarchical in a sense that the ECB mainly focuses on inflation and only subordinately on economic activity. This hierarchy cannot be confirmed by the results since our analysis reveals a stronger focus on economic activity than on inflation. Besides, we do not find evidence that further economic variables e.g. related to stock prices, exchange rates etc. matter for the ECB decision-making.

The model, which includes only the three most important variables – the (actual and expected) output gap and the HICP inflation rate – has a model probability of 31% (see Appendix A.4). If analyzing the ten best performing models in terms of their model probabilities it can be seen that considering these ten models, yields a cumulative model probability – an aggregated likelihood of these models – of 0.62. This result stresses that in case of model selection, where only one model specification is analyzed, the majority of the likelihood would have been neglected. Therefore, the results provide evidence to apply averaging techniques when analyzing monetary policy of the ECB in a precise manner. Further, it seems likely that central bankers do not consider one single model when they set monetary policy but a variety of different models.

2008 – 2018 Next, ECB monetary policy is analyzed in a post-crisis context for the time period after the outbreak of the financial crisis. The Wu and Xia (2016) shadow rate is used as the dependent variable as described in Section 4. The main results for the post-crisis period are displayed in Table 1 in columns six and seven. The findings suggest a potential shift in the ECB's monetary policy strategy. On the one hand, inflation stays highly robust. In the post-crisis period, the PIP is even higher and indicates that HICP inflation is included in almost all models. The sign of the coefficient is again positive – the magnitude of the coefficient is higher than in the pre-crisis period. Therefore, the results suggest that the ECB focuses more on the inflation rate after the bankruptcy of Lehman Brothers when determining the stance of monetary

Figure 5: Model sizes of the different time horizons



policy. On the other hand, none of the economic activity measures – actual and expected output gap and unemployment – seems to be relevant in the post-crisis period. For all these variables, the PIP is smaller than 0.1 indicating that the output gap is only included in a few relevant models.
The results suggest that the focus of the ECB has shifted from targeting both inflation and economic activity in the pre-crisis period to solely targeting the HICP inflation rate in the post-crisis period. This finding is strengthened by evidence from ECB communication. A textual analysis of ECB introductory statements supports this finding by showing that the ECB mentions terms related to inflation more often in the post-crisis period, while the amount of terms about economic activity has not increased.
Similar to the pre-crisis period, looking at the top ten models including eight variables in total, enables us to reach almost 80% of the cumulative model probability. The best model only includes HICP inflation and has a likelihood of 0.55. Again, the results indicate that the use of averaging methods increases the precision of ECB monetary policy analyses, even if the likelihood of one single model is higher than in the pre-crisis case.
To sum up, the criticism that the ECB does not account enough for the rate of inflation cannot be confirmed by our outcomes – neither in normal times nor in times of crisis. On the contrary, our results suggest that the ECB seems to focus its monetary policy decisions after Lehman bankruptcy mainly on developments of the HICP inflation rate, while before the financial crisis both inflation and economic measures seem to be relevant for ECB monetary policy.

Model size Inferences on the number of included regressors in the interest rate setting of ECB can be made by evaluating the distributions of the posterior model sizes. Figure 6 plots the posterior model sizes of the different BMA specifications depending on the period. The red plot refers to the period from 1999 until 2018, the green one from 1999 until 2008, and the blue one from 2008 until 2018. On the vertical axis, the model probability is shown. The horizontal axis depicts the model size.
It can be seen that the distribution of the model size does not vary substantially. Independently of the time

Table 2: Model Fit Evaluation

	Shadow Rate			EONIA		
	MSE	AIC	BIC	MSE	AIC	BIC
Taylor Rule	5.30	376.72	390.31	1.80	137.66	151.26
Taylor Rule with Expectation	4.95	361.38	374.97	1.70	125.02	138.61
BMA: One Period	3.55	302.16	339.54	0.46	-150.28	-112.90
BMA: Two Period	1.89	163.16	200.54	0.25	-287.14	-249.76

horizon considered, small models with a model size of less than two have a cumulative probability of zero. Also, large models with more than six regressors are very unlikely. Hence, a central bank is perceived that applies medium-sized models with between three and seven variables. However, the respective probability mass function and means vary depending on the time period considered. Our results suggest that, depending on the specification, the average number of determinants in the monetary policy reaction function is 1.6 (post-crisis), 2.4 (full period) and 3.7 (pre-crisis). This finding provides further evidence for a smaller number of determinants – with a higher focus on inflation – in the ECB's monetary policy reaction function after the financial crisis.

Model fit Next, the model fit of the BMA results is analyzed in form of an in sample prediction. The main results are presented in Table 2 and can be summarized as follows:

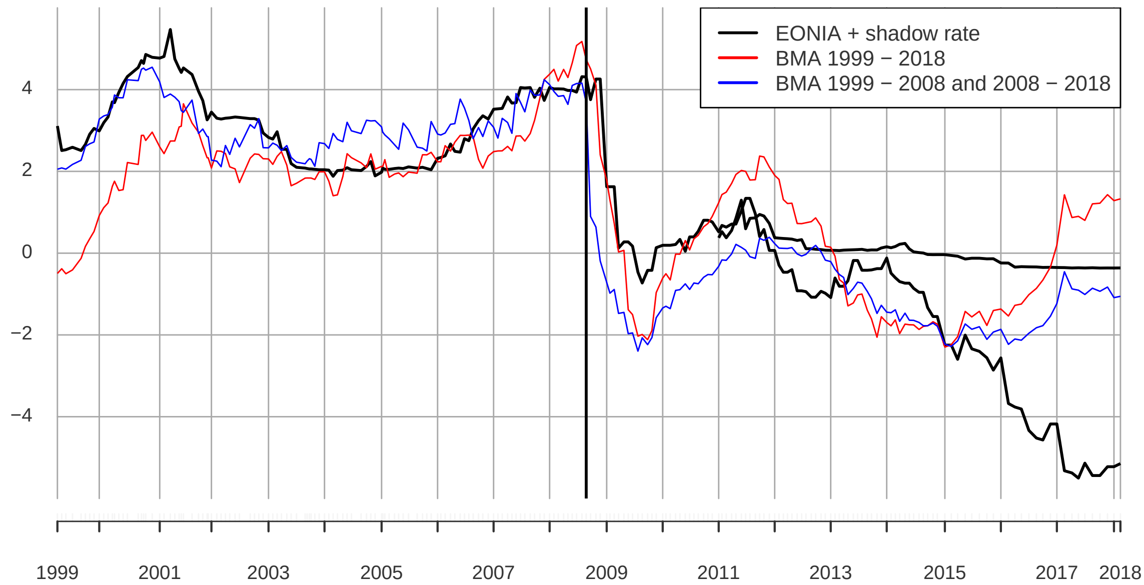
First, an improvement in explanatory power can be reached by using BMA. If we compare the BMA top ten models with the two standard Taylor rules plotted in the introduction, the goodness of fit improves between 28% and 75% according to the mean squared error (MSE) across the different specifications. While this improvement could potentially be due to overfitting, it is unlikely that overfitting is the sole driver of the better fit, since we have shown that the obtained top ten models include only a few variables. However, to further examine overfitting, we evaluate the topmodels utilizing alternative measures of goodness of fit as the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). For both criteria, we find similar improvements compared to the MSE.[18] Therefore, we argue that the demonstrated enhancement in fit is mainly due to increased information provided by the additional regressors included in the top ten models and not due to overfitting the data.

Second, the separation between pre- and post-crisis periods leads to a further substantial improvement in fit as indicated in Table 2. This finding is robust across both dependent variables, the EONIA and the shadow rate, with a decrease in the MSE by around 64%. In addition to that, we find similar improvements when controlling for the higher amount of variables in both alternative measures of goodness of fit, the AIC and BIC.

A graphical comparison of the two BMA estimations is shown in Figure 6. This figure illustrates the above mentioned improvement of the goodness of fit resulting from using BMA. Until 2016, both BMA specifications provide very similar results with little variation. However, from 2015 onwards, the BMA

[18] AIC and BIC provide more appropriate criteria for model selection compared to the MSE. A decrease in the MSE could be due to overfitting. AIC and BIC introduce a trade-off between overfitting and underfitting by including a penalty for the number of regressors. To analyze the robustness of our results, we estimate both measurements with the maximum number of possible variables instead of the actual maximum model size.

Figure 6: Comparison of BMA Taylor rule vs. actual interest rate



estimates diverged substantially. The increase in the BMA approximated interest rate for the whole period (red line) suggests more restrictive monetary policy measures over the last few years. The specification separating the whole period in the pre- and post-crisis period (blue line) supports the current expansionary monetary policy stance to a higher degree but also suggests restrictive monetary policy measures. The separated specification advocates an interest rate that would be greater than the current shadow rate, but still would lie below the ELB. One should keep in mind that inflation – the main determinant in the post-crisis period – has steadily increased since the end of 2015. This leads to the creation of both a positive trend and a divergence from the shadow rate. At the end of our observation period, the gap between our two BMA approximations is more than 2%.

6 Robustness checks

In this section, results of our robustness checks are discussed. They include the use of (1) prior modifications, (2) a varying date of the beginning of the financial crisis and (3) varying observation period and (4) the use of a different dependent variable. We conclude that our results are robust to a multitude of distinct model specifications.

6.1 Priors

As a first robustness check, the priors are altered. As mentioned in Section 3.2, the specification of priors is always a subjective choice by the researcher in the context of Bayesian econometrics. Therefore, it is essential to conduct robustness checks for different prior specifications.

Prior on the model space In the benchmark case, we have applied a binomial-beta distribution for the model prior in such a way that the probability of choosing a respective model is distributed equally in order to put as less information on the prior as possible. However, as discussed above, one can also assume that central bankers favor small models. Therefore, we applied a binomial-beta distribution putting a higher weight on smaller models.[19] Results are shown in Appendix A.5. It can be seen that the findings are very similar to those of the benchmark case. If the whole time period is considered, inflation and the expected unemployment rate turn again out to be the only robust variables. The respective posterior means of these variables tend to be almost identical. The findings do not substantially vary during the pre-crisis era, as well. The PIPs of HICP inflation, output gap and expected unemployment as well as their coefficients are quantitatively similar. The same applies to the post-crisis period, where the findings are almost identical to the benchmark scenario identifying the HICP inflation rate as the only robust variable.
To summarize, if a higher weight is put on smaller model sizes, the key findings remain the same.

Prior on the parameter space As a next robustness check, we have altered the prior on the parameter space. In the benchmark case, we adopted the BRIC g-prior as the prior on the parameter space. Remember that this prior constitutes a combination of the RIC and UIP priors. If $k^2 < N$ holds, it utilizes the RIC criteria. In our case with $k = 15$ and $N = 216$, the RIC dominates the UIP. Hence, applying the RIC rather than the BRIC does not alter the outcomes.
The results for a robustness check using the UIP prior can be seen in Appendix A.5. The findings are again almost identical with respect to the PIP and the posterior means to the benchmark case. We only find differences in posterior means at the second decimal place. To summarize, applying different priors on the model and the parameter space leads to very similar results.

6.2 Observation periods

In Section 4, we discussed the definition of the pre-crisis and post-crisis period as well as of the observation day of the independent variable. In the following robustness checks, we will demonstrate that our results hold independently of those choices.

Starting date of the crisis In our benchmark case, the beginning of the financial crisis has been set to the day of Lehman bankruptcy, where the crisis revealed its full potential and macroeconomic data indicated an upcoming recession. However, one can also date the beginning of the financial crisis 13 months earlier, precisely on August 9, 2007. On this day, the inter-banking market broke down characterized by drastic spreads indicating a high risk premium. The ECB reacted quickly and provided unlimited additional funding for banks, restricted to one day (Schnelltender; see Stark (2010)). We performed another robustness check setting August 9, 2007 as the starting date of the financial crisis. Results are shown in Table 6. Note that the findings for the entire period are not altered.
For the pre-crisis period, the robust variables are almost the same as in the benchmark case and most of PIPs, post means and post standard deviations are similar to the initial case, with two minor exceptions: The first exception is the expected unemployment rate, which was insignificant but robust in the benchmark case. In

[19]We have considered a very small model size with $m = 2$.

this robustness check, the indicator is both insignificant and not robust. The second exception is the inflation rate coefficient which decreases and becomes insignificant. However, the main findings remain the same, namely that output gap seems to be the most important determinant for the ECB monetary policy. For the post-crisis period, few small variations can be detected. First, the size of the HICP inflation coefficients increases from 0.941 to 1.000, indicating that the inflation rate is here included in all relevant models. Second, the coefficient of the inflation rate increases almost twofold, fulfilling the Taylor principle in this period.
To summarize, redefining the starting date of the crisis pronounces our main result for the post-crisis period even more, namely that inflation becomes the most relevant determinant in the post-crisis period, as the PIP and the coefficient size increases.

Exogenous observation period In the benchmark case, we observed monetary policy decisions on day t and regressed the set of exogenous variables on the interest rate at the day before the interest rate decision ($t-1$). The reason for this decision is the typical publication of macroeconomic data on the day before the governing council's meeting. In order to control for a potential influence of this choice, we reassess our benchmark case, with the regressors being observed one trading week before the decision ($t-5$).[20] The results of this robustness check are depicted in Appendix A.5.
The outcome is qualitatively and quantitatively similar. The only noteworthy differences can be seen in the pre-crisis period. Here, the PIP and the corresponding posterior means of the HICP inflation rate decrease. However, core inflation turns out to be robust and is included in some of the relevant models. Therefore, the results suggest a shift from HICP inflation to core inflation indicating that inflation in general remains relevant. Further, the importance of unemployment expectations increases indicated by an increase in the posterior mean and in the PIP. This change stresses our main finding even more that indicators of economic activity played an essential role for ECB monetary policy.

6.3 Endogenous variable

In Section 4, we discussed the endogenous variables for our analysis – the EONIA rate and the Wu and Xia shadow rate – and then addressed the benefit of using the shadow rate as our endogenous variable after the outbreak of the financial crisis. In this robustness check, we substitute the shadow rate with the EONIA rate in the post-crisis period meaning that we use the EONIA for the whole period from 1999 – 2018 as the endogenous variable.
The findings of this robustness check are shown in Table 7 in the appendix. For the whole period, the results are qualitatively very similar. However, the coefficients are – due to the current lower variance in the endogenous variable – smaller. Note that the results for the pre-crisis period remain the same. For the post-crisis period, our findings from the benchmark case seem to be qualitatively confirmed, as inflation still appears to be a main determinant of ECB monetary policy. Besides the inflation rate, the expected unemployment is robust and significant. Few other variables tend to be robust (output gap, commodity prices and core inflation), but they are either economically irrelevant or statistically insignificant.
In summary, our benchmark results appear to be robust and qualitatively independent from the selection of the endogenous variable.

[20] Lagging the variables by five trading days instead of ten or fifteen is an arbitrary choice. The aim of this specification is to exclude this last revision from the regression.

7 Conclusion

A standard Taylor rule, using inflation and economic activity data to explain the interest rate of the ECB, has lost substantial explanatory power over the last decade. Taylor rule-based approximations of the interest rate and the actual ECB interest rate have strongly diverged. This divergence might indicate that central bankers consider other variables beyond those suggested by this standard Taylor rule and employ more than one benchmark model.

In this paper, we mainly attributed this divergence to model uncertainty. We extend the standard Taylor rule by including additional possible determinants of ECB monetary policy, which are discussed in the literature, such as stock market prices or exchange rate. The main advantage of using a BMA framework is that it accounts for model uncertainty by averaging the results over the model space of all possible linear combinations of regressors This approach has – to the best of our knowledge – not been previously applied in the context of ECB monetary policy and does, therefore, address a gap in the literature. Accounting for a broad information set and analyzing a multitude of distinct models allows us to observe a perceived reaction function of the central bank. Besides, we accounted for a potential shift in the monetary policy strategy by separating pre-crisis and post-crisis periods.

Our key findings are the following. First, our results suggest that irrespective of the period analyzed, the inflation rate is a significant determinant. This result is in line with the ECB's official mandate to maintain price stability and, therefore, to consider inflationary developments in their decision-making. Second, the importance of inflation as a determinant has increased over time. In fact, for the past decade, inflation appears to be the only robust determinant in our analysis. This result appears to be in accordance with the communication provided by the ECB. Third, we find that the importance of the output gap seems to have decreased over the last decade. Fourth, central bankers appear to consider only single-digit models, which size is mostly distributed between three and seven variables. Fifth, the distribution of model probabilities shows that no single model can explain most of the observed data. This finding reaffirms using model averaging methods when evaluating monetary policy of central banks rather than selecting one single – e.g., standard Taylor rule-based – model. Nonetheless, we can explain most of the variation in the interest rate by analyzing ten models with a total of eleven variables.

This paper provides a first analysis of applying model averaging techniques for the ECB interest setting. Future research could extend the model averaging approach. First, dilution priors could be incorporated into BMA as an alternative approach to account for multicollinearity issues. Second, applying BMA to other central banks, such as the Fed or the Bank of England, could provide an interesting comparison of similarities and differences of monetary policy strategies of global central banks.

References

Aastveit, Knut, Gisle J. Natvik, and Sergio Sola (2013). *Economic uncertainty and the effectiveness of monetary policy*. Norges Bank Working Paper 17.

Albulescu, Claudiu, Daniel Goyeau, and Dominique Pépin (2013). *Financial instability and ECB monetary policy*.

Allen, William A. and Geoffrey Wood (2006). "Defining and achieving financial stability". In: *Journal of Financial Stability* 2.2, pp. 152–172.

Belke, Ansgar and Jens Klose (2010). "(How) Do the ECB and the Fed react to financial market uncertainty: The Taylor rule in times of crisis". In: *Discussion Papers of DIW Berlin* 972.

Bleich, Dirk, Ralf Fendel, and Jan-Christoph Rülke (2013). *Monetary policy and stock market volatility*. Bundesbank Discussion Paper.

Castro, Vítor (2011). "Can central banks' monetary policy be described by a linear (augmented) Taylor rule or by a nonlinear rule?" In: *Journal of Financial Stability* 7.4, pp. 228–246.

Cuaresma, Jesús Crespo and Tomas Slacik (2009). "On the determinants of currency crises: The role of model uncertainty". In: *Journal of Macroeconomics* 31.4, pp. 621–632.

ECB (2001). "Issues related to monetary policy rules". In: *Monthly Bulletin October*.

– (2010). *ECB Monthly Bulletin September*. ECB. URL: `https://www.ecb.europa.eu/pub/pdf/mobu/mb201009en.pdf`.

– (2017). *The future of monetary policy frameworks*. URL: `https://www.ecb.europa.eu/press/key/date/2017/html/ecb.sp170525.en.html`.

– (2019). *The definition of price stability*. URL: `https://www.ecb.europa.eu/mopo/strategy/pricestab/html/index.en.html`.

Fendel, Ralf M. and Michael R. Frenkel (2006). "Five years of single European monetary policy in practice: Is the ECB rule-based?" In: *Contemporary Economic Policy* 24.1, pp. 106–115.

Fernandez, Carmen, Eduardo Ley, and Mark F. J. Steel (2001). "Benchmark priors for Bayesian model averaging". In: *Journal of Econometrics* 100.2, pp. 381–427.

Ferrero, Andrea, Mark Gertler, and Lars E. O. Svensson (2008). *Current account dynamics and monetary policy*.

Foster, Dean P. and Edward I. George (1994). "The risk inflation criterion for multiple regression". In: *The Annals of Statistics*, pp. 1947–1975.

Friedman, Milton (1963). *Inflation: Causes and consequences*. Asia Publishing House.

Gerdesmeier, Dieter and Barbara Roffia (2004). "Taylor rules for the euro area: the issue of real-time data". In: *Swiss Journal of Economics and Statistics (SJES)*.

Gerlach, Stefan (2007). "Interest rate setting by the ECB, 1999-2006: Words and deeds". In: *International Journal of Central Banking* 3.3, pp. 1–46.

Hollo, Daniel, Manfred Kremer, and Marco Duca (2012). *CISS-a composite indicator of systemic stress in the financial system*. ECB Working paper.

Kaefer, Benjamin (2014). “The Taylor rule and financial stability – A literature review with application for the Eurozone”. In: *Review of Economics* 65.2.

Kass, Robert E and Adrian E Raftery (1995). “Bayes factors”. In: *Journal of the american statistical association* 90.430, pp. 773–795.

Koop, Gary M. (2003). *Bayesian econometrics*. John Wiley & Sons Inc.

Lane, Philip (2019). “Wir wollen positive Zinsen”. In: *Handelsblatt: Düsseldorf* 187.

Ley, Eduardo and Mark F. J. Steel (2009). “On the effect of prior assumptions in Bayesian model averaging with applications to growth regression”. In: *Journal of applied econometrics* 24.4, pp. 651–674.

Milani, Fabio (2002). *Monetary policy with a wider information set: a Bayesian model averaging approach*.

Molodtsova, Tanya and David Papell (2012). *Taylor rule exchange rate forecasting during the financial crisis*.

Moral-Benito, Enrique (2010). “Model averaging in economics”. In: *CEMFI Working Paper* 1008.

Obstfeld, Maurice and Kenneth S. Rogoff (2005). “Global current account imbalances and exchange rate adjustments”. In: *Brookings papers on economic activity* 2005.1, pp. 67–146.

Orphanides, Athanasios (2001). “Monetary policy rules based on real-time data”. In: *American Economic Review* 91.4, pp. 964–985.

Roskelley, Kenneth D. (2016). “Augmenting the Taylor rule: Monetary policy and the bond market”. In: *Economics Letters* 144, pp. 64–67.

Sauer, Stephan and Jan-Egbert Sturm (2007). “Using Taylor rules to understand European Central Bank monetary policy”. In: *German Economic Review* 8.3, pp. 375–398.

Stark, Jürgen (2010). *Geld- und Fiskalpolitik während und nach der Krise*. URL: `https://www.ecb.europa.eu/press/key/date/2010/html/sp101015.de.html`.

Sturm, Jan-Egbert and Timo Wollmershäuser (2008). “The stress of having a single monetary policy in Europe”. In: *CESifo working paper* No. 2251.

Svensson, Lars EO (2003). “What is wrong with Taylor rules? Using judgment in monetary policy through targeting rules”. In: *Journal of Economic Literature* 41.2, pp. 426–477.

Taylor, John B. (1993). “Discretion versus policy rules in practice”. In: *Carnegie-Rochester conference series on public policy*. Vol. 39. Elsevier, pp. 195–214.

Wang, Ran (2018). *Understanding multicollinearity in Bayesian model averaging with BIC approximation*.

Wu, Jing C. and Fan D. Xia (2016). “Measuring the macroeconomic impact of monetary policy at the zero lower bound”. In: *Journal of Money, Credit and Banking* 48.2-3, pp. 253–291.

Zellner, Arnold (1986). “On assessing prior distributions and Bayesian regression analysis with g-prior distributions”. In: *Bayesian inference and decision techniques*.

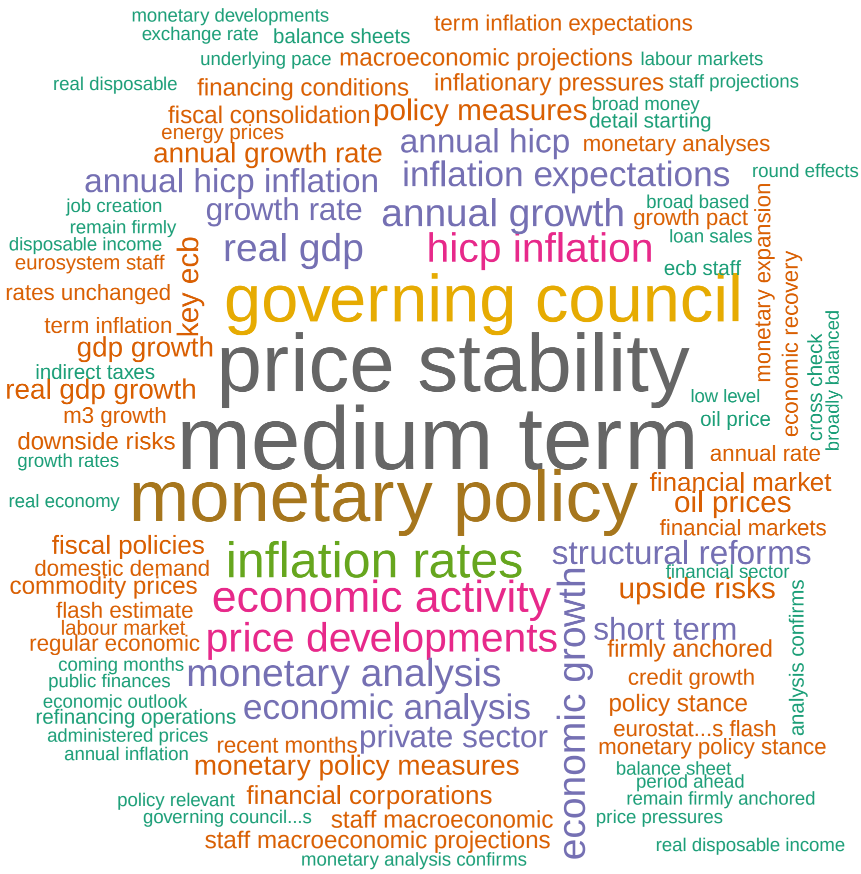
Zeugner, Stefan, Martin Feldkircher, et al. (2015). “Bayesian model averaging employing fixed and flexible priors: The BMS package for R”. In: *Journal of Statistical Software* 68.4, pp. 1–37.

A Appendix

A.1 Simple Taylor Rule

	Dependent variable:	
	EONIA	
	(1)	(2)
Inflation	0.975^{***}	
	(0.102)	
GDP	0.287^{*}	
	(0.170)	
Inflation (expected)		2.862^{***}
		(0.254)
GDP (expected)		0.774^{***}
		(0.080)
Constant	-0.010	-4.248^{***}
	(0.202)	(0.427)
Observations	224	221
R^2	0.339	0.560
Adjusted R^2	0.333	0.556
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

A.2 Textual analysis: Most Mentioned Terms in ECB Communication



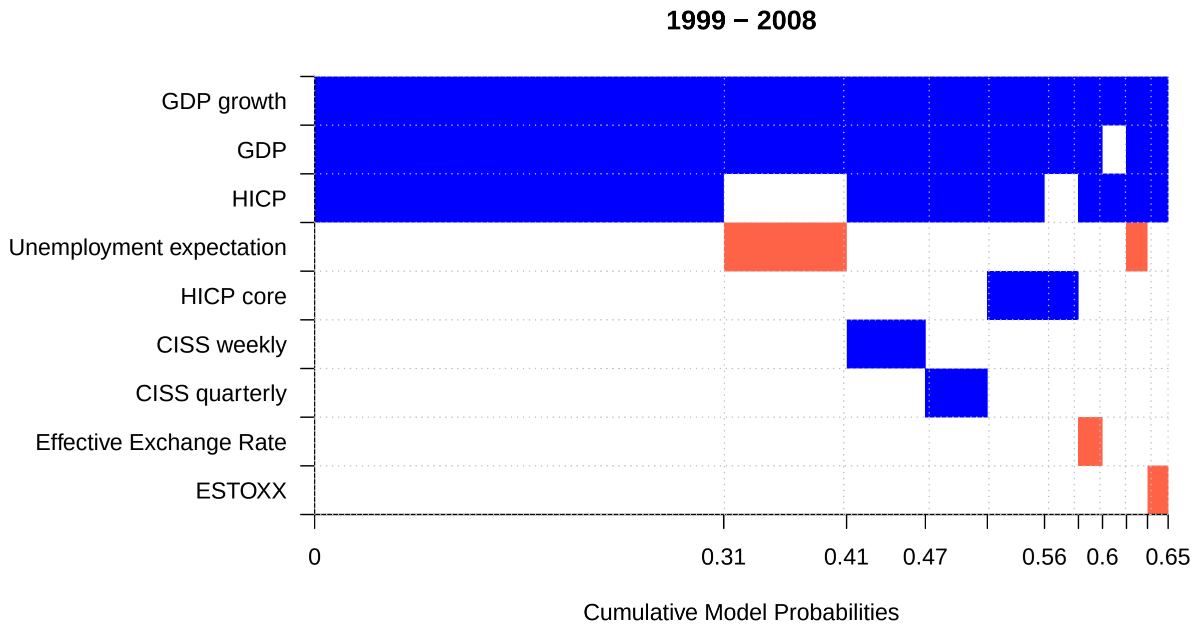
Source: ECB Press Conference Introductory Statement

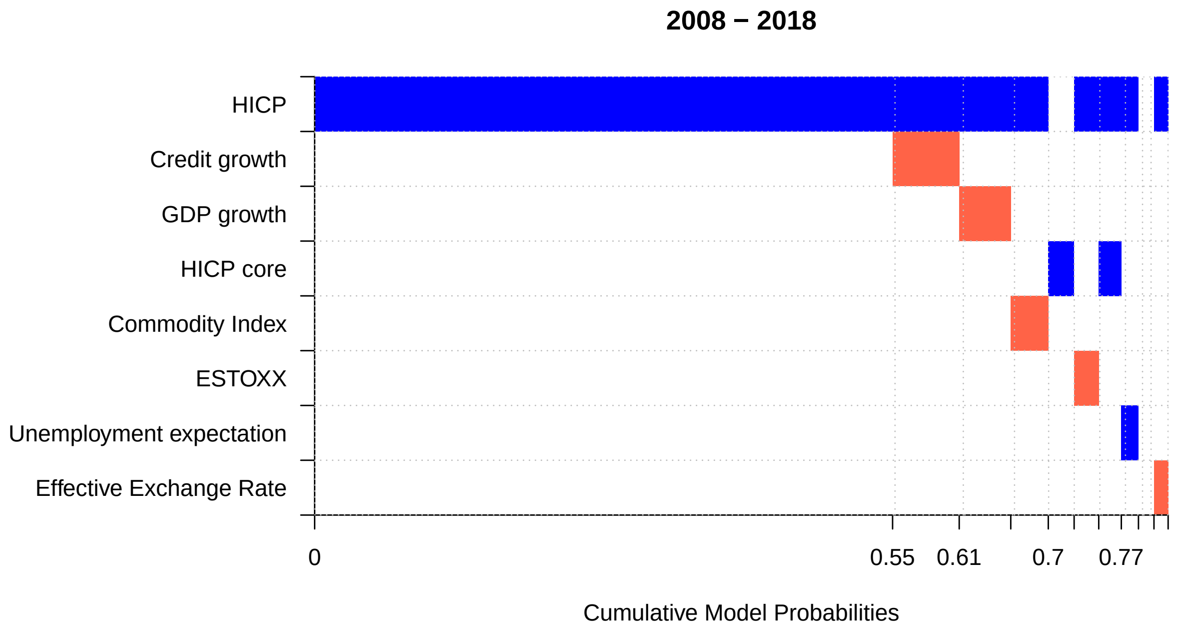
A.3 Summary of variables

Overview of used data and transformations.

Name	Source	Transformation
Dependent variables		
EONIA	Datastream	-
Shadow Rate	Quandl.com	-
Standard Taylor rule		
HICP inflation rate	ECB (RTDB)	Annual growth
Exp. inflation rate	ECB (SPF)	Annual growth
Core inflation rate	ECB (RTDB)	Annual growth
Commodity prices	IMF	Monthly growth
Output gap	ECB (RTDB)	HP transformed real GDP
Exp. output gap	ECB (SPF)	HP transformed exp. GDP
Unemployment	ECB (RTDB)	-
Exp. unemployment	ECB (SPF)	-
Financial stability		
Effective exchange rate	ECB (RTDB)	Monthly growth
Stock market prices (ESTOXX)	Datastream	Monthly growth
Stock market volatility (VSTOXX)	Datastream	Monthly growth
Total credit volume	ECB	Monthly growth
Uncertainty index	policyuncertainty.com	Monthly growth
CISS	ECB	Weekly + monthly growth
Others		
Money supply	ECB (RTDB)	Annual growth
Government bond yield	FRED	Monthly growth
Trade deficit	ECB (RTDB)	Quarterly growth

A.4 Top 10 models (pre- and post-crisis)





A.5 Robustness checks

Table 3: Robustness - Prior on the model space

	1999 – 2018		*1999 – 2008*		*2008 – 2018*	
	PIP	Post Mean	PIP	Post Mean	PIP	Post Mean
HICP Inflation Rate	1.000	1.100 (0.169)	0.719	0.313 (0.221)	0.931	0.770 (0.281)
Unemployment (expected)	1.000	-0.666 (0.110)	0.228	-0.069 (0.140)		
Output Gap (expected)			0.980	1.712 (0.456)		
Output Gap (actual)			0.952	0.490 (0.190)		
Observations		216		114		102

Notes: Only robust variables with a PIP ≥ 0.15 *are presented.*

Table 4: Robustness - Prior on the parameter space

	1999 – 2018		*1999 – 2008*		*2008 – 2018*	
	PIP	Post Mean	PIP	Post Mean	PIP	Post Mean
HICP Inflation Rate	1.000	1.094 (0.169)	0.748	0.310 (0.211)	0.948	0.778 (0.267)
Unemployment (expected)	1.000	-0.666 (0.111)	0.254	-0.068 (0.113)		
Output Gap (expected)			0.989	1.700 (0.427)		
Output Gap (actual)			0.977	0.502 (0.172)		
Observations		216		114		102

Notes: Only robust variables with a PIP ≥ 0.15 *are presented.*

Table 5: Robustness - Starting date of the crisis

	1999 – 2018		*1999 – 2007*		*2007 – 2018*	
	PIP	Post Mean	PIP	Post Mean	PIP	Post Mean
HICP Inflation Rate	1.000	1.095 0.169	0.224	0.091 (0.189)	1.000	1.216 (0.219)
Unemployment (expected)	1.000	-0.666 0.111				
Output Gap (expected)			0.971	1.890 (0.568)		
Output Gap (actual)			0.874	0.474 (0.349)		
Observations		216		101		115

Notes: Only robust variables with a PIP ≥ 0.15 *are presented.*

Table 6: Robustness - Observation period

	1999 – 2018		*1999 – 2008*		*2008 – 2018*	
	PIP	Post Mean	PIP	Post Mean	PIP	Post Mean
HICP Inflation Rate	1.000	1.131 0.167	0.533	0.218 (0.228)	1.000	0.896 (0.196)
Unemployment (expected)	1.000	-0.658 (0.109)	0.429	-0.1431 (0.183)		
Output Gap (expected)			0.963	1.600 (0.551)		
Output Gap (actual)			1.000	0.666 (0.176)		
Core Inflation			0.321	1.357 (0.222)		
Observations		216		114		102

Notes: Only robust variables with a PIP ≥ 0.15 *are presented.*

Table 7: Robustness - EONIA

	1999-2018		*1999-2008*		*2008-2018*	
	PIP	Post Mean	PIP	Post Mean	PIP	Post Mean
Unemployment (expected)	1.000	-0.694 (0.059)	0.238	-0.067 (0.135)	0.990	-0.191 (0.048)
HICP Inflation Rate	0.998	0.440 (0.094)	0.736	0.313 (0.216)	0.856	0.200 (0.101)
Output Gap (expected)			0.985	1.708 (0.438)		
Output Gap (actual)			0.967	0.498 (0.179)	0.609	-0.143 0.130
Commodity Prices					0.999	-0.061 (0.010)
Core Inflation Rate					0.299	-0.164 (0.281)
Observations		216		114		102

Notes: Only robust variables with a PIP ≥ 0.15 *are presented.*