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Working Paper
Estimating monetary policy reaction functions: A discrete choice approach

NBB Working Paper, No. 210

Provided in Cooperation with:
National Bank of Belgium, Brussels

Suggested Citation: Boeckx, Jef (2011) : Estimating monetary policy reaction functions: A discrete choice approach, NBB Working Paper, No. 210, National Bank of Belgium, Brussels

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Estimating monetary policy reaction functions: A discrete choice approach

by Jef Boeckx

February 2011  No 210

National Bank of Belgium
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ISSN: 1375-680X (print)
ISSN: 1784-2476 (online)
Abstract

I propose a discrete choice method for estimating monetary policy reaction functions based on research by Hu and Phillips (2004). This method distinguishes between determining the underlying desired rate which drives policy rate changes and actually implementing interest rate changes. The method is applied to ECB rate setting between 1999 and 2010 by estimating a forward-looking Taylor rule on a monthly basis using real-time data drawn from the Survey of Professional Forecasters. All parameters are estimated significantly and with the expected sign. Including the period of financial turmoil in the sample delivers a less aggressive policy rule as the ECB was constrained by the lower bound on nominal interest rates. The ECB's non-standard measures helped to circumvent that constraint on monetary policy, however. For the pre-turmoil sample, the discrete choice model's estimated desired policy rate is more aggressive and less gradual than least squares estimates of the same rule specification. This is explained by the fact that the discrete choice model takes account of the fact that central banks change interest rates by discrete amounts. An advantage of using discrete choice models is that probabilities are attached to the different outcomes of every interest rate setting meeting. These probabilities correlate fairly well with the probabilities derived from surveys among commercial bank economists.

Key Words: monetary policy reaction functions, discrete choice models, interest rate setting, ECB.

JEL Classification: C25, E52, E58.

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I would like to thank Luc Aucremanne, Paul De Grauwe, Hans Dewachter, Geert Dhaene, Emmanuel Dhyne, Gernot Doppelhofer, Petra Geraats, Glenn Rudebusch, Melvyn Weeks, Raf Wouters and seminar participants at the National Bank of Belgium, the Center for Financial Studies Summer School, Katholieke Universiteit Leuven and Study Center Gerzensee for helpful comments and discussion on this and previous versions of this work. Helge Berger, Michael Ehrmann, Marcel Fratzscher and colleagues at the National Bank of Belgium's financial markets department are greatly acknowledged for providing interest rate poll data. All remaining errors are my own.

The views expressed here are my own and do not necessarily reflect those of the National Bank of Belgium.
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1 Introduction

A lot of research is devoted to estimating monetary policy reaction functions which describe how a central bank sets policy interest rates. Most of these studies consider the interest rate as a continuous variable. In practice, however, rates are not adjusted continuously since most central banks adjust their policy rates by small increments, typically multiples of 25 basis points. Hu and Phillips (2004, hereafter HP) take account of this fact and they apply discrete choice methods to estimate the monetary policy reaction function of the US Federal Reserve. This allows them to assign numbers to the probability that the Federal Reserve will increase, decrease or keep the federal funds target rate the same at every scheduled meeting. Their methodology also allows to estimate a model implied desired interest rate under a realistic view of the Federal Reserve’s decision-making process where an explicit distinction is made between determining the latent and continuously evolving desired target rate and adjusting the actual target rate.

However, I will alter the methodology they propose in two ways. First, I will argue that the standard errors they report most likely underestimate the true uncertainty surrounding their estimates. An improved estimation technique can be employed by exploiting the restrictions which are imposed in the model. These allow to estimate a parameter which HP have to fix exogenously. As expected, using this new method leads to similar parameter estimates but the standard errors tend to be larger than the ones obtained by HP. Second, the estimated threshold parameters which govern policy rate adjustment in the model turn out to be implausibly high, possibly related to their assumption of a non-gradual policy rule. Hence, I propose to replace the restriction HP impose on the lagged interest rate by an alternative one, which leads to more realistic policy rule estimates without altering the model’s likelihood.

This alternative method for estimating monetary policy reaction functions has never been applied to the interest rate setting of the European Central Bank (ECB), so I estimate a forward-looking Taylor rule for the ECB using a real-time dataset of growth and inflation forecasts for the period 1999-2010. I do so for the full sample and one excluding the financial turmoil. All parameters are significant and have the expected sign. Some findings stand out.

First, the ECB seems to have reacted less aggressively to economic forecasts when the sample includes the post-Lehman period (October 2008-July 2010). This is probably due to the lower bound on nominal interest rates which has prevented the ECB - just like other central banks - from cutting rates further. At the same time, several measures have been taken to conduct a more expansionary monetary policy than suggested by simply looking at the policy rate. The monetary policy stance has been loosened since the fall of 2008 through a number of measures, including a fixed rate full allotment liquidity policy, a larger share of longer-term operations, a wider range of eligible collateral and securities purchase programmes.

Second, using the pre-turmoil estimates which are not influenced by the lower bound, I estimate significantly larger reactions to the economic outlook and a lower degree of gradualism in the desired rate when using the discrete
choice method compared to using ordinary least squares. The latter considers the policy rate as a continuous variable and does not take into account the friction that rates are altered by discrete amounts, requiring the desired rate to deviate by a given magnitude from the prevailing rate before policy rates are changed. Hence, keeping rates constant when the outlook changes is interpreted as a more passive desired monetary policy rule through the lens of continuous estimation methods.

Third, the model’s predictive performance is mixed: although the estimated probabilities of a rate decrease or increase clearly correlate with the actual decisions, the model cannot match the forecast performance of a Reuters poll of commercial bank economists’ policy rate expectations. Hence, not surprisingly, the performance of the model which uses only two explanatory variables lies between that of a naive forecast and a "full information" forecast of economists.

2 Literature review and plan

The literature on monetary policy rules is huge. Many efforts are devoted to trying to describe the way monetary policy is set by central banks, the most prominent by Taylor (1993). Most subsequent research is related to this seminal article by Taylor since they specify the interest rate as a continuous variable that is linearly related to a set of macroeconomic variables. Clarida, Gali and Gertler (1998) present estimates of this type of monetary policy rule for a range of countries, while Gerdesmeier and Roffia (2004) and Gorter, Jacobs and de Haan (2008) focus on the euro area.

As argued above, policy interest rates are not set in a continuous way. Typically, decisions on monetary policy are taken during meetings at pre-specified dates where rates are adjusted in small increments, mostly multiples of 25 basis points. These considerations led authors to employing discrete choice models where the dependent variable is not the policy rate but rather the decision to increase, decrease or keep the policy rate constant.

Gascoine and Turner (2004) estimate ordered discrete choice models for the Bank of England’s interest rate decisions over the period 1997-2003. They find a significant effect of output while inflation is not found to be significant. However, the predictive power of their model is very low and they cannot interpret the obtained estimates as coefficients in an interest rate rule because only the marginal effects on the probabilities of every outcome are identified in standard ordered probit models.

Gerlach (2007) tries to improve the forecasting performance of an ordered probit model for the ECB’s decision-making process during the period February 1999-June 2006 by including indicator variables on macroeconomic variables constructed using the editorials in the ECB’s Monthly Bulletin. He finds economic sentiment and indicator variables on output to be important, while inflation is not significant. He relates the latter to the fact that the high inflation rates were mainly seen as the result of relative price shocks which can in principle be accommodated by a central bank. Money enters his model in a significant way given the importance the ECB assigns to monetary aggregates.
Using press articles during the short period from January 1999 to May 2002, Jansen and de Haan (2009) construct variables on the direction a macroeconomic variable or the policy rate is likely to develop according to ECB officials. They include these variables in an ordered probit model. Using only macroeconomic variables, expected inflation and economic sentiment (as a proxy for the expected output gap) are both significant while in a backward-looking model neither is significant. Adding the communication variables does not generally add information although they enter significantly in some specifications. Yet, this does not yield a very successful predictive model for the monetary policy moves by the ECB.

Lapp, Pearce and Laksanasut (2003) estimate a wide range of ordered probit models using real-time data for the FOMC meetings under the chairmen Volcker and Greenspan. Although they find highly significant coefficients using publicly available data, their model has poor predictive power. Adding information that only the FOMC had at its disposal at the time of the meeting does not improve the forecasting performance of the model. In related work, Dupor, Mirzoev and Conley (2004) use internal Federal Reserve forecasts to compare two sets of estimates. The first set of estimates is obtained using the actual federal funds rate decisions as the dependent variable. The second set is obtained using the bias announcement as the dependent variable. The FOMC used to make this announcement to give an indication of the likely direction of the next policy move. They find consistency between the estimates using the bias announcement and the actual decision for the inflation forecast. The evidence for the output and unemployment forecast is mixed. In that sense, the Federal Reserve does not always do what it says it expects to do. Dueker (1999) tries to explain inertia in the federal funds target rate by estimating an ordered probit model and realizing that the estimated thresholds for increasing or cutting rates are higher than the increment by which rates are usually adjusted. A drawback of the approach taken by Dueker is that it requires to impose an ad hoc variance for the error term in order to give an economic interpretation to the relevant parameters.

This problem can be avoided using the approach of HP that is presented and motivated in the next section. This methodology also allows an economic interpretation of the estimated parameters, in contrast to the above papers. Except for Dupor et al. (2004), standard discrete choice models are used so that estimated parameters do not have a straightforward interpretation as coefficients in a monetary policy rule. I also explain why this methodology can be improved upon and I propose an alternative methodology. The discrete choice method is then applied to the interest rate setting by the ECB using a data set of monthly real-time growth and inflation forecasts. The discrete choice estimates are compared to Taylor rules estimated by linear regression methods. The model’s predicted probabilities of different policy rate moves are compared with the predictions from the Reuters poll on ECB interest rate decisions. A final section concludes.
3 Econometric methodology

Traditional Taylor rules specify the desired interest rate $i_t^*$ as

$$i_t^* = \alpha + \beta(\pi_t - \pi^*) + \gamma(z_t - z^*)$$

with $\alpha$, $\beta$ and $\gamma$ parameters, $\pi_t$ and $z_t$ measures of (expected) inflation and output, respectively, and $\pi^*$ and $z^*$ the central bank’s target for inflation and output, respectively.

Acknowledging the fact that the central bank may act gradually, a smoothing parameter $\rho$, which is restricted to lie between 0 and 1, is introduced leading to

$$i_t = \rho i_{t-1} + (1 - \rho) i_t^*.$$  

Several reasons have been proposed to motivate the inclusion of a lagged interest rate in the central bank’s policy rule. First, it turns out Taylor rules with gradualism have a much better empirical fit than non-gradual ones. This finding will also be confirmed in the present study. Second, there may be rationales for a central bank conducting a gradual policy (Rudebusch 2006). For instance, uncertainty on the part of the central bank may lead it to be cautious when changing rates. Hence, rates will be adjusted in a gradual manner. A central bank may also care about volatility of interest rates and asset prices. A gradual Taylor rule makes the policy rate less volatile which in turns helps to reduce interest rate and asset price volatility. Finally, gradualism can also be optimal when agents are forward-looking as it acts as a lever on expectations, making monetary policy more effective (Woodford 2003). Indeed, small rate changes are then expected to be followed by further changes in the same direction, making a single interest rate move have larger effects.

Although monetary policy gradualism is optimal in that class of models, the interpretation of the smoothing parameter as deliberate gradualism or partial adjustment by the central bank is subject to discussion. Rudebusch (2006), for instance, argues that empirical evidence obtained from expectations of future monetary policy indicates limited predictability of policy interest rates over the quarters ahead. This contrasts with the high predictability of interest rates which is inherent in the partial adjustment specification. Indeed, most empirical studies using quarterly data find an estimate of the smoothing parameter of around 0.8, implying very predictable interest rates over the quarters ahead.

When estimating the above equations using linear regression methods, two implicit assumptions are made. Firstly, one has to assume interest rates are adjusted in a continuous way. Secondly, when one wants the estimated rule to be a contingency plan describing what policy the central bank should pursue, one has to assume we always observe that desired rate when estimating the model. This is a strong assumption, even more so when one realizes that most Taylor rules are estimated using quarterly data where the dependent variable is the average policy rate over the quarter. The use of limited dependent variable techniques can provide a solution to these two problems.
3.1 The model of Hu and Phillips (2004)

Following HP, a more realistic view would be to distinguish explicitly between the process of determining the desired interest rate (they assume it can be described by a continuous variable such as the rule in equation (1)) and the process of adjusting the policy interest rate at each meeting of the interest rate setting body. One then has to realize that we do not always observe the desired rate but that we only observe how interest rates are adjusted at each meeting. This view on central bank interest rate setting - which is different from the ”traditional Taylor rule view” - implies that one has to use other estimation techniques than least squares since the dependent variable is now discrete and not continuous.

Formally, the central bank is assumed to have the following unobservable desired rate $i^*_t$ which changes continuously:

$$i^*_t = \beta' x_t + \varepsilon_t$$  \hspace{1cm} (3)

where $\beta$ is a vector of parameters and $x_t$ is a vector of macroeconomic variables (possibly forecasts). The error term $\varepsilon_t$ is assumed to be normally distributed with mean zero and variance $\sigma^2$. The unobservable desired rate is not specified as an autoregressive process so that no lagged rate enters the specification of the desired rate. That is because, in the HP model, the central bank lets the current assessment of the economic outlook - and not past interest rates - determine the desired rate in a smooth way. In implementing policy, the central bank is not obliged to keep the policy rate smooth, however. Hence, they take the view that the central bank sees no merit in acting in a gradual manner.

They then define the latent variable $y^*_t$ that measures the deviation of the current unobserved desired rate from the prevailing policy rate $i_{t-1}$ which was set in the previous meeting:

$$y^*_t = i^*_t - i_{t-1}.$$  \hspace{1cm} (4)

The variable $y^*_t$ can be interpreted as the desired change in the policy rate at each meeting which drives actual policy rate changes. They define a triple-choice specification since the central bank can choose to increase ($y_t = 1$), decrease ($y_t = -1$) or keep constant ($y_t = 0$) its policy rate at each meeting. It is also possible to consider more categories by, for instance, differentiating between large and small increases or decreases leading to 5 categories. The central bank will change its policy rate when the prevailing rate $i_{t-1}$ is too far away from the current desired rate. At each meeting, we observe

$$y_t = \begin{cases} 
-1 & \text{if } y^*_t < \mu_L \\
0 & \text{if } \mu_L \leq y^*_t \leq \mu_H \\
1 & \text{if } y^*_t > \mu_H 
\end{cases}$$  \hspace{1cm} (5)

where $\mu_L$ and $\mu_H$ are two threshold parameters for which it holds that $\mu_L < \mu_H$. These expressions are implicitly related to the following quote by Dueker (1999, p. 3): “How far does the FOMC let the prevailing target funds rate get out
of line, relative to a shadow desired level that changes continuously?”. The estimated parameters $\mu_L$ and $\mu_H$ indicate by how much the current desired rate $i^*_t$ has to deviate from the prevailing rate $i_{t-1}$ before the central bank chooses to change its policy rate. This may be a reasonable description of actual monetary policy when central banks are uncertain about the economic environment and the appropriate monetary policy stance. In that case, policy makers may be reluctant to quickly change policy rates and they may rather wait for convincing evidence, here in the form of a deviation of the prevailing rate $i_{t-1}$ from the desired rate $i^*_t$, before changing interest rates. The implemented change does not need to correspond to the desired change, as is evident from most central banks changing rates by multiples of 25 basis points.

By using equations (3), (4) and (5) and by defining an indicator variable $I(y_t = j)$, the log likelihood for the above model and $T$ observations is

$$\log L(\beta, \mu_L, \mu_H, \sigma) = \sum_{t=1}^{T} \sum_{j=-1}^{1} I(y_t = j) \log P_j$$

where $P_j = P_j(x_t, i_{t-1}; \beta, \mu_L, \mu_H, \sigma)$ is given by:

$$P_j = \begin{cases} 
1 - \Phi \left( \frac{\beta' x_t - i_{t-1} - \mu_L}{\sigma} \right) & \text{if } y_t = -1 \\
\Phi \left( \frac{\beta' x_t - i_{t-1} - \mu_L}{\sigma} \right) - \Phi \left( \frac{\beta' x_t - i_{t-1} - \mu_H}{\sigma} \right) & \text{if } y_t = 0 \\
\Phi \left( \frac{\beta' x_t - i_{t-1} - \mu_H}{\sigma} \right) & \text{if } y_t = 1
\end{cases}$$

and $\Phi(\cdot)$ is the cumulative standard normal distribution. Maximization of the log likelihood gives the maximum likelihood estimates and standard asymptotic inference is justified asymptotically even when the variables in $x_t$ are not stationary (Phillips, Jin and Hu 2007). Yet, most macroeconomic series relevant for central banks are highly persistent but do not have a unit root.

### 3.2 Identification of the parameters in the monetary policy rule

It is well known that in standard discrete choice estimation, assumptions must be made to identify the parameters of interest (Greene 2003, p. 669). Standard discrete choice estimation only identifies the marginal effect of the explanatory variables on the probabilities of the different outcomes, $j = -1, 0, 1$. It does not identify the scale and location of the underlying latent variable. For instance, when two thresholds are to be estimated in a model with three outcomes, one cannot include a constant in the vector of explanatory variables $x_t$. Such restriction on the constant in $x_t$ pins down the location of the latent variable.

Also the scale of the latent variable needs to be pinned down in standard discrete choice estimation by setting a value for the variance of the error term. However, in the present application, since the latent variable $y^*_t$ in (4) includes the lagged interest rate $i_{t-1}$ with parameter $-1$, $\beta$ is identified and $\sigma$ can be estimated so no value for $\sigma$ needs to be chosen a priori. In contrast, in standard discrete choice estimation with no constraints on the slope coefficients, the most common choice is to set $\sigma = 1$. That also holds for most research on
estimating monetary policy reaction functions using discrete choice models. Yet, this precludes an economic interpretation of the estimated parameters as coefficients in a monetary policy rule and only allows to estimate marginal effects on the probabilities of the different outcomes.

In the model presented here, the latent variable $i^*_t$, which is directly derived from $y^*_t$, does have an economic interpretation as it is the central bank’s current desired interest rate. In this case, $\sigma$ should be the standard deviation of the disturbances $\varepsilon_t$ if the estimates of the parameters $\beta$, $\mu_L$ and $\mu_H$ are to have a meaningful economic interpretation. Moreover, the location of the latent variable $i^*_t$ can be made comparable to the actually observed interest rate by imposing an appropriate restriction on the constant in $x_t$.

Combining the model implied restriction on the parameter of $i_{t-1}$ with the restriction that the mean of the estimated desired rate $i^*_t$ equals the sample mean of the actually observed rate $i_t$ allows to estimate the parameters in $\beta$, the standard deviation $\sigma$ and pins down the location of the latent variable so that the two thresholds $\mu_L$ and $\mu_H$ can be estimated too. To do this, I maximize the log likelihood in (6) directly using STATA’s built-in maximum likelihood optimizer `ml` with the restriction that the average model implied desired rate equals the average of the actually observed policy rate.

3.3 Identification by Hu and Phillips (2004)

HP approach the identification as follows when estimating the interest rate setting behaviour of the Federal Reserve over the period January 1994 until December 2001.¹

To pin down the location of the latent variable $i^*_t$, they follow the same strategy. Hence, they include a constant in the vector of explanatory variables $x_t$ and impose the restriction that the mean of the estimated desired interest rate $i^*_t$ equals the sample mean of the actually observed interest rate $i_t$. This allows them to estimate the two thresholds $\mu_L$ and $\mu_H$ in the same way as in the previous section.

To pin down the scale of the latent variable, they estimate a linear regression of the actually observed interest rate $i_t$ on the explanatory variables in $x_t$, yielding an estimate of the variance of the residuals. This estimated value of $\sigma$ is then imposed when maximizing the log likelihood in equation (6) with respect to $\beta$, $\mu_L$ and $\mu_H$. The authors argue that this should make the estimated model implied desired interest rate “easier to compare with” the actual interest rate.

As shown above, imposing this second restriction is not necessary since one restriction on the slope coefficients is available in the model presented in equations (3), (4) and (5). This means that only the location of the latent variable needs to be fixed using an exogenous restriction and they therefore estimate an overidentified model as they impose one additional restriction by fixing a value for $\sigma$.

Moreover, the above procedure is not entirely correct because of two reasons. Firstly, when estimating $\sigma$ by estimating a linear regression of the actual interest

¹What follows is based on personal communication with the authors.
Table 1: Monetary policy rule and threshold parameter estimates using the HP dataset. Standard errors are in parentheses.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>M2</td>
<td>-0.2787</td>
<td>-0.2738</td>
</tr>
<tr>
<td></td>
<td>(0.0954)</td>
<td>(0.0492)</td>
</tr>
<tr>
<td>Unemployment Claims</td>
<td>-0.0203</td>
<td>-0.0175</td>
</tr>
<tr>
<td></td>
<td>(0.0103)</td>
<td>(0.0033)</td>
</tr>
<tr>
<td>Consumer confidence</td>
<td>0.0336</td>
<td>0.0314</td>
</tr>
<tr>
<td></td>
<td>(0.0156)</td>
<td>(0.0074)</td>
</tr>
<tr>
<td>New Orders</td>
<td>0.0593</td>
<td>0.0392</td>
</tr>
<tr>
<td></td>
<td>(0.0323)</td>
<td>(0.0115)</td>
</tr>
<tr>
<td>$\mu_L$</td>
<td>-0.0110</td>
<td>-0.0094</td>
</tr>
<tr>
<td></td>
<td>(0.0025)</td>
<td>(0.0021)</td>
</tr>
<tr>
<td>$\mu_H$</td>
<td>0.0125</td>
<td>0.0107</td>
</tr>
<tr>
<td></td>
<td>(0.0032)</td>
<td>(0.0021)</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.0062</td>
<td>na</td>
</tr>
<tr>
<td></td>
<td>(0.0018)</td>
<td>na</td>
</tr>
</tbody>
</table>

rate on the explanatory variables in $x_t$, HP implicitly assume that $i_t = i^*_t$. However, this contradicts the central bank not always implementing the desired interest rate. Formally, the actual interest rate can be represented as

$$i_t = i^*_t + \eta_t = \beta' x_t + \varepsilon_t + \eta_t$$  \hspace{1cm} (8)

where $\eta_t$ represents the disturbance related to the fact that the central bank does not always implement its desired interest rate. When estimating equation (8) by least squares, one can obtain an estimate of the variance of the composite error term $\varepsilon_t + \eta_t$. If this procedure is to yield a correct estimate of the variance of $\varepsilon_t$, one has to assume that $\sigma^2_{\eta} = 0$. However, if this assumption holds, there is no point in estimating an ordered probit model because the central bank always implements its desired rate.

Secondly, even if the above procedure yields a consistent estimate of $\sigma$, it is still an estimated parameter. However, after having estimated $\sigma$, HP proceed as if $\sigma$ is a known value by plugging it into equation (6) before maximizing this log likelihood. The standard errors of the resulting estimates of $\beta$, $\mu_L$ and $\mu_H$ are then likely to underestimate the true uncertainty surrounding these estimates. These two problems are circumvented using the method described in section 3.2.

Applying that method to the dataset used by HP, provides support for the above assertion. They explain Federal Reserve interest rate decisions between January 1994 and December 2001 by ex post data on money growth, consumer confidence, initial unemployment claims and new orders. This set of explanatory variables is determined on the basis of a general-to-specific modeling strategy. In a first step, they include 11 series in the estimated model.

---

The final model only retains the 4 above mentioned variables whose coefficients were significant in the first step.

Table 1 shows that the point estimates of the slope coefficients using the new method are more or less similar to the ones reported by HP, but the new estimates have larger standard errors. This is most likely a consequence of taking into account the uncertainty regarding $\sigma$, whose estimated value is reported for the new method. HP do not report the value of $\sigma$ they impose in the estimation, however.

Using the new method, the thresholds are estimated somewhat larger but they do reveal the same asymmetry reported by HP in that the deviation of the prevailing rate from the desired rate must be greater to increase than to decrease rates. Moreover, the estimated thresholds are large: 110 and 125 basis points for a decrease and an increase, respectively. Also the HP thresholds are very large, especially when gauged against the usually very small increment by which rates are adjusted at monetary policy meetings. The next section will propose a further modification that allows to estimate the degree of gradualism and will turn out to reduce the estimated thresholds considerably.

3.4 Relieving the restriction on the lagged interest rate

HP do not allow the desired rate (equation (3)) to be gradual: they take the view that current economic conditions determine the desired rate but that, in implementing policy, the central bank does not keep the policy rate constant but adjusts it in a discontinuous way.

Here I take a more agnostic view and let the data determine the degree of gradualism. Hence, the desired rate which drives interest rate decisions may be gradual: the $x_t$ vector includes the lagged interest rate in equation (3). Therefore, the parameter on $i_{t-1}$ is no longer fixed at $-1$ in equation (4). In order to still be able to estimate the model, I have to replace the ”$-1$” restriction with another one. I propose to add a restriction which imposes that the average absolute desired rate change when the model predicts a rate change (i.e. when the probability of increase/decrease is larger than that of a decrease/increase and keeping the rate constant) equals the average actually observed absolute rate change for the months in which rates are changed. A priori, one expects this will also reduce the estimated thresholds to more reasonable values.

That way, the magnitude of the desired rate changes is comparable to the actually observed rate changes. In a sense, this restriction on the scale of the latent variable is similar to the one which fixes the location of the desired rate by imposing that the average of the desired rate equals the actually observed policy rate. The next section applies this method to ECB interest rate setting since 1999.
4 Application to the ECB: a forward-looking Taylor rule

The motivation for applying the method to the ECB is threefold. First, I am not aware of research that uses discrete choice methods and allows an economic interpretation of the estimated parameters to study ECB interest rate setting. Gerlach (2007) comes closest to this purpose but his model does not allow for a straightforward interpretation of the estimated parameters as coefficients in a policy rule. On top, an ECB application will illustrate the modification to the HP method which estimates the degree of gradualism by adding a restriction on the size of the model implied desired rate changes. Finally, in contrast to HP, whose general-to-specific model selection strategy might lead to artificially good results as only significant variables are retained, I follow an a priori model selection strategy and see how such a model performs.

Indeed, I will try to explain ECB interest rate decisions using monthly real-time forecasts of GDP growth and inflation, constructed using the ECB’s quarterly Survey of Professional Forecasters (SPF). These SPF data have been used already by ECB policy makers in describing ECB policy rules (Orphanides 2010). I compare the model’s estimates for a full sample spanning the period March 1999-July 2010 and a shorter pre-crisis sample which runs from March 1999 until September 2008. I also compare the ordered probit results with those from traditional least squares estimates. Finally, the model’s ability to predict ECB interest rate decisions is assessed against the results from the monthly interest rate poll published by Reuters that can be regarded as a full-information forecast of the ECB’s upcoming interest rate decision.

4.1 Background on monetary policy in the euro area

Since January 1999, the ECB has the responsibility for monetary policy in the euro area which, since 1 January 2009, has 16 members.

The primary objective of monetary policy in the euro area is achieving price stability, which the ECB has defined as a euro area HICP inflation rate below, but close to, 2%, to be achieved over the medium term. When the primary objective is not endangered, monetary policy can also contribute to other goals such as a high level of employment and sustainable and non-inflationary growth.

Decisions on monetary policy are taken by the Governing Council which consists of the governors of the national central banks from the euro area member states and the 6 members of the ECB’s Executive Board. The Governing Council usually takes decisions on the stance of monetary policy every first Thursday of the month and these decisions are explained by the President and vice-President at a press conference after the meeting. It should be noted that before November 2001, two meetings at which monetary policy decisions were taken were scheduled every month.

In order to achieve its goal of maintaining price stability, the ECB sets the minimum bid rate on the main refinancing operations (MRO). The decision regarding this key interest rate which signals the monetary policy stance is the focus of the present analysis.
Yet, during the 2007/2009 financial crisis, the signal stemming from the MRO rate regarding the monetary policy stance, became blurred. This complicates the analysis presented here.

Indeed, from the onset of the financial crisis in the summer of 2007, the ECB altered the terms of its liquidity provision. Initially, overnight interest rates remained close to the MRO rate, so there was no visible effect on the monetary policy stance. As the financial turmoil reached unprecedented heights in October 2008, the ECB stepped up its liquidity provision and allowed this to have a downward impact on short term money market rates and, hence, the monetary policy stance. From then on, it supplied unlimited amounts of liquidity to counterparties by granting full allotment at a fixed rate - usually the MRO rate - in all refinancing operations, not only the weekly main refinancing operations but also longer-term operations. Moreover, the share of longer-term operations increased considerably. To prevent banks from not being able to have access to central bank refinancing due to a lack of adequate collateral, the list of eligible collateral was expanded. Operations in foreign currency (USD, CHF) helped to accommodate banks’ finance needs in foreign currency.

In May 2009, a further set of measures was announced. First, three refinancing operations with a maturity of one year were introduced, at a fixed rate with full allotment. Second, a programme to purchase EUR 60 billion of covered bonds was announced. Third, the European Investment Bank became an eligible counterparty in Eurosystem transactions, allowing them to expand their lending activity.

In May 2010, in response to government bond turmoil in some euro area countries, the ECB also intervened in public and private debt securities markets under the Securities Markets Programme. Central bank liquidity remained demand-driven as weekly operations were still conducted with a fixed rate full allotment procedure, putting downward pressure on Eonia. In May 2010, it was also decided to re-introduce the fixed rate full allotment procedures for longer-term operations, which were previously abandoned as part of the phasing-out from the exceptional measures. Finally, banks were again given the opportunity to obtain liquidity in USD.

These changes in the operational framework, which are referred to as "enhanced credit support", blur the signal on the monetary policy stance stemming from the MRO rate. The stance has indeed been more accommodative than suggested by the MRO rate at 1%, the level at which the key ECB rate was brought in May 2009. Firstly, the sizeable increase in the outstanding amount of refinancing led to overnight interest rates hovering considerably below the policy rate from October 2008. Between October 2008 and July 2010, Eonia hovered on average some 54 basis points below the policy rate. Secondly, the one year operations brought down longer-term money market rates, thereby making monetary policy more expansionary than judged only by the level of the policy rate. Finally, the measures generally supported the transmission of monetary stimuli to the real economy by facilitating banks’ liquidity management, by helping to re-activate markets for bank funding (such as that for covered bonds) and by insulating it from government bond turmoil.

All this implies it has become difficult - or perhaps even impossible - to
summarize the monetary policy stance in one single figure, in this application the ECB’s MRO rate. Therefore, I estimate the model for 2 sample periods: a short sample spanning March 1999-September 2008 and a full sample spanning the period March 1999-July 2010. Given the above, the method proposed in this paper seems better suited to deal with the pre-turmoil sample in which the monetary policy stance was neatly summarized in a single policy rate which can be changed at pre-set dates.

4.2 Data

In contrast to HP, I take an a priori approach to the model selection strategy and explain ECB interest rate decisions by variables which are universally accepted to matter for a central bank: inflation and growth forecasts. Ideally, one would use one year ahead internal central bank forecasts of growth and inflation to explain adjustments in central bank interest rates. This would answer both the need for using real-time data and the need to use forecasts of real activity and inflation over the policy-relevant horizon instead of backward-looking realizations of macroeconomic variables. Indeed, as the ECB tries to achieve an inflation rate below, but close to, 2% over the medium term, it pays a great deal of attention to expected economic developments rather than past realizations.

Such internal ECB forecasts at the policy meeting frequency are not publicly available, however. Therefore, I resort to inflation and real GDP growth forecasts from the Survey of Professional Forecasters. Since March 1999, the ECB asks a panel of professional forecasters about their expectations of growth, inflation and unemployment over different horizons, including the one year ahead horizon. Timing is as follows. For the 2010Q2 survey round, the one year ahead growth forecast refers to year on year growth of real GDP in 2010Q4 and the one year ahead inflation forecast refers to the March 2011 annual HICP inflation rate. This survey is conducted only on a quarterly basis, however. Therefore, I construct monthly forecasts from these quarterly forecasts using a real-time interpolation method. For the months in which no new SPF is available, I estimate the change in the growth and inflation forecast from the most recent survey using the changes in indicators from the European Commission monthly business and consumer surveys.

For growth, I estimate a linear regression of the change, compared to the most recent survey round, in the one year ahead SPF forecast for real GDP growth on the change in the European Commission’s Economic Sentiment Indicator (ESI, a composite indicator summarizing industrial, services, retail, construction and consumer confidence) over the same period. This estimated equation will allow - for months in which no SPF is available - to update the latest available SPF forecast using changes in the ESI since the last month in which an SPF forecast was published.

For inflation, the change, compared to the most recent survey round, in the one year ahead inflation forecast is regressed on the change in price expectations of consumers, industry, the construction sector and the retail sector over the same period, as measured by the monthly European Commission business and consumer survey. These questions ask the different sectors on their expectations
of prices for the next months and should hence provide a good indicator of how inflation will move. The estimated equation will allow - for months in which no SPF is available - to update the latest available SPF inflation forecast using changes in the four sectors’ price expectations statistic since the last month in which an SPF forecast was published.

Both equations’ estimated parameters are significant and the $R^2$ of the updating equations come to .70 and .66 for growth and inflation, respectively.$^3$

Figures 1 and 2 plot the quarterly SPF forecasts and the monthly interpolated forecasts which are used in the estimation. In the interpolation and estimation, due care is taken of timing issues: only information which was actually available at the time of an ECB rate setting meeting is used. For instance, from 2002 onwards, the results of the second quarter survey round are already available in May instead of June.

When there are two scheduled meetings in a given month, I consider them as one because I only have monthly data for the explanatory variables. Moreover, there has never been a month in which there were two scheduled meetings at which a rate change has been decided. Because rates are at some meetings adjusted by 50 or 75 basis points instead of the more common 25 basis points, I could have distinguished between large and small adjustments. To keep the model compact, only the decisions to increase (1), decrease (−1) or keep the rate the same (0) are considered without considering the magnitude of the adjustment. In total, there are 14 decisions to decrease, 105 decisions to keep the rate the same and 16 decisions to increase the policy interest rate in our

$^3$The details of the estimation/interpolation procedure are provided upon request.
full sample spanning the period March 1999 (i.e. the first SPF survey round) until July 2010. The shorter sample contains 7 decreases, 90 decisions to keep rates constant and 16 rate increases between March 1999 and September 2008.

4.3 Policy rule estimation

The first two columns in Table 2 present the estimation results for the full sample and the one excluding the turmoil period. All parameters are estimated significantly different from zero and have the expected sign. I find a gradual policy rule with the coefficient on the lagged interest rate being around 0.9. This value of the smoothing parameter estimated using monthly data is in line with other estimates in the literature which typically estimate $\rho$ between 0.8 and 1. Being around 25 basis points, the thresholds are estimated at reasonable values. This is in contrast with the very large estimated thresholds which are found if the model is estimated when the desired rate is imposed to be non-gradual, as is the case in HP$^4$. Hence, the a priori expected result that thresholds will be smaller if the restriction on the lagged rate is dropped does hold in practice. The thresholds show an asymmetry in that a larger deviation of the desired rate from the prevailing rate is needed to decrease rates than to increase rates. In practice, it also turns out that rate decreases are often of greater magnitude than rate increases, which happened to amount to 50 basis points only twice. Rate cuts by 50 or 75 basis points were more frequent, however. Hence, it may be that the deviation to trigger a rate decrease may be larger but that the subsequent monetary policy loosening is larger as well.

$^4$The estimates for this model are not shown but are available upon request.
Table 2: Estimated monetary policy rules for full sample (March 1999-July 2010) and pre-turmoil sample (March 1999-September 2008). Standard errors are in parentheses.

Comparing the results using the full sample and the shorter one, the estimated reactions to the outlook for both growth and inflation are smaller while the desired rule is more gradual in the full sample, as \( \rho \) is estimated larger in the longer sample. The thresholds are estimated to be smaller in absolute value for the full sample, suggesting that, although the reaction to changes in the outlook is less pronounced, a smaller deviation is needed than in the short sample to induce a rate change. These smaller coefficients on inflation and growth are most likely due to the fact that monetary policy was constrained by the lower bound on nominal interest rates. The MRO rate and deposit rate have been brought to a level of 1% and 0.25%, respectively, since May 2009. If such lower bound would not have existed, rates would most likely have been brought even lower, and the estimates for the long sample would not necessarily be smaller. Peek, Rosengren and Tootell (2009) find similar results for the US. Using least squares, they estimate forward-looking Taylor rules using unemployment and Greenbook forecasts of output growth and inflation for the period 1985Q1-2009Q1 and 1985Q1-2008Q2. They find the responses of the Fed to unemployment and forecasts of growth and inflation to have decreased quite substantially when the three turmoil quarters are included. Moreover, the monetary policy stance has been looser than suggested by the MRO rate which is used in this analysis. Indeed, as argued above, the "enhanced credit support measures" have brought overnight interest rates below the policy rate and close to zero since mid 2009 while they have also had a downward impact on longer-term money market rates. Figure 3 illustrates how the overnight interest rate Eonia has hovered below the policy rate since the fall of 2008 and how also longer-term money market rates, like the important three month Euribor rate, indicate a looser stance than implied by the level of the MRO rate. On top, the
abundant liquidity and covered bonds purchases have supported the supply of credit by banks to the non-financial sector and made monetary policy therefore more accommodative. All this implies that the results from the short sample are more reliable and that care should be taken when interpreting the results from the analysis using the full sample or when comparing results between the two sample periods.

Table 2 allows to compare the estimated model parameters using the ordered probit method with ordinary least squares estimates. This shows that the two sets of estimates differ, especially for the short sample which I argue is the more reliable one. For both samples, the discrete choice view delivers a more active policy rule with higher coefficients on growth and inflation and a lower degree of gradualism. For the short sample, the ordered probit coefficients on growth and inflation are significantly larger than those estimated using least squares but the difference is not statistically significant for $\rho$.

A possible and tentative explanation for this finding goes as follows. If the decision process within a central bank follows the discrete choice view, i.e. a deviation in the desired rate from the current rate is required before rates are changed, but the model is estimated with OLS, it can be that part of the inertia in changing rates is attributed to the smoothing parameter $\rho$ in the desired rate. That parameter then captures the gradualism in the desired rate and the fact that there is some friction in adjusting rates, namely that the desired change has to be of a certain size before rates are actually changed. Indeed, if a central bank keeps rates constant although its desired rate has changed, the OLS method will interpret this as a higher degree of gradualism in the desired rate (a higher $\rho$). Yet, in reality the desired rate has changed but not enough to induce a rate change. The discrete choice method, in contrast, will take this friction into account.

Figure 3: Money market and ECB policy rates
Figure 4: Actual MRO rate and estimated desired rates from ordered probit model and OLS regression for the full sample

Figure 5: Actual MRO rate and estimated desired rates from ordered probit model and OLS regression for the pre-turmoil sample
account and estimate a smaller $\rho$. The same holds for the estimated parameters on the growth and inflation forecast: the discrete choice method will take into account that a change in these variables needs to be large enough to induce a rate change and does not necessarily interpret a constant policy rate as no change in the desired rate. Hence, the OLS parameters will be smaller than the ordered probit estimates.

Figures 4 and 5 exhibit the estimated desired rates from the ordered probit method and OLS and compare them with actually observed MRO rate, both for the full and shorter sample. Comparing the full and the short sample, the graphs confirm the somewhat more volatile desired rate when estimated over the shorter sample, reflecting the larger parameters on growth and inflation and the lower $\rho$. Comparing across methods, the ordered probit rate with its higher coefficients on growth and inflation is more volatile than the estimated OLS desired rate for the short sample.

The estimated desired rate for the long sample indicates a monetary policy shortfall in mid-2009. The MRO rate was brought to 1% while the desired rate decreased to some 25 basis points after which it recovers and has been hovering around 1% since early 2010. Yet, as indicated above and illustrated by figure 3, the actual monetary policy stance was more accommodative than suggested by the 1% level of the MRO rate. That compensated for the perceived monetary policy shortfall. Moreover, although the desired rate has been close to 1% since early 2010, short term money market rates have remained below 1% in the first half of 2010.

A monetary policy shortfall is not unique to the euro area: Rudebusch (2009) estimates a non-gradual Taylor rule for the US Federal Reserve and finds that the Federal Reserve should bring the Federal Funds Target Rate as low as -5% at the end of 2009 if it were to act consistently with past behaviour. Yet, he indicates that through communication on the future path of the policy rate and unconventional policy tools which changed the size and composition of the Federal Reserve’s balance sheet, at least some of the monetary policy shortfall is compensated for. This is very much in line with what is observed for the ECB.

4.4 How well can the model explain interest rate decisions?

This subsection explores how the forward-looking Taylor rule performs in predicting ECB interest rate decisions. In a first part, a strict decision rule to predict meeting outcomes is used. In a second part, I check how well the model’s implied probabilities correlate with actual decisions. The model’s forecasting performance is compared against that of a survey of commercial bank economists by Reuters.

4.4.1 A strict decision rule

At every scheduled meeting, I compute the probability of every meeting outcome and predict the outcome according to the highest estimated probability. In practice, this test requires at least a 50% model implied probability before an
### Table 3: Forecast evaluation for the full sample: Model/Reuters proportion

<table>
<thead>
<tr>
<th>Actual decisions</th>
<th>Decrease</th>
<th>No change</th>
<th>Increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decrease was predicted</td>
<td>5/12</td>
<td>3/2</td>
<td>0/0</td>
</tr>
<tr>
<td>No change was predicted</td>
<td>9/2</td>
<td>102/102</td>
<td>16/3</td>
</tr>
<tr>
<td>Increase was predicted</td>
<td>0/0</td>
<td>0/1</td>
<td>0/13</td>
</tr>
</tbody>
</table>

### Table 4: Forecast evaluation for the pre-turmoil sample: Model/Reuters proportion

<table>
<thead>
<tr>
<th>Actual decisions</th>
<th>Decrease</th>
<th>No change</th>
<th>Increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decrease was predicted</td>
<td>0/6</td>
<td>1/2</td>
<td>0/0</td>
</tr>
<tr>
<td>No change was predicted</td>
<td>7/1</td>
<td>87/87</td>
<td>15/3</td>
</tr>
<tr>
<td>Increase was predicted</td>
<td>0/0</td>
<td>2/1</td>
<td>1/13</td>
</tr>
</tbody>
</table>

An action is predicted by this rule, which makes this a very ambitious test. Tables 3 and 4 present the model’s predictive performance on that basis. For instance, in the full sample there were 5 meetings at which a rate cut was decided that was also predicted by the model, while there were also 9 meetings at which rates were decreased although not predicted by the model. Using this rule, the model correctly predicts 79% and 78% of all meeting outcomes for the long and short sample, respectively.

Following Kaminsky, Lizondo and Reinhart (1998), I assess the model’s performance using a so-called "adjusted noise to signal ratio". Kaminsky et al. (1998) define this statistic as follows. Let \( A \) be the event that the action is predicted and happens. Let \( B \) denote the event that an action is predicted but does not happen. Let \( C \) be the event that an action is not predicted but happens. Finally, let \( D \) be the event that an action is not predicted and does not happen. The "adjusted noise to signal ratio" is then defined as \( \frac{B}{B + D} \). Lower values of this statistic are preferred to higher ones. Table 5 reveals that both the long and shorter sample models have high ratios - given zero entries in the tables 3 and 4, the ratio cannot be computed for both options in both samples -, indicating relatively poor predictive power. For instance, HP report for their Fed model, which uses more explanatory variables that are selected on the basis of their model fit, ratios of 0.085 for rate decreases and 0.038 for rate increases.

It is useful to compare the model’s predictive performance against a benchmark. A natural benchmark is a model without any explanatory variables (constant-only model) which will attach fixed probabilities for every possible meeting outcome (equal to their sample proportion). Hence, for every meeting the decision rule will predict the most frequent outcome in the sample: keeping rates constant. Although such model will never correctly predict any
rate change, its correct forecasting ratio comes to 78% and 80% for the long and short sample, respectively. Ironically, this implies a better forecast performance for the naive model in the pre-turmoil sample. This may be explained by the fact that ordered probit models maximize the model’s joint likelihood and not its predictive performance based on this strict decision rule. Another benchmark is the best informed prediction which takes all available information - including central bank communication - into account. Hence, I resort to a monthly poll on the outcome of the upcoming ECB Governing Council, organised by Reuters. This poll is organized and published since the start of EMU, but is not consistently available from a single source, however. Details, coverage and sources of the data are available in appendix A.

A probability measure which is available for every scheduled meeting since March 1999, covers the proportion of economists in the Reuters poll expecting a rate increase/decrease or no change in the upcoming meeting.

Tables 3, 4 and 5 show that the predictions based on the Reuters proportion clearly perform better than the model. This is not surprising as the poll respondents take all information into account. Especially communication on the part of the central bank may be important information shaping expectations which is not accounted for by the model. A prominent example is the late 2005-mid 2007 tightening cycle, during which ECB communication through so-called code words very much helped in predicting ECB interest rate decisions. The growing importance of communication in predicting Governing Council outcomes becomes also clear when looking at the probability measures over time, as is done in the next subsection.

### 4.4.2 Comparing implied probabilities

The above tables record predictions only as successful when both direction and timing are correct. This is a strict way to evaluate the performance of probability-based predictions. On top, a meeting outcome is only predicted if its probability is the highest (in practice larger than 50%), hence no distinction is made between large or small probabilities for a given outcome. Therefore, figures 6, 7, 8 and 9 may be more informative as they allow to assess for every meeting the likelihood of the meeting outcome.

For both the full and the pre-turmoil sample, the figures show actual decisions against three probabilities: the proportion of economists surveyed by Reuters expecting that outcome (the Reuters probability measure used before), the implied probability from the ordered probit Taylor rule estimated before and the mean probability which economists surveyed by Reuters attach to that

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>Pre-turmoil sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct forecasting percentage</td>
<td>79.2/94.1</td>
<td>77.8/93.8</td>
</tr>
<tr>
<td>Noise to signal ratio for increases</td>
<td>na/0.01</td>
<td>0.329/0.013</td>
</tr>
<tr>
<td>Noise to signal ratio for decreases</td>
<td>0.069/0.019</td>
<td>na/0.022</td>
</tr>
</tbody>
</table>

Table 5: Summary statistics : Model/Reuters proportion
meeting outcome. Indeed, since March 2000, Reuters asks its poll contributors to assign probabilities to the different meeting outcomes so that a mean probability can be calculated. This delivers a more detailed view on economists’ expectations for the next meeting’s outcome compared to the proportion measure used before. Yet, these mean probabilities are only available for the meetings between March 2000-January 2005 and July 2009-July 2010 (see appendix A).

The ordered probit model probabilities correlate well with the actual decisions although the implied probabilities are low - which is consistent with the tables 3 and 4 -, especially so for the full sample. Indeed, comparing the two sample periods, it appears that the massive and rapid monetary policy loosening since the fall of 2008 has adversely affected the model’s ability to track interest rate changes in the pre-turmoil period. Model-implied probabilities for the meeting outcomes are indeed much lower in the pre-turmoil turmoil period when estimated over the full sample.

The rate increase in July 2008 which was motivated largely by risks of second-round effects from commodity price increases and rising longer-term inflation expectations, is not anticipated at all by any of the two models. Yet, this decision was almost perfectly anticipated by most Reuters respondents as the Governing Council had hinted at a rise in the policy rate. Comparing the model-based probabilities with the ones derived from the Reuters poll in the figures, it appears that the latter indeed fare better in tracking rate changes. The Reuters probabilities have become better at tracking meeting outcomes over time as ECB communication increasingly helped to make decisions more predictable, a marked example being the late 2005-mid 2007 tightening cycle. Indeed, in the early ECB years there was a considerable number of Governing Council meeting outcomes which were not anticipated or wrongly timed by economists.

The figures suggest that model-implied probabilities computed from the pre-turmoil sample correlate fairly well with the mean probabilities derived from Reuters responses in the early ECB years. This also holds for periods when no rate changes were implemented but both the model and respondents nevertheless changed their assessment on the likelihood of a rate change. The summer of 2002 and, to a less extent, the fall of 2004 are examples. This suggests that Reuters respondents - in absence of central bank communication - attach a considerable weight to the outlook for growth and inflation in their assessment regarding the outcome of the upcoming meeting.

Tables 6 and 7 summarize the figures by showing the mutual correlations between actual decisions and the three probability measures for the two samples. Not surprisingly, the Reuters proportion shows the highest correlation with actual decisions. The model’s correlation with rate increases is adversely affected when estimated over the full sample, at the benefit of a better correlation with rate decreases. For the pre-turmoil sample, the model’s probabilities show the highest correlation with the Reuters mean, suggesting that Reuters respondents indeed do attach weight to the economic outlook when forming their expectations on rate decisions.

In summary, the model with only two variables which are selected a priori seems to provide only a rough description of actual monetary policy making as
Figure 6: Actual decisions to decrease rates and predicted probabilities of rate decreases from the full sample

Figure 7: Actual decisions to increase rates and predicted probabilities of rate increases from the full sample
Figure 8: Actual decisions to decrease rates and predicted probabilities of rate decreases from the pre-turmoil sample

Figure 9: Actual decisions to increase rates and predicted probabilities of rate increases from the pre-turmoil sample
Table 6: Correlations between different probability measures and outcomes (1 if increase/decrease, 0 if no change) for the full sample estimates: increase/decrease. The Reuters mean is not available for all meetings.

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Model</th>
<th>Reuters proportion</th>
<th>Reuters mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/1</td>
<td>0.36/0.52</td>
<td>1/1</td>
<td></td>
</tr>
<tr>
<td>0.87/0.84</td>
<td>0.35/0.54</td>
<td>1/1</td>
<td></td>
</tr>
<tr>
<td>0.79/0.69</td>
<td>0.39/0.18</td>
<td>0.92/0.94</td>
<td>1/1</td>
</tr>
</tbody>
</table>

Table 7: Correlations between different probability measures and outcomes (1 if increase/decrease, 0 if no change) for the pre-turmoil sample estimates: increase/decrease. The Reuters mean is not available for all meetings.

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Model</th>
<th>Reuters proportion</th>
<th>Reuters mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/1</td>
<td>0.47/0.42</td>
<td>1/1</td>
<td></td>
</tr>
<tr>
<td>0.87/0.78</td>
<td>0.47/0.44</td>
<td>1/1</td>
<td></td>
</tr>
<tr>
<td>0.79/0.69</td>
<td>0.75/0.53</td>
<td>0.92/0.94</td>
<td>1/1</td>
</tr>
</tbody>
</table>

its predictive performance is mixed. It has difficulties predicting rate changes at specific meeting dates as the probabilities attached to the different outcomes remain fairly small, but it nevertheless does manage to track rate decisions in a time-series context. In that respect, the model does a better job than a naive model - which attaches a constant probability to a rate increase/decrease, equal to its in-sample frequency -, but fares worse than a full information prediction like the ones derived from the monthly Reuters poll. This is not surprising as the latter take all information into account, including communication by the central bank.

5 Conclusion

This paper builds on the work of Hu and Phillips (2004) to propose a novel discrete choice methodology for estimating monetary policy reaction functions. Their method provides estimates of the probabilities that the central bank will increase, decrease or keep the policy rate. Moreover, it also allows the estimation of a model implied desired interest rate under a realistic view of the central bank’s decision process which distinguishes between determining the desired rate and actually changing interest rates. Yet, the uncertainty surrounding their estimates is most likely underestimated given the identification strategy they use which leads to an overidentified model. Hence, I propose to use the restrictions implicit in the model, which leads to an exactly identified model. Using the data set used by HP, I find estimates that are very similar to theirs although, as expected, the standard errors using the alternative method-
ology are larger. However, these bigger standard errors are more appropriate than the ones reported by HP since they estimate an overidentified model.

HP’s model specification does not allow for policy gradualism and yields large threshold parameters which govern rate adjustment. Hence, I propose to modify their model specification by allowing the desired rate to be gradual and by adding an extra restriction on the size of the desired rate changes in order to keep the model identified.

HP specify a model for the Federal Reserve using a general-to-specific modeling strategy. In the present analysis, I estimate a simple and universally accepted forward-looking Taylor rule for the ECB using one year ahead growth and inflation forecasts based on the ECB’s Survey of Professional Forecasters. Not surprisingly, I find that the lower bound on the nominal interest rate significantly influences the model’s estimates as the estimated reactions to growth and inflation are considerably smaller when the post-September 2008 turmoil period is included. Using the more reliable pre-turmoil estimates, I find that the ECB’s estimated desired rate which drives rate changes is more aggressive and has a lower degree of gradualism when estimated using the discrete choice method than when estimated using least squares. This can be explained by the fact that the least squares method ignores the friction that rates are usually changed by discrete amounts, leading to an overly inertial estimated desired rate.

The ordered probit model assigns probabilities to the possible interest rate meeting outcomes, making it a potentially useful tool for forecasting central bank decisions. The present model shows a mixed performance in tracking ECB interest rate decisions. The predictions are compared with those derived from a Reuters poll which asks commercial bank economists on their expectations for the upcoming interest rate decision. Not surprisingly, the model fares worse than the poll which takes all information, including central bank communication regarding future interest rate moves, into account. Hence, the model seems only a rough description of actual monetary policy making but may however complement other sources for predicting monetary policy meeting outcomes.

I opted to estimate a standard forward-looking Taylor rule which takes into account only limited information. Actual policy decisions are based on a wide set of information, however. This may be tackled by including more variables in the model, as HP did using a general-to-specific modeling strategy. Another possibility is to use model averaging techniques that explicitly account for model uncertainty (Hoeting, Madigan, Raftery and Volinsky 1999). Economic applications using such techniques are given by, inter alia, Sala-i-Martin, Doppelhofer and Miller (2004) and Wright (2009). In future research, similar model averaging techniques could be applied so that the problem of model uncertainty can be addressed in a coherent way and an optimal forecasting model can be designed.
Appendix A  Reuters poll data coverage and sources

Reuters poll data set used in this article combines four different sources, each of them covering part of the sample. The questions asked in the poll have become more detailed over the years, for instance also asking for the probability attached to each meeting outcome.

Factiva Reports: Through Factiva, news reports regarding the Reuters poll were obtained. These allow to calculate the proportion of economists expecting a rate increase/decrease or constant rates for the period March 1999-February 2000. In this period, Reuters did not ask respondents to provide probabilities of the different moves.

Berger, Ehrmann and Fratzscher (2009): They use detailed data from the Reuters poll for the period March 2000-January 2005, which were kindly provided by the authors. The data contain respondents’ probabilities of the different meeting outcomes, allowing to calculate a mean probability and a proportion measure, based on the most likely outcome for every economist surveyed.

NBB Data: At the National Bank of Belgium, data on the monthly Reuters poll are stored in spreadsheets for internal usage, yet not in a consistent manner nor with all details as the Berger, Ehrmann and Fratzscher (2009) data. It is possible to obtain, for the period October 2004-July 2010, the proportion of economists expecting each of the different meeting outcomes, however. Yet, given the availability of more detailed Berger et al. (2009) data and original Reuters summaries, I use the internal data only for the period February 2005-June 2009.

Reuters Poll Summaries: From July 2009-July 2010, original Reuters summaries of the poll are available through wire services. These provide full detail and allow to calculate both the mean probabilities and proportions of the different meeting outcomes.

Prior to November 2001, two meetings were scheduled per month. Reuters also asks when, if rates are not changed the upcoming meeting, the next rate change will take place and by how many basis points. Hence, I can calculate the proportion of economists expecting a rate decrease/increase at the next two meetings of the current month. The mean probabilities, based on individual economists’ probability distributions of the upcoming meeting outcomes, do refer only to the upcoming meeting, however. Hence, the numbers for this statistic may not entirely reliable for the period March 2000-October 2001.

In summary, the probabilities for meeting outcomes based on the individual economists’ probability distributions are available for the periods March 2000-January 2005 and July 2009-July 2010. They allow to calculate a mean probability measure. The probabilities for meeting outcomes based on the economists’ point estimates are available for all meetings between March 1999-July 2010. They allow to calculate the proportion of economists expecting a particular meeting outcome.
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Limited liability company
RLP Brussels – Company’s number: 0203.201.340
Registered office: boulevard de Berlaimont 14 – BE-1000 Brussels
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Layout: Analysis and Research Group
Cover: NBB TS – Prepress & Image
Published in February 2011