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DEPARTMENT OF ECONOMICS

A discrete-choice econometrician's tale of monetary policy identification and predictability

Andrei Sirchenko

Thesis submitted for assessment with a view to obtaining the degree of Doctor of Economics of the European University Institute

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European University Institute
Department of Economics

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Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
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ABSTRACT

This thesis studies the econometric identification and predictability of monetary policy. It addresses the discrete and collective nature of policy decisions, and the use of the real-time versus currently available revised data.

The first chapter combines the ordered probit model, novel real-time data set and policy-making meetings as a unit of observation to estimate highly systematic reaction patterns between policy rate decisions and incoming economic data. The paper proposes a methodology to measure the empirical significance of the rate discreteness and demonstrates that both the discrete-choice approach and the real-time "policy-meeting" data do matter in the econometric identification of monetary policy. The estimated rules surpass the market anticipation made one day prior to a policy meeting, both in and out of sample.

The second chapter provides empirical evidence that a prompter release of policymakers' votes could improve the predictability of policy decisions. The voting patterns reveal strong and robust predictive content even after controlling for policy bias and responses to inflation, real activity, exchange rates and financial market indicators. They contain information not embedded in the spreads and moves in the market interest rates, nor in the explicit forecasts of the next policy decision made by market analysts. Moreover, the direction of policymakers' dissent explains the direction of analysts' forecast bias.

The third chapter develops a two-stage model for ordinal outcomes (such as discrete changes to the policy interest rates) that are characterized by abundant observations, potentially generated by different processes, in the middle zero category (no change to the rate), and where the positive and negative outcomes can be also driven by distinct sources. In the context of policy rate setting, the first stage, a policy inclination decision, determines policy stance (loose, neutral or tight) as a reaction to economic conditions, whereas two amount decisions at the second stage are more of a tactical and institutional nature. This approach separates different decision-making paths for three types of zero observations: "neutral" zeros, generated directly by the neutral policy stance, and two kinds of "offset" zeros, "loose" and "tight" zeros, generated by the loose or tight stance, offset at the second stage. The model is applied to the individual policymakers' votes for the interest rate. Both the empirical applications and simulations demonstrate superiority with respect to the conventional models.

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 DOI: 10.2870/60780

CONTENTS

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Part I

Introduction

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Many academic economists and central bank practitioners nowadays seem to agree that transparent and predictable behavior not only promotes the credibility and democratic accountability of an independent central bank but also creates a stable environment to manage the private sector expectations, reduces uncertainty in financial markets, and, eventually, enhances the transmission and effectiveness of monetary policy itself, thus leading to social benefits. To study the econometric identification and predictability of monetary policy, this thesis develops an empirical methodology (well suited for many central banks), combining the use of regression techniques for a discrete ordered dependent variable, decision-making meetings of monetary authority as a unit of observation, voting records of interest-rate-setting meetings, and real-time data.

The proposed methodological framework carefully mimics the actual policy-action-generating process since: (i) most major central banks alter interest rates by discrete-valued adjustments, typically multiples of 25 basis points; (ii) policy decisions are naturally made using information available in the real-time setting; (iii) they are typically made 6-12 times per year at special policymaking meetings; (iv) the vast majority of central banks entrust the conduct of monetary policy to a committee, composed of heterogeneous and quite often dissenting members; and (v) no-change decisions commonly constitute an absolute majority and can be potentially generated by different decision-making processes.

However, empirical studies routinely estimate the monetary policy rules by (i) applying the regression methods for a continuous dependent variable; (ii) using currently available series of economic data; (iii) analyzing the systematic responses of policy rate's averages to economic data averages for a given month or quarter; (iv) modeling the policy decisions made by a committee and disregarding the disagreement among the policymakers; and (v) treating all of the observations as coming from the same data-generating process and applying a single-equation model.

Obviously, such practice leads to misspecification of the actual data-generating process and distorts the inference because: (i) the regression methods for a continuous dependent variable are shown to be inadequate when the dependent variable is discrete; (ii) the latest versions of statistical data may differ from the real-time ones due to the revisions; (iii) the time aggregation of data misaligns the timing of policy decisions and the availability of statistical data as well as raises the problem of simultaneity; (iv) the failure to address the heterogeneity of policy preferences can lead to an inefficiency (and even bias, if the model is non-linear); besides this, the dissent among the policymakers at the last meeting may carry a strong hint about where policy rates might move in the future; and (v) the assumption of a homogeneous population, when the data are actually generated by different processes, causes bias in estimates.

A separate contribution of this thesis is a new methodology for modeling the ordinal variables, which is likely to be fruitfully applied to the ordered data (such as the attitudes, opinions, or discrete changes to the ranking) that are characterized by the abundant observations in the middle neutral or zero category.

Another separate contribution is the compilation of novel Polish real-time data set incorporating the original time series, available to policymakers at each policy-setting meeting during the 1998-2009 period.

The first chapter assesses separately the statistical effects of using the linear regression model instead of the ordered probit (OP) model and the latest revised monthly-averaged data instead of real-time data with the policy-making meetings as a unit of observation. The formal comparison demonstrates that the discreteness and real-time data indeed matter in the empirical identification of Polish monetary policy.

The study detects structural breaks in policy, which switched its focus from current to expected inflation and from exchange rate to real activity. The response to inflationary expectation is shown to be highly asymmetrical depending on whether the expectation is above or below the inflation target. The policy rate appears to be driven by key economic indicators without evidence for intentional interest-rate smoothing by the central bank. The estimated rules correctly explain 95 percent of observed policy actions and surpass the market anticipation made one day prior to a policy meeting, both in and out of sample.

The second chapter provides empirical evidence as regards whether the voting records of the last policymaking meeting could improve the predictability and private sector anticipation of the next policy rate decision in Poland. The case of Poland, where the voting records become available only after the subsequent policy meeting, provides an interesting opportunity to investigate whether the disclosure of votes could create news for the private sector as late as one day before a policy meeting, when information on the state of the economy available to the public is as close as possible to that available to the policymakers at their meeting the next morning. If the voting records add information, they can improve the public's understanding of the systematic policy responses and decision-making process of the central bank.

This work not only extends the scarce empirical literature, but also makes a contribution in the following directions. First, do voting records (in addition to relevant economic data) help to forecast the next policy rate decision? Second, could dissenting votes, if they were available, add information to the market expectations of upcoming policy decisions? Third, do voting records enhance policy predictability beyond the private sector anticipation? And

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

fourth, can the direction of dissents and the dispersion of votes explain the direction of bias and the uncertainty of private sector forecasts? The answer to all the above questions is yes.

All of the findings are based upon the voting patterns only, without knowledge of the policymakers' names attached to each vote. Therefore, they might be of interest to the central banks that do not currently publish the voting records because of the reluctance to disclose the votes of individual members (e.g., the European Central Bank).

The second chapter provides clear policy messages. First, the National Bank of Poland can further improve the predictability and public understanding of its monetary policy by publishing the voting records as soon as possible, preferably in its press releases immediately after a policy meeting. Second, the voting records should include the proposed policy choice of each dissenting member.

The ordinal outcomes, such as the attitudes, opinions, discrete changes to the ranking or policy interest rate, are often characterized by abundant observations in the middle neutral or zero category (e.g., the indifferent attitude to survey questions, or no change to the ranking or rate). Such excessive zeros can be generated by different population groups or separate decision-making processes. Besides, the positive and negative outcomes can be driven by distinct sources. In such a situation, it would be a misspecification to treat all the observations as emanating from the same process and to apply a standard ordered-response model based on a single latent equation. The third chapter develops a more flexible cross-nested model for such types of ordinal variables, combining three OP latent equations with possibly different sets of covariates.

The proposed middle-category-inflated ordered probit model (MIOP) allows the separate mechanisms to determine what I call the inclination decision ($\Delta y \leq 0$ versus $\Delta y = 0$ versus $\Delta y \geq 0$, interpreted as a loose, neutral or tight policy stance) and two amount decisions (the magnitude of Δy when it is nonpositive or nonnegative), conditional on the loose or tight policy stance. The inclination decision is driven by reaction to the changes in the macroeconomic environment, whereas the amount decisions let policy stance be offset by the institutional features of monetary policymaking. The probability of a no-change outcome is inflated, since there are the following three types of zeros: the "always" or "neutral" zeros, generated directly by the neutral policy reaction to the economic developments, and two kinds of "not-always" or "offset" zeros, the "loose" and "tight" zeros, generated by the loose or tight policy inclinations offset by the institutional factors. The model also allows for the possible correlation among the three latent decisions.

The Monte Carlo results suggest good performance of the MIOP model in the finite samples and demonstrate its superiority with respect to the conventional and nested OP models.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

The MIOP model is then applied to explain policy rate decisions of the National Bank of Poland, using the panel of the individual votes of policymakers and real-time macroeconomic data available at the policy meetings. The two-stage three-regime approach attempts to address the worldwide stylized facts of interest rate setting such as the discreteness, preponderance of no-change decisions and inertia. The voting preferences appeared to be well-modeled by such an approach. Not only does it fit the data much better, but it also has some important advantages over the single- and two-equation models, such as the standard OP, multinomial probit and zero-inflated OP models. The empirical application demonstrates the advantages of the MIOP model in separating different decision-making paths for three types of zeros and estimating the proportion of zeros generated by each regime.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Part II

Chapters

 DOI: 10.2870/60780

Chapter 1

Modeling monetary policy in real time: Does discreteness matter?

1.1 Introduction

> "The central bank must have a highly regular and predictable policy rule or response pattern that links policy actions to the state of the economy."
>
> – W. Poole, then-President of the Federal Reserve Bank of St. Louis[1]
>
> "It is not possible to make use of a simple policy rule, which could be known ex ante to market participants."
>
> – Monetary Policy Council, National Bank of Poland[2]

The discreteness of policy rates, both in magnitude (the adjustments are typically made in multiples of 25 basis points) and timing (the policy actions take place usually 6-12 times a year) is a common feature of contemporary monetary policy-making in many countries. This study applies an empirical methodology (well suited for many central banks) in order to identify the monetary policy by combining the use of discrete-choice approach, real-time data and policymaking meetings of monetary authority as a unit of observation. The paper estimates highly systematic response patterns between the interest rate decisions of the National Bank of Poland (NBP) and incoming economic data, available both for policymakers and for private public in the real-time setting. The specification search is conducted with a wide spectrum of potential explanatory variables among those monitored by the central

[1] See Poole (2003).
[2] See "Monetary policy guidelines" for the years 2005, 2006 and 2007; e.g., see NBP (2006), p. 5.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

bank, and is refined by the Andrews' tests for a structural change with an unknown change point. This paper compares the discrete-response versus conventional continuous approach to estimate the policy rules, and also shows that using the monthly averages of ex post revised data instead of real-time non-aggregated data distorts our understanding of policy decisions.

A separate contribution of this paper is the compilation of Polish real-time data set incorporating the original time series, which were actually available to policymakers at each policy-setting meeting during the period 1998 - 2007. To the best of my knowledge, such a data set has never been used in modeling Polish monetary policy and has proved to be fruitful.

Many economic decisions rely on inflationary expectations, while inflation predictability depends on the consistency of monetary policy. More transparent and predictable behavior of central bank itself improves the transmission and effectiveness of monetary policy, as many academic economists and central banks' practitioners nowadays seem to agree[3]. Over the past two decades most central banks, including the NBP, have radically increased their public communication, as well as the disclosure of internal information and methodology used in monetary policy-making[4].

An obvious way to facilitate the predictability of monetary policy is to utilize a "rule", which is "nothing more than a systematic decision-making process that uses information in a consistent and predictable way" (Meltzer 1993). Starting at least with a classic paper by Kydland and Prescott (1977), many economists conclude that pre-commitment to a rule can have both beneficial and stabilizing outcomes[5]. Operating under the policy rule not only enhances a central bank's accountability, credibility and transparency, but, according to Poole (1999), "also provides the surest method to pass the accumulated knowledge about the effective operation of monetary policy to future generations", and, perhaps provides the only way of improving monetary policy practice. Indeed, in order to improve it we must obtain a clear empirical description of what is going to be improved, for example, an econometric identification of current policy. It is really difficult to evaluate the policy without describing it, using an algebraic formula or "rule".

In the light of the NBP statement that "it is not possible to make use of a simple

[3]See, e.g., Bernanke (2007), Blinder (1998, 2005), Carpenter (2004), Faust and Svensson (2001), Geraats (2001, 2002), Ingves (2007), Issing (2005), Kennedy (2008), Kohn (2008), Poole (2003, 2005), Thornton (2003).

[4]See Łyziak et al. (2006) on the transparency of NBP monetary policy.

[5]See, e.g., Barro and Gordon (1983a, 1983b), Barro (1986), Calvo (1978), Clarida et al. (2000), Dennis and Soderstrom (2006), Svensson (1999a, 1999b, 2002), Taylor (1993, 1999), Woodford (1999a). The "rules versus discretion" academic debate has a long history – see, e.g., Wicksell (1898), Simons (1936).

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

policy rule which could be known ex ante to market participants" (NBP 2006), it is an interesting empirical exercise: to uncover a systematic component of a central bank's policy. Such econometric modeling can help market participants to make more efficient decisions by minimizing the uncertainty regarding future policy actions: "What the market needs to know is the policy response function by which the central bank acts in a consistent way over time" (Poole 2003). Besides, the policy rate is a key determinant of other short-term market interest rates. Furthermore, "if practitioners in financial markets gain a better understanding of how policy is likely to respond to incoming information, asset prices and bond yields will tend to respond to economic data in ways that further the central bank's policy objectives" (Bernanke 2007).

It must be the case that the central bank pursues the regularity of some sort, though there is no simple and fixed policy rule, mechanically followed under all circumstances. Rather, the central bank pays attention to a variety of statistical data and other information, and considers several alternative rules, used as policy guidelines and combined with anecdotal evidence and judgment. We can reasonably assume that the policy-generating process consists of two components, namely a regular and a non-regular component: the central bank reacts consistently to some internal sophisticated assessment of the economy, but occasionally (in the case of transitory or anomalous shocks to the economy, strike, financial crisis, natural disaster, etc.) departs from the regularity. The specific characteristics of the systematic component are inside a black box – they are unobservable for public. However, we can proxy for the underlying determinants of policy actions by looking at the consequential systematic links between adjustments to policy rates and movements in various observable fundamentals.

The estimated models, representing a simplification of true policy-making process, might effectively reflect its essence, and could be applied as a useful benchmark for explaining past policy decisions and predicting future ones, even though the NBP certainly does not view itself as implementing a "simple policy rule". Besides, knowing a central bank's correct "reaction function" is also a necessary element of macroeconomic models, used to forecast developments in the economy and to evaluate the effects of economic shocks and monetary and fiscal policy actions. Finally, "clarity about the central bank's policy objectives and strategy may help anchor the public's long-term inflation expectations, which can substantially improve the efficacy of policy and the overall functioning of the economy" (Bernanke 2007).

This paper differs from the previous empirical research on Polish monetary policy rules in the following aspects: (i) it accounts for the discreteness of policy rates by applying an

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

ordered probit model; (ii) it models the policymakers' response to an information set available at the decision-making meetings of monetary authority rather than the relationship between the monthly or quarterly averages of policy rate and economic indicators; (iii) it avoids the distortion of information by using only the real-time data, i.e. the historical time series as they were known at any policy-making meeting, rather than the latest revised versions of data; (iv) it avoids the problem of simultaneity, which is typical for the time-aggregated data due to possible interactions between the policy rate and other economic variables that can happen during a period of aggregation; (v) it conducts thorough tests for structural changes in policy regime with unknown change point; (vi) it directly models the administered policy rate rather than the market short-term interest rates; (vii) it analyzes the period 1999 - 2007, when the short-term interest rates have been a principal tool and a single measure of monetary policy; (viii) instead of the level rules it estimates the difference rules that are more operational and transparent for public[6]; (ix) it is not focused on a limited amount of statistical data, but instead uses in the specification search a wide spectrum of economic and financial indicators; and (x) the estimated interest rate rules have far higher measures of fit and out-of-sample forecasting performance.

The paper proceeds as follows. Section 1.2 provides review of the related literature. Section 1.3 discusses the background of the monetary policy in Poland. Section 1.4 describes the data and methodology. Some econometric results are presented in Section 1.5. Section 1.6 demonstrates that both the real-time "policy-meeting" data do matter in the econometric identification of Polish monetary policy. Section 1.7 focuses on the comparison of the discrete-response versus conventional continuous approach to estimate the policy rules. The last section provides the summary and concludes.

1.2 Related literature

The literature on Polish monetary policy rules is summarized in Table 1.1. These studies estimate the interest rate rules for the period from 1991-1995 through 2000-2004. However, prior to 1998 the Polish monetary policy was rather eclectic with the managed exchange rate regime and changing policy instruments: the direct inflation targeting with the short-term interest rates as a principal tool of monetary policy was only fully implemented in 1999.

Several studies estimate NBP reaction functions in the context of vector autoregression (VAR) modeling of the Polish economy (Golinelli and Rovelli 2005, Hristov 2005, Kłos and

[6] See Orphanides and Williams (2006) for a comparison of the level and difference rule approaches under the framework of imperfect knowledge.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Wróbel 2001, Kokoszczyński et al. 2006, Maliszewski 2003, Wróbel and Pawłowska 2002). However, the VARs are focused on identifying the monetary policy shocks and responses of key economic indicators to them rather than on identifying the interest rate reaction functions. The policy rules estimated using the VAR models typically have poor in- and out-of-sample forecasting performance, compared to the non-VAR models (see Rudebusch 1998a, b). Rudebusch points out the following shortcomings of the standard VAR interest rate rules: a) time-invariant and linear structure; b) a limited information set, which leads to omitting the relevant explanatory variables; and c) long distributed lags, resulting in spurious in-sample fitting.

Brzozowski (2004) and Mohanty and Klau (2004) estimate the non-VAR policy rules. Both studies use quarterly data averages (the latter also tries the monthly averages), short-term market interest rates as a dependent variable and the Taylor-rule specification[7].

Only a few papers in the empirical literature on monetary policy rules apply the discrete regression techniques to address the discreteness of policy rates. Studies by Dupor et al. (2005), Hu and Philips (2004), Lapp et al. (2003) and Piazzesi (2005) use the ordered probit to model three possible policy choices (to decrease, leave unchanged or increase the interest rate) of the US Federal Reserve (Fed), while Dueker (1999) and Hamilton and Jorda (2002) employ the ordered probit with five categories (corresponding to 50, 25, 0, -25 and -50 basis point changes). Eichengreen et al. (1985) and Davutyan and Parke (1995) apply the dynamic ordered probit with three and five categories, respectively, to model the Bank of England's policy interest rate changes. Dolado et al. (2005) estimate the interest rate-setting behavior of the Banque de France, the Bundesbank, the Banco de España, and the Federal Reserve, using the ordered probit model with five categories. Podpiera (2007) combines the ordered probit and censored regressions to estimate the interest rate rules of the Fed and the Czech National Bank. Kotłowski (2006) estimates a triple-choice ordered logit, modeling the direction of change in the restrictiveness of monetary policy proposed by a given member of the Monetary Policy Council in Poland. The restrictiveness is measured by the proposed change of policy bias and/or change to the reference rate. Unfortunately, the sample includes only 18 monthly observations for the period 2004/02 – 2005/07, not enough for a reliable likelihood estimation.

A growing number of recent works employ real-time data to address the subsequent re-

[7] Taylor (1993) proposed a monetary policy rule, where the US Federal Reserve alters the federal funds rate (FFR) according to $FFR_t = \pi_t + 0.5Y_t + 0.5(\pi_t - \pi^*) + R$, where R - the "equilibrium" real interest rate, π^* - the long-run inflation target, π – the inflation rate over a year (as a proxy for the expected inflation), Y – the output gap (the percent deviation of real GDP from the potential one). Taylor assumed $R = 2$ and $\pi^* = 2$. The Taylor rule contributed to a better understanding of monetary policy and was widely modified and extended in a number of ways in the subsequent literature.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

visions of statistical data, and overwhelmingly show that different vintages of US, Japanese, Euro area, German, Swiss and Norwegian data lead to significantly different results[8]. Therefore, the estimation of policy rules based on ex post revised data distorts our understanding of past monetary policy – an obvious point, but one that is routinely neglected by most studies.

Using the decision-making meetings of monetary authorities as a unit of observation represents an approach that carefully mimics the actual decision-making process, but seems to be commonly ignored in the literature. Instead, researchers habitually estimate the systematic relationship between the monthly or quarterly averages of policy rates and economic variables.

1.3 Background of Polish monetary policy

In the 1995-1997 period the NBP conducted its monetary policy by controlling the money supply growth and targeting the exchange rate. The exchange rate regime was gradually transformed from a managed to a free-floating regime during the 1990s. The monthly rate of crawl was progressively reduced from 1.8 percent in 1991 to 0.3 percent in 1999. The preannounced crawling peg system was superseded by the crawling band regime in May 1995. The crawling band width was widened from ±7 percent in 1995 to ±15 percent in 1999, and was finally abandoned – in April 2000 the zloty officially began to float. Actually, the NBP suspended foreign exchange interventions already in mid-1998, *de facto* entering the floating exchange rate regime (Pruski and Szpunar 2005). Consequently, during the 1990s the exchange rate has been steadily losing its role as an operating tool of monetary policy.

The critical institutional changes in Polish monetary policy occurred in 1998. In January the direct inflation targeting (DIT) was implicitly adopted as a primary monetary policy strategy. The DIT assumes the direct target for official consumer price index and a lack of indirect targets such as the money supply or exchange rate. In October the DIT was officially declared by the Monetary Policy Council (MPC) – a new independent policy-making body[9]. The MPC was founded in February 1998, soon after the independence of the NBP had been strengthened by the new Constitution and the new Act on the NBP. The Council consists of the President of the NBP and nine other members appointed in equal proportions by the

[8]See, e.g., Bernhardsen et al. (2004), Croushore and Stark (2001, 2003), Clausen and Meier (2005), Gerberding (2004), Gerdesmeier and Roffia (2005), Ghysels et al. (2000), Kamada (2004), Kugler et al. (2004), Lansing (2002), Orphanides et al. (2000), Orphanides (2001a, 2001b, 2002, 2003), Perez (2000), Runkle (1998), Sterken (2003), Tetlow and Ironside (2005).

[9]See NBP (1998).

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

President of Poland, the Sejm and the Senate of the Parliament for a term of six years.

The MPC immediately stopped the long-term interest rate operations by shortening the maximum maturity of NBP's money bills from 270 to 28 days, abandoned the monetary base targeting, expanded the exchange rate flexibility toward the free floating system, increased the role of short-term interest rates as a primary way of pursuing the DIT, and began declaring an inflation target in the form of annual growth rate of consumer price index. Since 1998 every fall the MPC announces the inflation target (along with the permissible bandwidth around it) to be attained by the end of next year (see Figure 1.1). From 1998 to 2006 the annual growth rate of consumer prices in Poland has dropped from 14 to less than 2 percent (see Figure 1.1) – arguably, an impressive outcome of implemented monetary policy[10].

Overall, since 1998 the short-term interest rates may undoubtedly be treated as a principal instrument and a single measure of Polish monetary policy. Since the policy rates have been always set administratively by the monetary authorities and have never been the outcome of market interaction of supply and demand, they are of special interest for econometric modeling.

There are three NBP policy rates. The reference rate[11], introduced in January 1998, sets the path of monetary policy and "determines the minimum yield obtainable on main open market operations, influencing, at the same time, the level of interbank deposit rates for comparable maturities" (NBP 2005). The deposit and lombard rates, introduced in 1993, set the fluctuation band for overnight interbank interest rates. The open market operations – the sale or purchase of securities or foreign currencies and issue of own-debt securities – help to balance the demand and supply of funds held by the commercial banks at the central bank, and have been used to manage the short-term interest rates on the interbank market since 1993.

1.4 Data and modeling framework

1.4.1 Discreteness of policy rates

The dependent variable is a change (including non-zero ones) to the reference rate made by the MPC at a decision-making meeting. The NBP has always altered the levels of policy

[10]For the related applications of an ordered probit model with such a triple classification to study, for example, the US Federal funds rate target see, e. g., Dupor et al. (2005), Hu and Philips (2004), Lapp et al. (2003).

[11]The rate on 28-day (from 1998 to 2003), 14-day (from 2003 to 2005), and 7-day (since 2005 to present) NBP money market bills.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

rates in discrete adjustments – the multiples of 25 basis points (a quarter of one percent). Table 1.2 shows the history of the reference rate for the period 1998/02 - 2006/10. The frequency distribution of the reference rate adjustments is reported in Table 1.3: all 105 historical rate changes took only eleven values, between -250 and 250 basis points. Table 1.3 and Figure 1.2 exhibit two distinct phases in the historical behavior of the reference rate: the high-volatility period prior to April 2002 (when all changes, except the first one in February 1998, were by absolute value between 100 and 250 basis points) and the low-volatility period since April 2002 (when all changes were by absolute value either 25 or 50 basis points).

The reference rate adjustments are distributed heterogeneously: 95 out of 105 changes fall into 5 out of 11 observed discrete cases. There are three or less observations in six categories of dependent variable. This is not sufficient for a reliable maximum likelihood estimation. A usual approach under such circumstances is to consolidate some adjacent categories with a small number of observations. For example, we could merge all observed changes into four categories: "decreases of 1% or more", "decreases of 0.25% or 0.50%", "no change" and "increases" with 8, 63, 20 and 14 observations, respectively. However, due to the two aforementioned periods with different volatility of the reference rate, such a quadruple classification does not allow for the conducting of the tests for structural change. Indeed, during the high-volatility period 1998/02 - 2002/03, all rate changes fall into following three categories: "decreases of 1% or more", "no change" or "increases", while during the low-volatility period 2002/04 - 2006/10 the only three realized cases are: "decrease of 0.25% or 0.50%", "no change" or "increases" (see Table 1.3). After splitting the sample at any point prior to March or after April 2002, the dependent variable will have a different number of categories (three and four) in the two sub-samples. Therefore, to make possible performing the parameter instability tests, all observed rate changes are combined into following three categories: "decrease", "no change" or "increase" (see Table 1.3). The only consequence of such consolidation is the loss of efficiency – adding (or deleting) another cutpoint does not affect the structural latent model given by (1.1) and (1.2) below. However, it is still definitely able to represent the essence of the NBP operating policy.

Fortunately, after detecting a structural break in April 2002, the period 2002/04 - 2006/10 was analyzed using the finer quadruple classification: "down 0.50%", "down 0.25%", "no change" and "up" – with 3, 32, 11 and 9 observations, respectively (see Table 1.3). This classification closely corresponds to the historical policy rate adjustments in this period: only two observed adjacent categories – the "up 0.25%" and "up 0.50%" with one and two observations, respectively – have been consolidated.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

1.4.2 Ordered probit model

To address the discreteness of dependent variable, this paper employs an ordered probit approach, which forms a probabilistic forecast of discrete adjustments to the policy rate as a nonlinear function of explanatory variables. This approach assumes an underlying level of the reference rate RR_t^* that would have been observed had the NBP been willing to make the continuous (rather than discrete) changes to the rate. At every policy-rate-setting meeting t the NBP determines the change $\Delta RR_t^* = RR_t^* - RR_{t-1}^*$ in this latent rate according to the following formula:

$$\Delta RR_t^* = \mathbf{X}_t \boldsymbol{\beta} + \varepsilon_t, \tag{1.1}$$

where $\varepsilon_t \sim iid\ Normal(0, \sigma^2)$ and $\mathbf{X}_t$ is a matrix that may incorporate any data relevant for the policymakers and available at date t. Matrix $\mathbf{X}_t$ may include the variables in any form (levels, first and second differences) and at any original data frequency.

Although RR_t^* is unobserved, the NBP announces the official (i.e. observed) adjustments to the reference rate ΔRR_t^* according to the following rule:

$$\Delta RR_t = \begin{cases} k_1 & \text{if} \quad \Delta RR_t^* \leq \alpha_1, \\ k_j & \text{if} \quad \alpha_{j-1} < \Delta RR_t^* \leq \alpha_j \text{ and } 1 < j < J, \\ k_J & \text{if} \quad \alpha_{J-1} < \Delta RR_t^*, \end{cases} \tag{1.2}$$

where $k_1, k_2, \ldots, k_{J-1}, k_J$ – observed discrete-valued changes to the policy rate (multiples of the 25 basis points), J is a number of observed discrete cases, and $-\infty = \alpha_0 < \alpha_1 < \alpha_2 < \ldots < \alpha_{J-1} < \alpha_J = \infty$ are unknown thresholds to be estimated.

Assuming a Gaussian cumulative distribution function F of ε_t, it follows that the probabilities of observing each possible outcome of ΔRR_t are

$$\Pr(\Delta RR_t = k_j | \mathbf{X}_t, \boldsymbol{\beta}, \alpha) = \begin{cases} F(\alpha_1 - \mathbf{X}_t \boldsymbol{\beta}) & \text{if} \quad j = 1, \\ F(\alpha_j - \mathbf{X}_t \boldsymbol{\beta}) - F(\alpha_{j-1} - \mathbf{X}_t \boldsymbol{\beta}) & \text{if} \quad 1 < j < J, \\ 1 - F(\alpha_J - \mathbf{X}_t \boldsymbol{\beta}) & \text{if} \quad j = J. \end{cases} \tag{1.3}$$

The estimates of $\boldsymbol{\beta}$ and α can be obtained by making identifying assumptions (typically, that $Var(\varepsilon_t | \mathbf{X}_t) = 1$ and the intercept $\beta_0 = 0$) and maximizing the log likelihood function

$$\ln L = \sum_{t=1}^{N} \sum_{j=1}^{J} d_{tj} \ln[F(\alpha_j - \mathbf{X}_t \boldsymbol{\beta}) - F(\alpha_{j-1} - \mathbf{X}_t \boldsymbol{\beta})], \tag{1.4}$$

where N is the sample size, and $d_{tj} = 1$ if $\Delta RR_t = k_j$ and 0 otherwise.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

1.4.3 Policy meetings as a unit of observation

The paper departs from a common practice of employing the quarterly or monthly data averages and instead uses more adequate sample construction. The sample observations are all MPC meetings, when the decisions on the policy rate have been made. The MPC has always taken such decisions once a month, during the second half of the month. The dependent variable is a reference rate change made at a given MPC meeting. The data on the right-hand-side variables is taken as it was observed at a date of making policy decision, so it consists of already predetermined variables, which are independent of the rate setting at that MPC meeting. The raw data is used in all types of original frequency: daily, monthly and quarterly.

The above data construction avoids the simultaneity problem, which can occur in modeling the systematic responses of policy rates' averages to economic variables' averages for a given month or quarter due to possible interactions between the policy rate and the other variables that can happen during a period of aggregation. Furthermore, this sample design mimics carefully the timing of policy decisions and availability of statistical data, and hence carefully simulates the actual policy-action-generating process.

1.4.4 What does the MPC watch?

The empirical research on monetary policy tends to focus on a limited amount of data. Indeed, the central banks look at everything and monitor hundreds of economic variables: "The central bank takes into account all available information about factors increasing or decreasing inflationary pressure and causing a rise or fall of probability of achieving the inflation target assumed in the given period" (NBP 1999). What does the MPC monitor? Typically at each policy-setting meeting the Council discusses an impact on the future inflation, resulting from the current tendencies and forecasts of various economic and financial factors such as: the prices and inflationary expectations; the real sector of economy; the money supply; credit and lending; the market interest rates; the exchange rates; the external economic conditions; the situation in the balance of payments and in public finance sector; the labor market and wages.

After each policy meeting the MPC issues a press statement, announcing the decision made and its justification. The Inflation Report, released quarterly, contains the description of monetary policy conduct during the last three months along with the minutes of MPC meetings. Starting in April 2007, the minutes of MPC meetings have been published separately each month, a week before the next policy-making meeting. This study utilizes

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

careful reading of MPC statements in order to identify the determinants of policy actions, and considers a wide spectrum of economic and financial indicators as candidate explanatory variables.

Table 1.4 describes the data used in the specification search. The potential explanatory variables are divided into twelve groups: current inflation (price indexes), inflationary expectations, gross domestic product and its main components, other measures of real activity, real sector expectations, labor market and wages, employment expectations, market interest rates, exchange rates, exchange rates' expectations, foreign policy interest rates, lending and credit. All variables are measured in various forms: levels, growth rates over different time spans, spreads and deviations, moving averages, changes (or growth rates) since the last MPC meeting and since the date of the last non-zero move in the policy rate. Table 1.5 describes the transformations made to the original data. In addition, the study checks for asymmetric responses to the negative and positive shocks.

1.4.5 Real-time data

To make the realistic assumptions about the timing of latest information available to the MPC at any meeting in the past the study pays careful attention to the historical release dates of all candidate explanatory variables and carefully scrutinizes MPC press statements following each policy-setting meeting.

Major economic data are released at either monthly or quarterly intervals with a publication lag of up to three months. Some monthly economic indicators are usually available for the policymakers with a one-month lag, while the others are known with a two-month lag. The policy decisions sometimes take place in a middle of the month, prior to some regular data releases, as happened, for example, at a meeting on December 16-17, 2003, when "until the meeting of the Council the November figures relating to the industrial and construction sector output, retail sales, the PPI, the unemployment rate, base inflation and inflationary expectations were not disclosed" (NBP 2003). All the above-mentioned indicators are typically available for the previous month. Similarly, the availability of quarterly data at each meeting varies from month to month and from year to year, depending on the varying dates of quarterly data releases and MPC meetings. For example, at a meeting on November 24^{th}, 2004 the third quarter's data on GDP was already available, while at a meeting on November 26^{th}, 2003, the most recent available data related to the second quarter only.

Table 1.6 reports the timing and availability of quarterly and monthly statistical data at each policy meeting. The information on historical release calendars for all potential regressors was gathered both from the official web-sites and via requests to appropriate

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

statistical agencies. The data released daily is taken for the business day preceding the day of the meeting itself.

To avoid the distortion of information, this study compiles and uses the novel Polish real-time data set, containing the historical time series actually available to the policymakers at each decision-making meeting during the period 1998-2007. The latest versions of data commonly used in the empirical research may differ from the real-time data due to revisions. Table 1.4 describes the "MPC meeting" data set, which contains the real-time vintages of about 140 economic and financial indicators such as: price indexes; inflationary expectations; gross domestic product and its main components; data from business tendency survey in construction, industry and retail trade and Reuters survey of commercial banks' analysts; industrial production; retail and whole sale of goods; investments; labor market and wages; market interest rates; exchange rates; foreign policy rates; and lending and credit. Most of the above variables are not subject to statistical revisions, so the real-time aspect of these data deals only with the accurate synchronization of the dates of policy decisions and timing of data releases. The variables that have been revised since the beginning of sample period include: the consumer price index; the real indexes and values (in current prices) of domestic demand, final consumption expenditure of households, gross domestic product, gross fixed capital formation and gross value added; the industrial production, both total and manufacturing; and the registered number of unemployed persons.

1.4.6 Tests for structural change

This study thoroughly checks for breaks in policy regime using Andrews' sup-LR test for structural change with an unknown change point (due to Andrews 1993). It is the generalization of Chow breakpoint test for a wide class of linear and non-linear parametric models. Instead of testing for a single break at a given point, in Andrews' test the likelihood ratios between the restricted and unrestricted models are computed for all points in the testing period (in the restricted model, the parameters are restricted to be constant for the whole period, while in the unrestricted one the parameters are estimated separately for the two sub-periods). To do so, the first 34 and the final 35 observations in the sample period 1999/02 – 2006/10 are preserved, the separate estimations for each sub-sample are performed, and the LR is computed for each monthly point from November 2001 through November 2003. The point with the maximum LR is the best candidate for the structural change, provided that the LR exceeds an asymptotical critical value, which depends on the size, both the whole sample and of the testing period.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

1.5 Estimation results

1.5.1 Tests for stationarity

All variables are checked for stationarity using the Augmented Dickey-Fuller (ADF) unit root tests. The lag order of lagged first differences of dependent variable in the tests is chosen according to a criterion of no serial correlation among residuals. The serial correlation among residuals up to the twelfth order is checked using the Ljung-Box Q-statistic. Table 1.7 reports the stationarity tests for all variables used in the reported results. All but two are stationary at a significance level of less than 5 percent. The indexes of gross domestic product and gross value added (growth rate in percent since corresponding period of the previous year) $GDPnaiy$ and $GVATnaiy$ are stationary at 7 percent level; however, it is likely due to insufficient power of the test due to the small sample size.

1.5.2 An interim year of 1998

The estimated reaction functions become more regular if the first twelve MPC meetings, from February 1998 through January 1999, are omitted from the sample. For example, Table 1.10 compares the estimations of two specifications for the periods 1998/03-2002/03 and 1999/02-2002/03: specification 10.1, which includes the month-to-month change in the deviation of annual rate of $CPIxac$ less administratively controlled prices from the inflation target and exchange rate of zloty to euro, and specification 10.2, which includes two measures of current inflation: Ind_CPI_T – an indicator variable, equaled to one, when CPI is above the inflation target, and zero otherwise, and $CPxac\_T\_YC$ – the change in the deviation of annual rate of core CPI less administratively controlled prices from the inflation target since the date of the last move in the policy rate. Dropping observations prior to February 1999 results in the considerable increase of parameters' estimates and improvements of fit in both specifications: LR (likelihood ratio) is 31.0 vs. 40.2 for model 10.1 and 21.5 vs. 39.3 for model 10.2, count R^2 (proportion of correct predictions) is 0.71 vs. 0.87 and 0.69 vs. 0.95, McKelvey & Zavoina R^2 is 0.67 vs. 0.96 and 0.50 vs. 0.97, respectively.

The detected significant differences in policy behavior before and after February 1999 can be explained by the following institutional facts. First, the year of 1998 represented a period of gradual transition (an "interim" year – see Polański (2004) for more information) from the monetary base targeting to a new framework of DIT that was officially declared only in October 1998 and that was formally supposed to be implemented since the beginning of 1999. Second, in the middle of 1998, the zloty started floating de facto – obviously, this

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

switch from the a managed to a floating exchange rate regime affected the conduct of interest rate policy later on. Third, the monetary policy in 1998 was complicated by the Russian crisis in August – a strong external demand shock, which cut short Polish exports to Russia and boosted the supply in the domestic market. The four rate cuts by a total amount of 6 percent from September 1998 through January 1999 were caused to a large extent by the Russian default and appear to be the sample outliers.

Therefore, a sample from 1999/02 through 2006/10 is used for the further estimation.

1.5.3 The stability of policy responses

The Andrews' sup-LR tests with unknown change point detect highly significant structural breaks in the year of 2002 for many two-variable specifications, chosen among more than hundred and sixty economic indicators from Table 1.4. For example, Figure 1.3 shows the plot of sup-LR test for the specification with $ExInf\_T\_M$ (monthly change in the spread between the expected rate of inflation over the next 12 months from Ipsos survey and the inflation target) and $GVARna\_Y$ (the annual growth rate of gross value added in current prices less annual growth rate of CPI for the corresponding quarter). The models, including instead of gross value added other measures of real activity, such as the real gross domestic product and real domestic demand, have the similar patterns of sup-LR tests and also reveal the drastic structural break in April 2002. The dating of the structural break precisely matches the cut-off point between the above-discussed two sub-periods with high and low volatilities of the reference rate changes.

The separate estimations of four specifications, all including inflationary expectation $ExInf\_T\_M$, but different measures of real activity for the two sub-periods 1999/02-2002/03 and 2002/04-2006/10 are reported in Table 1.8. The difference in the fit before and after April 2002 is impressive for all four specifications. For example, for the specification 8.2 with $ExInf\_T\_M$ and $GDPRna\_Y$ (the annual growth rate of gross domestic product in current prices less annual growth rate of CPI for the corresponding quarter) the LR is 11.97 vs. 75.18, count R^2 is 0.71 vs. 0.98 and McKelvey & Zavoina R^2 is 0.41 vs. 0.97; besides, $ExInf\_T\_M$ is not significant at 36% level prior to April 2002, but significant at 1% level since then.

Table 1.9 compares four two-variable models, estimated for both sub-periods separately, and all including the same measure of real activity $GDPnaiy$ (the growth rate in percent since corresponding period of previous year of the index of gross domestic product), but different measures of current or expected inflation. The response to real activity becomes much stronger (the parameter estimates are 2-4 times larger) and more systematic in the

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

second sub-period (p-values are smaller than 0.01 percent) than in the first one (p-values are between 1 and 7 percent). The responses to all three measures of current inflation are significant at 5% level in both sub-samples. However, the measure of expected inflation $ExInf\_T\_M$ is not significant at 17% level prior to April 2002, but significant at 0.1% level later on (see model 9.1). The overall fit of all specifications is much better for the second sub-period than for the first. More importantly, Table 1.9 demonstrates a clear shift from the backward-looking to forward-looking policy behavior: the measures of current inflation have a far more systematic relationship with the policy rate than the inflationary expectation prior to April 2002, but vice versa since then. Indeed, the best model for the first sub-period – the specification 9.4 with the backward-looking measure of inflation $CPIxac\_T\_YM$ (the monthly change in the deviation of annual rate of core CPI less administratively controlled prices from the inflation target) – has a much better fit than the specification 9.1 with forward-looking measure of inflation ($ExInf\_T\_M$): LR is 25.63 vs. 7.81, count R^2 is 0.82 vs. 0.71, McKelvey & Zavoina R^2 is 0.69 vs. 0.28. Quite the reverse, the best model for the second period – the forward-looking specification 9.1 – definitely outperforms all specifications with the measures of current inflation, including the best one among them, the specification 9.2 with $CPIxmf\_T\_YM$ (the monthly change in the deviation of annual rate of core CPI less the most volatile and fuel prices from the inflation target): LR is 69.92 vs. 46.68, count R^2 is 0.91 vs. 0.86, McKelvey & Zavoina R^2 is 0.91 vs. 0.73.

1.5.4 Policy reaction prior to April 2002

Table 1.10 presents the parameter instability tests for the two two-variable specifications, which also reveal the structural break in April 2002. The specification 10.1 includes $Ereu$ (the exchange rate of zloty to euro) and $CPIxac\_T\_YM$. The specification 10.2 contains two measures of current inflation: Ind_CPI_T – an indicator variable, equaled to one, when CPI is above the inflation target, and zero otherwise, and $CPxac\_T\_YC$ – the change in the deviation of annual rate of core CPI less administratively controlled prices from the inflation target since the date of last move in the policy rate. Figure 1.4 also shows the plot of sup-LR test for structural change with unknown change point for the model 10.1. The tests detect the structural break in April 2002 for both specifications 10.1 and 10.2 at significance levels 1% and 5%, respectively. The fit of both models is certainly better for the first sub-period compared to the second one: LR is 40.20 vs. 15.17 (for model 10.1) and 39.26 vs. 28.91 (for model 10.2), count R^2 is 0.87 vs. 0.62 and 0.95 vs. 0.73, McKelvey & Zavoina R^2 is 0.96 vs. 0.32 and 0.97 vs. 0.57, respectively. The reaction to exchange rate is significant at 1% level prior to April 2002 and not significant at 9% level since then. The response to current

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

inflation is several times stronger prior to April 2002 than later on. In the first sub-period, both specifications have considerably better fits than any model including the inflation and real activity measures from Table 1.9, and vice versa in the second sub-period.

These results show that in the first sub-period the NBP mainly paid attention to the current inflation and reacted to the real activity far less, but to the exchange rate far more regular than in the second sub-period.

1.5.5 Interest rate smoothing?

The autocorrelation of policy rates is frequently attributed to the intentional interest-rate smoothing and intrinsic gradualism of central bank behavior. The empirical estimations of central bank reaction functions often treat such a sluggish adjustment of policy rates as endogenous to the central bank and incorporate a lagged interest rate on the right-hand side. The estimated significant coefficient on the lagged dependent variable is commonly viewed as evidence of "monetary policy inertia" or "interest-rate smoothing", and is explained by the central banks conservatism, the dislike of frequent reverses in the direction of interest rates' changes, the desire to reduce volatility in the financial markets, the caution caused by the imperfect knowledge of current state and structure of economy, and the desire to make the future path of short-term interest rates more predictable[12].

Alternatively, the observed partial adjustment of policy rates can be explained by the slow cyclical fluctuations of key macroeconomic indicators, such as inflation or output growth, which exogenously drive the central bank decisions. For example, Poole (2003) argues that there is no partial adjustment: "... future policy actions are almost entirely contingent on the arrival of new information." Moreover, as Rudebusch (2002, 2006) has recently demonstrated, the actual real-world amount of endogenous policy inertia is quite low and the illusion of it can reflect the mistaken omission of autocorrelated determinants of policy from the estimated reaction function[13].

Is there any evidence for the purposeful inertia of Polish interest-rate policy? The first-order Pearson correlation coefficients for the reference rate are 0.96 and 0.99 for the periods 1999/02-2002/03 and 2002/04-2006/10, respectively, while the first-order correlation coefficients for the changes to the reference rate are far smaller, 0.11 and 0.54, correspondingly. Table 1.11 reports the results of first-order autoregression of the reference rate changes before

[12] See, e.g., Amato and Laubach (1999), Bernanke (2004), Brainard (1967), Estrella and Mishkin (1999), Goodfriend (1987, 1991), Goodhart (1996, 1999), Levin et al. (1999), Lowe and Ellis (1997), Orphanides (2003), Sack (2000), Sack and Wieland (2000), Smets (1998), Woodford (1999b).

[13] See also Castelnuovo (2003, 2006), English et al. (2003), Gerlach-Kristen (2004), Groth and Wheeler (2008), Lansing (2002), Sack (2000).

and after April 2002 in the context of ordered probit model (see models 11.1.1 and 11.2.1, respectively). The difference is substantial: in the first sub-sample the lagged dependent variable is not significant at a level of 34%, but significant at a level of 1% in the second one. Thus, the existence of partial adjustment in the context of policy rule in differences does not seem to be an issue in the first sub-period at all. Not surprisingly, the lagged reference rate changes added to the specifications 10.1 and 10.2 (the favored models for the first sub-period) are not significant at 20% and 40% level, respectively (see models 11.1.2 and 11.1.3). The LR-tests confirm also the redundancy of first two lags of dependent variable with p-values 0.07 and 0.26 for specifications 10.1 and 10.2, respectively.

Nevertheless, in spite of strong autoregressive property of the reference rate changes after April 2002, the lagged reference rate change, added to the specifications 8.2 and 8.3 (the favored models for the second sub-periods), is not significant at 56% and 55% level, respectively (see models 11.2.2 and 11.2.3). The LR-tests overwhelmingly reject also the relevance of two lags of dependent variable with p-values 0.85 and 0.52, respectively. The lagged reference rate change does not provide additional explanatory power, when inflation expectation and real activity indicator are employed.

Thus, during the entire period of study the policy rate appears to be driven by the key economic variables without evidence of deliberate interest-rate smoothing by the central bank. The observed positive serial correlation of the reference rate changes after April 2002 arise from the NBP's systematic responses to persistent shocks in the real sector of economy. Indeed, the gross domestic product and gross value added demonstrate strong positive autocorrelation – Pearson correlation coefficients are 0.90 and 0.95 for $GDPRna\_Y$ and $GVATnaiy$, respectively. On the contrary, prior to April 2002 the NBP does not react to the real activity, but reacts to the changes in the CPI; these changes, however, appear to be less autocorrelated – the Pearson correlation coefficient is 0.28 for $CPIxac\_T\_YM$.

1.5.6 Comparison with market anticipation

How well does the market foresee the decisions on the policy interest rate? As a measure of market anticipation, I use the forecast of next change to the reference rate from the Reuters survey of bank analysts in Poland. The survey is conducted two to three times a month among 12-22 analysts from commercial banks and is usually updated for the last time one day prior to a MPC meeting. Since February 1999, all individual forecasts of forthcoming rate changes have been in the range from -200 to 200 basis points. I combine the individual forecasts into three categories ("cut", "no change" and "hike") to compare them with the models' predictions. The predicted choice is that with the highest predicted

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

probability. Alternatively, I also use the movements in the Warsaw interbank offer rates (WIBOR) employing them as an explanatory variable in the ordered probit model. For example, the spread between the WIBOR and reference rates at a day prior to an MPC policy meeting is assumed to represent the market ability to predict MPC decisions.

The market does a good job in anticipating the next monetary policy decisions. Table 1.12 presents the market anticipation during two sub-periods, prior to and after April 2002. The spreads between the 3-, 6-, 9-, and 12-month WIBOR and reference rate predict the policy decisions far better than rates with shorter maturities. The 6-month WIBOR demonstrates the best likelihood in both sub-samples, predicting correctly 82 and 85 percent of forthcoming policy decisions with the average likelihood of observed outcomes 77 and 81 percent in the first and second sub-periods, respectively. Bank analysts from the Reuters survey foresee 87 and 89 percent of forthcoming policy actions with the average likelihood of observed outcomes 80 and 82 percent, correspondingly (see Table 1.13).

However, the predictive power of market anticipation is clearly inferior when compared to the models 10.2 (for the first sub-sample) and 8.2 (for the second): though the model-implied forecasts are not optimized with respect to percentage of correct predictions, they predict 95 and 98 percent of next policy decisions with the average likelihood of observed outcomes 83 and 90 percent, respectively (see Table 1.13). Even one day before an MPC meeting the market anticipated the following day's policy decision far worse than the estimated simple rules, including only two economic indicators, the data on which is generally available for the public even earlier!

1.5.7 Policy reaction after April 2002

In contrast to the first sub-period, since April 2002 the measures of expected inflation and real activity predict the changes in the reference rate better than any other combination of economic indicators from Table 1.4. The further specification tuning for the period 2002/04 – 2006/10 is performed with the following four categories of dependent variable: "down 0.50%", "down 0.25%", "no change" and "up 0.25% or 0.50%" with 3, 32, 11 and 9 observations, respectively. This quadruple classification depicts the actual policy decisions after April 2002 almost ideally: only a single 0.25% hike was combined with the two observed 0.50% hikes into a joint category.

Table 1.16 presents the four models: the specification 16.1 with $ExInf\_T\_M$, $GDPnaiy$ and $ExInf\_T\_M$ multiplied by the dummy variable Ind_ExInf_T (equaled one, when the expected inflation is above the inflation target, and zero otherwise); the specification 16.2, which in addition to the above three variables includes $WIBOR12m\_ZP$ (the change

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

since the last MPC meeting in the 12-month WIBOR if the change is positive, and zero otherwise); and the specifications 16.3 and 16.4, which are the same as 16.1 and 16.2, respectively, but instead of $GDPnaiy$ they include $GVATnaiy$ (the index of gross value added total, growth rate in percent since corresponding period of previous year).

The NBP appears to respond far aggressively to the spread between the expected inflation and inflation target, when the expected inflation is above the target (the coefficient estimate is several times bigger). The estimated models 16.1 and 16.3, including only inflationary expectation and real activity measures, have remarkable measures of fit: the count R^2 is 0.91 and McKelvey & Zavoina R^2 is 0.96 for both models. Adding changes in the 12-month WIBOR to the models 16.1 and 16.3 considerably improves the log likelihood from -15.51 to -7.13 (model 14.2) and from -15.49 to -8.15 (model 16.4), respectively. The models 16.2 and 16.4 correctly predict 53 and 52 out of 55 policy decisions (forecasting performance – 96% and 95%), correspondingly. Not only do financial markets watch the NBP, but vice versa! Indeed, the MPC press releases indicate that the Council pays attention to the movements in the market long-term money rates as an indicator of future inflation. Definitely, changes in the WIBOR include extra forecasting information about future inflation not encompassed by the inflationary expectation of individual consumers from the Ipsos survey.

Table 1.14 reports the market anticipations of the reference rate changes, represented by the models including the spreads between the 1-, 3-, 6-, 9- and 12-month WIBOR and reference rates and estimated by the ordered probit with four categories. The specification 14.3 with the spread between 6-month WIBOR and reference rates has the best likelihood. Table 1.15 compares the predictions of the next policy decision, implied by the models 16.1 and 16.2, with the market anticipation, represented by predictive ability of the movements in the spread between 6-month WIBOR and reference rates (model 14.3) and by the forecast from the Reuters survey of banks' analysts. The spread between 6-month WIBOR and reference rates and bank analysts predict, respectively, 69 and 84 percent of next policy decisions correctly with the average likelihood of observed outcomes 63 and 78 percent and with a mean absolute error (MAE) of 10.27 and 7.25 basis points, respectively. Also noteworthy is the fact that the market anticipations are made one day prior to an MPC meeting. However, the simple model 16.1, based on inflationary expectations from the Ipsos survey and GDP, data on which is available for the public much earlier than one day prior to a policy meeting, without doubt does better job than the market: it predicts correctly 91 percent of next policy actions with average likelihood of observed outcomes 84 percent and 4.60 basis points MAE, though once again the ordered probit model is not optimized with respect to the proportion of correct predictions. If at a day prior to an MPC meeting the banks' analysts accurately

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

paid attention to the movements in the 12-month WIBOR in addition to the inflationary expectations from the Ipsos survey and GDP, they would be able to predict (see model 16.2 in the Table 1.15) 96 percent of next policy decisions instead of 84 percent as they did, making only 2.84 instead of 7.25 basis points MAE with the average likelihood of observed outcomes 0.92 instead of 0.78.

To test again for evidence of deliberate interest-rate smoothing, I added the lagged dependent variable to the specifications 16.1 and 16.3 (see models 17.1 and 17.2 from Table 1.17, respectively). In both cases the lagged rate change is not significant at a level of 50 percent, at least. The LR-tests show the insignificance of adding three lags of dependent variable to both models at 5% and 8% levels, respectively. The lagged reference rate changes do not provide additional explanatory power, when inflation expectation and real activity measure are included into the model; however, the reference rate itself and its first difference are autocorrelated with correlation coefficient 0.99 and 0.54, respectively. Once again, the observed monetary policy inertia does not seem to be a consequence of intentional interest-rate smoothing by the central bank.

In Figure 1.5, the upper graph plots the actual and predicted reference rate changes, and the lower one plots the actual and expected changes for the specification 16.4. A particular policy decision is predicted if its predicted probability exceeds the predicted probabilities of the alternatives. The expected changes are computed using the formula $E(Y|X) = -0.5\,\Pr(Y = -0.5|X) - 0.25\,\Pr(Y = -0.25|X) + m\,\Pr(Y > 0|X)$, where $m = (0.5 + 0.5 + 0.25)/3 = E(Y|Y > 0, X)$ – sample mean of "hike" category. The model-implied forecast of discrete policy changes is not only very accurate – it correctly predicts 52 out of 55 decisions, but also it is made with high degree of certainty: the average likelihood (i.e., the average predicted probability of realized outcomes) is 0.91, and the mean absolute error between actual and expected policy changes is 3.10 basis points. Figure 1.6 reports the predicted probabilities of all four possible policy actions on the background of the observed changes to the reference rate.

All estimated models from Table 1.16 satisfy the parallel regression assumption with p-values from 0.17 to 0.37, making it superfluous to employ the generalized ordered probit model, which is too richly parameterized for our small sample size. To make the further models' diagnostics Figure 1.7 reports the correlograms of generalized residuals[14] from models 16.2 and 16.4: the null of no serial correlation among residuals up to the twelfth order is overwhelmingly accepted at least at 60% and 44% level, respectively. It makes unessential

[14] The generalized residuals are defined as uncorrelated with the explanatory variables of the model. See Chesher and Irish (1987), and Gourieroux et al. (1987) for details.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

to use far more computationally demanding dynamic ordered probit approach that accounts for the serial correlation among residuals, but cannot be directly estimated by maximizing the likelihood function.

Table 1.18 compares the actual and predicted policy decisions. The model anticipates all hikes and 50 basis points cuts, and overlooks only two 25 basis points cuts and one no change. The 'adjusted noise-to-signal' ratios[15] for four possible policy actions - 'hike', 'no change', '0.25% cut' and '0.50% cut' – are, correspondingly, 0%, 4.5%, 2.8% and 2.2%. The above noise measures are far lower than the reported ones in the related triple-choice ('hike', 'no change', and 'cut') empirical models for the US Federal Open Market Committee's decisions on the Federal funds rate target. For example, in Hu and Phillips (2004) these ratios for hikes, no changes and cuts are 3.8%, 44.6% and 8.5%, while in Piazzesi (2005) they are 10.6%, 71.8% and not defined, respectively.

1.5.8 Out-of-sample forecasting

An out-of-sample forecasting exercise is performed for the period 2006/03 through 2007/10, including 20 policy decisions of the MPC. The out-of-sample forecasting is compared to the market anticipation of policy actions, represented by the probabilities of four possible policy choices ("increase", "no change", "0.25% decrease", and "0.50% decrease"), derived from the individual forecasts made by commercial banks' analysts in the Reuters survey one day prior to an MPC meeting. In this survey, each analyst predicts the most likely level of the reference rate to be set at a meeting. The predicted rate's level can be easily transformed into the predicted change; during the period 2006/03 – 2007/10 only two likely outcomes were anticipated: either 'no change' or '0.25% hike'. The probability of a particular outcome is its fraction amongst all of the predicted choices. The final prediction is the most popular outcome, i.e. the choice with the largest predicted probability. Recently, the banks' analysts were highly successful in forecasting the following day's policy decision: in the period 2005/07 – 2007/10 they correctly anticipated 27 policy actions out of 28; while in the period 2002/04 – 2005/06 only 30 out of 39.

Table 1.19 reports the out-of-sample forecast along with the market anticipation. The out-of sample predictions are accomplished using specifications 16.3 and 16.4, estimated for

[15] An adjusted noise-to-signal ratio, introduced by Kaminsky and Reinhart (1999), is defined as follows: let A denote the event that the decision is predicted and has occurred; let B denote the event where the decision is predicted but has not occurred; let C denote the event where the decision is not predicted but has yet occurred; let D denote the event where the decision is not predicted and has not occurred. The desirable outcomes fall into categories A and D, while noisy ones fall into categories B and C. A perfect prediction would contain no entries in B and C, while a noisy prediction would have many entries in B and C, but few in A and D. The adjusted noise-to-signal ratio is defined as $[B/(B+D)]/[A/(A+C)]$.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

the period 2002/04 - 2006/02 without rolling re-estimations[16]. The model 16.3 predicts all seventeen "no changes", making a mistake in the timing of first hike (May instead of April 2007), failing to foresee the second hike in June 2007 (only predicting it with probability 25%), and correctly forecasting the last hike in August 2007. The model 16.4 predicts all seventeen "no changes" and all three hikes, erroneously forecasting only the timing of first hike – May instead of April. The market correctly foresees all seventeen "no changes", but only two of three rate hikes, overlooking a rate increase in June 2007.

The policy decision in April 2007 appears to be rather atypical. An MPC press release, following the meeting, reports that "according to the April inflation projection, the growth of consumer prices will be lower than in the January projection over the whole projection horizon... In the Council's assessment, in the second half of 2007 CPI inflation will temporarily decrease markedly below the inflation target of 2.5%." (NBP 2007). However, despite the decline in NBP inflation projections, the MPC decided to increase the policy rates, because "in the Council's assessment, in the medium term, the probability of inflation running above the target is larger than the probability of its running below the target, which persuaded the Council to tighten the monetary policy".

The MPC judgment with respect to the future inflation has been confirmed in the next month by an increase in the expected rate of inflation over the next 12 months from the Ipsos survey: in May it raised by 0.7% compared to 0.1% in April. Both models predict for May an "increase" with almost complete certainty. However, the rate was not changed in May – the MPC reacted preemptively already in April.

The estimated ex-post policy rules, even those with high measures of in-sample fit, generally have a quite low out-of-sample forecasting performance, caused by the instability of the policy regime and/or the small-sample biasedness of estimation. The conducted out-of sample forecasting demonstrates the structural stability of estimated policy reaction up to 20 months ahead, almost ideally predicts all policy moves and outperforms the market anticipations, made one day prior to each policy meeting.

1.6 Does real-time 'policy-meeting' data matter?

A common approach to identify the monetary policy rules is to estimate the relationship between monthly or quarterly averages of policy rate and economic indicators, using data currently available for an econometrician. In reality, the policy decisions are usually made

[16] The models 16.3 and 16.4, estimated over the sub-period 2002/04 – 2006/02, have the following measures of fit: LR is 79.55 and 94.73, count R^2 is 0.89 and 0.96, McKelvey & Zavoina R^2 is 0.96 and 0.99.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

6-12 times per year, and the policymakers react to the incoming original non-aggregated data, as it was known at a day of policy meeting. By and large, the information set used in the policy-making process may differ from one used by the econometrician thanks to three reasons: data revisions, inaccurate aligning the timing of data releases and policy decisions, and time aggregation.

This section assesses the statistical effects of using the ex post revised and time-aggregated data on the empirical identification of Polish monetary policy. The policy rules, estimated using the real-time data and decision-making meetings as a unit of observation, are compared with the rules, estimated using the currently available data at monthly frequency. Since the policy-making meetings have taken place every month and only once per month during the sample period, the two data sets – the real-time "MPC-meeting" data set, which mimics as much as possible the true information set used in the policy-making process, and the ex post revised monthly data set used by the econometrician – have the same number of observations. Moreover, they have absolutely the same values of dependent variable – monthly changes to the reference rate. This allows us to apply the same regression technique (an ordered probit) for estimation of alternative policy rules, and provides a straightforward way to compare them. However, the values of right-hand-side variables in two data sets are in general not identical. Therefore, we will determine whether these discrepancies can lead to statistically different inference.

How to align the timing of left- and right-hand side variables in the revised monthly data set? We can apply the same assumption for all variables in the data set by allowing, say, a month's lag in the arrival of monthly statistical data, i.e. we can match the reference rate change in a given month with the values of independent variables for a previous month. However, to give the revised averaged data the best chance to match the data truly available for policymakers, I use such a lag length that is typical for a given series. For example: inflationary expectation from the Ipsos survey is usually available for a current month, without a lag; CPI is typically available for a previous month, i.e. with a month lag; the quarterly data on GDP and components is usually released with a two-month lag.

The estimations of the same four specifications as in Table 1.16 are performed for both data sets for the period 2002/04 – 2006/10 using the ordered probit model with four categories of dependent variable: "0.50% or 0.25% increase", "no change", "0.25% decrease", and "0.50% decrease". Table 1.20 reports the policy rules' estimations based on the ex post revised monthly data. The differences between the estimations, using the real-time and revised data sets, are in favor of the real-time one: for the specifications 16.1 and 16.3, log likelihood lowers from -15.51 and -15.49 (see Table 1.16) to -18.20 and -17.24 (see Table

1.20), and the percentage of correctly predicted outcomes decreases by 6% and 4%, respectively. The time-aggregation effect is not strong in this case, because during the period of study, the MPC have always taken policy decisions during the second half of each month after all major statistical releases, including inflationary expectations and GDP. All regressors remain highly significant, and parameters' estimates are not statistically different. Such results are not surprising: these models are based on two indicators, released monthly: inflationary expectation measure, which is never revised, and GDP index, which is only slightly revised. The observed difference in goodness-of-fit is, however, caused mainly by these minor revisions.

The difference drastically changes for the specifications 16.2 and 16.4, which contain an extra variable $WIBOR12m\_ZP$: the log likelihood drops from -7.13 and -8.15 to -18.4 and -17.22, the percentage of correctly predicted outcomes decreases by 11% and 8%, respectively. The coefficient on $WIBOR12m\_ZP$ becomes highly insignificant with the revised monthly data (p-values are 0.72 and 0.82 for specifications 16.2 and 16.4, respectively), while being significant at 3% level with the real-time data. These results are not surprising either: though the data on WIBOR is never revised, the calendar month averaging overlooks the critical information about the movements in the WIBOR between MPC meetings and in the days around them.

Table 1.21 compares the estimation performed using the two alternative data sets for the specification including $ExInf\_T\_M$, $GDPRna\_Y$, and $ExInf\_T\_M * Ind\_ExInf\_T$: the use of revised monthly data decreases the log likelihood from -19.04 to -29.48, and lowers the percentage of correctly predicted outcomes by 9%. Now the differences in the goodness-of-fit are far larger than for the specifications 16.1 and 16.3, including $GDPnaiy$ and $GVATnaiy$ instead of $GDPRna\_Y$, respectively. Indeed, the difference between the real-time and revised versions of $GDPRna\_Y$ is more substantial: the correlation coefficient between the latest revised vintage of $GDPRna\_Y$ and its real-time version is 0.72, while for both $GDPnaiy$ and $GVATnaiy$ the correlation is about 0.99.

Thus, despite the facts that the degree of ex post revisions of statistical data in Poland is quite low and the policy-making meetings take place regularly in the second half of each month, which diminish the difference between the two alternative sample constructions, the real-time data set with the decision-making meetings of monetary authority as a unit of observation is shown to produce statistically different estimation results with better measures of fit. The calendar month averages are not capable of detecting the strong systematic relationship between intermeeting changes in the daily financial market data (closely monitored by the central bank) and policy rate changes.

Thus, the use of a real-time data set with the policy-making meetings as a unit of observation does matter in the econometric identification of Polish monetary policy!

1.7 Does discreteness matter?

The used ordered probit model (OPM) elegantly accounts for the discreteness of policy rate and the impact of explanatory variables. However, can we address the above problems via the conventional simpler linear regression model (LRM)? This section compares the performance of OPM and LRM in order to show that using special regression methods for a discrete dependent variable does make a difference in the econometric identification of Polish monetary policy.

Such a comparison is complicated because the OPM, based on the maximum likelihood (ML), is designed to estimate the probabilities of limited discrete outcomes of the dependent variable while the LRM, based on the ordinary least squares (OLS), is designed to estimate the expected value of dependent variable, which is assumed to be an unlimited continuous one. Therefore, all measures of fit for the LRM (such as the coefficient of determination R^2, etc.) cannot be constructed for the OPM, because they are based on the OLS, and cannot be directly compared with the pseudo R^2 measures of fit for the OPM, since they are all based on the ML.

It is appealing to estimate the LRM by ML as a generalized linear model (GLM) with identity link function and normal probability distribution, and compare it with the OPM using some kind of test for non-nested models, for instance, Santos Silva's test (Silva 2001), based on the likelihood. However, the comparison of GLM and OPM on the basis of the likelihood is still not legitimate. The problem is with the likelihood per se: the likelihood functions of GLM and OPM have different natures. In the OPM (as in other models for a categorical dependent variable), the individual observation's contribution to the likelihood is the probability of observing the realized discrete event, while in the GLM the likelihood is not the probability (the integral under the *p.d.f.* between the two cut-points), but rather the value of the continuous normal *p.d.f.* at some point (hence, it can be greater than one).

Unfortunately, it seems impossible to construct a formal test based on the likelihood to compare the LRM and OPM. Are there any other appropriate ways to compare them? One possible approach is to define the expected value of the dependent variable $E(Y|\mathbf{X})$ for the OPM and compare it with its LRM counterpart. For the LRM the $E(Y|\mathbf{X}) = \mathbf{Xb}$, where coefficients $\mathbf{b}$ are estimated by OLS or ML; for the OPM we can naturally assume that the $E(Y|\mathbf{X}) = -0.5\Pr(Y = -0.5|\mathbf{X}) - 0.25\Pr(Y = -0.25|\mathbf{X}) + (0.5+0.5+0.25)\Pr(Y > 0|\mathbf{X})/3$,

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

where probabilities are estimated by ML[17]. Then we can calculate, for example, the mean absolute error, i.e. the arithmetic average of absolute differences between the observed and expected rate changes (denoted as "MAE of $E(Y|\mathbf{X})$").

An alternative approach is to compute the conditional distribution of rate changes by defining the probabilities of discrete events for the LRM and to compare them with the OPM counterparts. Let us ignore for a moment the discreteness of policy rate and evaluate the following simple LRM using OLS:

$$\Delta RR_t = \mathbf{X}_t\boldsymbol{\beta} + \varepsilon_t, \tag{1.5}$$

where ΔRR_t – the reference rate change, $\mathbf{X}_t$ - vector of explanatory variables, and ε_t – disturbance term, assumed to be distributed as $i.i.d.$ $Normal(0, \sigma^2)$. We can define the probabilities of discrete outcomes of ΔRR_t as

$$\begin{aligned}
\Pr(\Delta RR_t = -0.50) &= \Pr(-\infty < \mathbf{X}_t\boldsymbol{\beta} + \varepsilon_t < c_1), \\
\Pr(\Delta RR_t = -0.25) &= \Pr(c_1 < \mathbf{X}_t\boldsymbol{\beta} + \varepsilon_t < c_2), \\
\Pr(\Delta RR_t = 0) &= \Pr(c_2 < \mathbf{X}_t\boldsymbol{\beta} + \varepsilon_t < c_3), \\
\Pr(\Delta RR_t \geq 0.25) &= \Pr(c_3 < \mathbf{X}_t\boldsymbol{\beta} + \varepsilon_t < \infty),
\end{aligned}$$

where $-\infty < c_1 < c_2 < c_3 < \infty$ are some known fixed cut-points.

These probabilities can be computed using the normal cumulative distribution function F of ε_t and estimated OLS coefficients $\boldsymbol{\beta}$ as follows

$$\begin{aligned}
\Pr(\Delta RR_t = -0.50) &= F(c_1 - \mathbf{X}_t\boldsymbol{\beta}), \\
\Pr(\Delta RR_t = -0.25) &= F(c_2 - \mathbf{X}_t\boldsymbol{\beta}) - F(c_1 - \mathbf{X}_t\boldsymbol{\beta}), \\
\Pr(\Delta RR_t = 0) &= F(c_3 - \mathbf{X}_t\boldsymbol{\beta}) - F(c_2 - \mathbf{X}_t\boldsymbol{\beta}), \\
\Pr(\Delta RR_t \geq 0.25) &= 1 - F(c_3 - \mathbf{X}_t\boldsymbol{\beta}).
\end{aligned} \tag{1.6}$$

Let us refer to such a LRM, extended to estimate the probabilities of discrete events, as to a 'rounded linear regression' model (RLRM). To compute the probabilities in (6) we just have to choose the values of cut-points.

The probabilities of discrete outcomes for the RLRM in (1.6) can be now contrasted to the corresponding probabilities for the OPM in (1.3). For example, we can compute and compare the percentage of correctly predicted outcomes, where the predicted outcome is the outcome with the highest probability (denoted as 'Count R^2'), the proportion of correct predictions beyond the number that would be correctly guessed by choosing the outcome category with the largest percentage of observed cases (denoted as 'Adjusted count R^2'),

[17] The $E(Y|Y>0, \mathbf{X})$ is taken to be equal to (0.5+0.5+0.25)/3, which is the sample mean.

and the average predicted probability of realized outcomes, i.e. the average likelihood of individual observations (denoted as 'Average likelihood').

The above measures of fit are useful in comparing competing models, but can only provide some level of rough guidance in selecting the preferred model. Without conducting a formal test, however, it is unclear which model is the best one. Formal comparison of RLRM and OPM can be undertaking by noting that the former is actually a special case of the latter.

Indeed, the formulas (1.6) are identical to ones for a censored interval regression model (also known as a 'grouped regression' model), which is defined by (1.1)-(1.4) like the OPM, but with the fixed cut-points c_j instead of estimated α_j and estimated $\sigma^2 = Var(\varepsilon_t|\mathbf{X}_t)$ instead of assumed to be equal to one. The interval regression model (IRM) can be estimated by maximizing the log likelihood function $\ln L$ of $\boldsymbol{\beta}$ and σ:

$$\ln L = \sum_{t=1}^{N}\sum_{j=1}^{J} d_{tj} \ln[F(c_j - \mathbf{X}_t\boldsymbol{\beta}) - F(c_{j-1} - \mathbf{X}_t\boldsymbol{\beta})], \tag{1.7}$$

where in our case $j = 1, 2, 3, 4$; N is the sample size; $d_{tj} = 1$ if $\Delta RR_t = k_j$ and 0 otherwise; $\{k_1, k_2, k_3, k_4\} = \{-0.5, -0.25, 0, \text{greater than } 0.25\}$ – four categories of the reference rate changes; and F is the normal cumulative distribution function with mean zero and variance σ^2.

The probabilities of discrete events in the IRM and RLRM, though given by the same formulas in (1.6), are, in general, different, because in the RLRM the β and σ^2 are estimated by minimizing the squares of residuals from the equation (1.5), while in the IRM the β and σ are estimated by maximizing the log likelihood function in (1.7) from the equation (1.1). Yet, the probabilities and likelihood, defined respectively by (1.6) and (1.7), for the RLRM are identical to ones for the IRM, if β and σ^2 in the IRM are constrained to be equal to the OLS estimates from the LRM instead of being estimated by maximizing (1.7). In this respect our extended RLRM is a special case of IRM. Furthermore, the IRM itself is actually nested in the OPM, since we can treat the OPM as a more general model, in which the assumption of fixed thresholds is relaxed (so the thresholds have to be estimated) and the intercept β_0 and $Var(\varepsilon_t|\mathbf{X}_t)$ are fixed to be the same as they have been estimated in the IRM (as a rule, $Var(\varepsilon_t|\mathbf{X}_t)$ and β_0 in the OPM are assumed to be equal to one and zero, respectively, but these identifying assumptions are arbitrary and affect only the slope coefficients in $\boldsymbol{\beta}$ – they do not affect the estimated probabilities and likelihood).

Thus, the IRM is nested in the OPM, if $Var(\varepsilon_t|\mathbf{X}_t)$ and β_0 in the OPM are assumed to be equal to their counterparts from the IRM. Consequently, all three models – the RLRM, which is equivalent to the constrained IRM with the β_{LRM} and σ^2_{LRM}, the unconstrained IRM, and the OPM with $Var(\varepsilon_t|\mathbf{X}_t) = \sigma^2_{IRM}$ and $\beta_0 = \beta_{0_{IRM}}$ – are nested inside each other, can be estimated by ML and, hence, may be compared using, for example, the likelihood ratio chi-square test[18].

Table 1.22 presents the two LRM, estimated for the period 2002/04 – 2006/10 by OLS with the same specifications as in the OPM 16.3 and 16.4, using the historical (not classified) values of the reference rate changes. The coefficients of determination are about 0.68, and the coefficients on $ExInf\_T\_M$ and $GVATnaiy$ are significant at 1% level for both specifications. However, in contrast to the OPM, in the specification 14.3 the LRM coefficient on $ExInf\_T\_M * Ind\_ExInf\_T$ is not significant at 24% level, and in the specification 16.4 both the coefficients of $ExInf\_T\_M * Ind\_ExInf\_T$ and $WIBOR12m\_ZP$ are not significant at 29% and 61% level, respectively, while all being significant in both OPM specifications at 2% level at most. These results send the preliminary signal about incapability of LRM to be an adequate substitute to OPM.

Table 1.23 compiles the goodness-of-fit measures of two specifications 16.3 and 16.4, obtained for estimations in the context of RLRM (which is equivalent to the constrained IRM with all coefficients β and σ^2 restricted to be the OLS ones from the LRM), unconstrained IRM and OPM. The RLRM are estimated using four alternative sets of fixed cut-points: biased-toward-tightening [-0.5, -0.25, 0], biased-toward-easing [-0.25, 0, 0.25], equally-spaced [-0.375, -0.125, 0.125] and zero-inflated [-0.5, -0.25, 0.25]. The RLRM have practically the same likelihood and other measures of fit for both specifications, being unable (like the LRM) to detect the predictive power of additional variable $WIBOR12m\_ZP$. The RLRM with equally-spaced and zero-inflated thresholds correctly predict 78 and 73 percent of observed rate's changes and have very similar log likelihood (about -36) and MAE (about 10 basis points); their fit is considerably higher than the fit of RLRM with the other two sets of thresholds, biased-toward-tightening and biased-toward-easing, where the percent of correct predictions is about 55 and 43, the log likelihood is about -55 and -52, and MAE is about 17 and 14 basis points, respectively. The equally-spaced and zero-inflated thresholds seem to be rather reasonable assumptions: the RLRM have practically the same MAE as the LRM (about 10 basis points), while biased-toward-tightening and biased-toward-easing cut-points lead to larger MAE than the LRM equivalent.

The estimations of unconstrained IRM are reported only for the equally-spaced and

[18] See Hausman et al. (1992) for the related comparison of LRM estimated by OLS and OPM in this context. They set up the extended 'rounded' version of LRM as a special case of OPM, in which all the thresholds are fixed and equally spaced, and apply the Wald chi-square test to check this restrictions. This is the only known to me example of formal testing of the LRM against the OPM in the literature.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
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zero-inflated thresholds[19]. The likelihood maximization in the IRM with the equally-spaced cut-points produces similar estimates of intercept and slope coefficients for $ExInf\_T\_M$ and $GVATnaiy$ as in the RLRM (for instance, for the specification 16.4 they are (standard errors are in parentheses), respectively, -0.381 (0.041), 0.201 (0.058), and 0.079 (0.011) in the LRM and -0.367 (0.031), 0.202 (0.046), and 0.074 (0.009) in the RLRM) and the same 10 basis points MAE, but triples the size and considerably improves the significance of slope coefficients for $ExInf\_T\_M * Ind\_ExInf\_T$ and $WIBOR12m\_ZP$ (p-values are 0.291 and 0.619 in the RLRM versus 0.004 and 0.107 in the IRM, respectively), and increases the log likelihood from -36.2 to -29.7. Moreover, in the IRM with zero-inflated thresholds the likelihood maximization alters the estimates of intercept and all four slope coefficients for $ExInf\_T\_M$, $GVATnaiy$, $ExInf\_T\_M * Ind\_ExInf\_T$ and $WIBOR12m\_ZP$: -0.381 (0.041), 0.201 (0.058), 0.079 (0.011), 0.106 (0.099) and 0.058 (0.115) in the RLRM versus -0.530 (0.029), 0.275 (0.052), 0.101 (0.009), 0.508 (0.106) and 0.424 (0.115) in the IRM, respectively. It also makes all coefficients to be significant at the level less than 1%, increases the log likelihood from -36.16 to -15.58, and reduces the MAE from 10 to 5 basis points. In contrast to the RLRM, the ML estimation of IRM reveals a large difference between the specifications with equally-spaced and zero-inflated cut-points. The zero-inflated thresholds, where the distance between the cut-points in the "no change" category is twice bigger than in the "-0.25% decrease" category, result in considerable improvement of fit, compared to the equally-spaced ones, where these distances are the same: the log likelihood is -15.58 versus -29.70, and the MAE is 5 versus 10 basis points.

Finally, the OPM demonstrates the further sharp improvement of fit, compared to the RLRM and IRM: for example, in the specification 16.4 the log likelihood raises to -8.2 (versus -36.2 and -15.6 for the RLRM and IRM, respectively), the MAE drops to 3 basis points (versus 10 and 5, respectively), the proportion of correct predictions reaches 95% (versus 78% and 87%). The OPM seems to more adequately reflect the central bank reluctance to move the policy rate by allowing the underlying continuous rate changes and estimated cut-points to have the different scale with the observed discrete changes. In our case, the OPM estimates the distance between the cut-points for the "no change" category to be almost four times bigger than for the "-0.25% decrease" category in both specifications.

To formally compare the OPM, IRM and RLRM, estimated with the same data set for two specifications, Table 1.23 reports the results of likelihood ratio chi-square tests of

[19] The IRM estimations with the biased-toward-tightening and biased-toward-easing sets of cut-points have only different intercept estimates, but produce the same slope coefficients, probabilities and likelihood as with the equally-spaced cut-points, because all three sets have the same distances between adjacent cut-points and differ among themselves by a parallel shift of 12.5 basis points.

several versions of RLRM and IRM with alternative sets of cut-points against a more general unconstrained OPM that nests all of the above ones. All tests are in favor of the OPM: imposed by the null hypothesis constraints are rejected at marginal 7% significance level only for one model, the IRM with the specification 16.3 and zero-inflated cut-points, while for all other models, they are overwhelmingly rejected at less than 1% level.

Thus, not only does the OPM reveal considerably better measures of fit than the RLRM and IRM, but it is also clearly superior on the basis of formal statistical test. The information gained by a more complex discrete-response technique like OPM is not attainable with the simpler continuous-response linear regression techniques.

Ergo, discreteness does matter!

1.8 Summary and conclusions

> "It is highly desirable that policy practice be formalized to the maximum possible extent. Or, more precisely, monetary economists should embark on a program of continuous improvement and enhanced precision of the Fed's monetary rule..."
>
> – W. Poole, then-President of the Federal Reserve Bank of St. Louis[20]

The aim of this study is not to describe the current practice of Polish monetary policy by an algebraic equation, or "rule". Rather, the paper allows the data to speak in support of the statement that the policy decisions are highly predictable by observing the arriving economic and financial news in the real-time setting and using an appropriate econometric technique. Though the NBP looks at everything in formulating policy decisions, the estimated reaction functions, based on a small number of economic variables, correctly explain 95 percent of observed discrete policy adjustments in the period 1999/02 – 2006/10. In an out-of-sample forecasting of next twenty monthly policy decisions from 2006/03 through 2007/10 the empirical model correctly predicts seventeen 'no changes' and three 'hikes', erroneously forecasting only the timing of one hike with a monthly lag. Such forecasting performance surpasses the market anticipations of next policy move, made one day prior to a policy meeting. The market (represented by the Reuters survey of banks' analysts) correctly predicted only 84 percent of policy-rate decisions in the period 1999/02 – 2006/10 and overlooked one hike in the period 2006/03 – 2007/10.

The reported in- and out-of-sample forecasting performance, exceeding the typical one in the literature, is shown to be (at least, partially) a consequence of the employed empirical

[20] See Poole (2006).

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

methodology, combining the use of regression techniques for a discrete dependent variable, real-time data and decision-making meetings of monetary authority as a unit of observation. This methodological framework carefully mimics the actual policy-action-generating process since: (i) most major central banks alter interest rates by discrete-valued adjustments; (ii) policy decisions are naturally made using information available in the real-time setting; and (iii) they are typically made 8-12 times per year at special policy-making meetings. However, the empirical studies routinely estimate the monetary policy rules by: (i) applying the regression methods for a continuous dependent variable; (ii) using currently available series of economic data; and (iii) analyzing the systematic responses of policy rate's averages to economic data averages for a given month or quarter. Obviously, such practice distorts the actual data-generating process because: (i) regression methods for a continuous dependent variable are shown to be inadequate when the dependent variable is discrete; (ii) the latest versions of statistical data may differ from the real-time ones due to revisions; and (iii) time aggregation of data misaligns the timing of policy decisions and the availability of statistical data as well as raising the problem of simultaneity.

On the other hand, it is not apparent that these distortions are significant enough to make a difference from a practical point of view, i.e. in the econometric identification of monetary policy rules. This issue has been only partially analyzed in the literature. It was demonstrated for several countries that ex post revised and real-time data lead to significantly different estimation results. There were only a few studies that model the policy rules using a discrete choice approach. To the best of my knowledge, there were no attempts to assess how the use of discrete regression techniques affects the empirical identification of monetary policy; neither were there any attempts to estimate the policy rules using the decision-making meetings of monetary authority as a unit of observation. This study assesses separately the statistical effects of using the linear OLS regression model instead of ordered probit one and the latest revised monthly-averaged data instead of real-time one with the policy-making meetings as a unit of observation. The formal comparison shows that discreteness and real-time data do matter in the empirical identification of Polish monetary policy.

The proposed methodological framework is well suited to identify the monetary policy of many central banks and can help market participants to minimize the uncertainty about the future monetary policy actions.

The performed ordered probit analysis of the response patterns between the reference rate changes and incoming economic real-time data reveals briefly the following:

- The first twelve policy decisions of the MPC prior to February 1999 (during an interim period of transition to a new policy regime) significantly differ from the regular policy

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

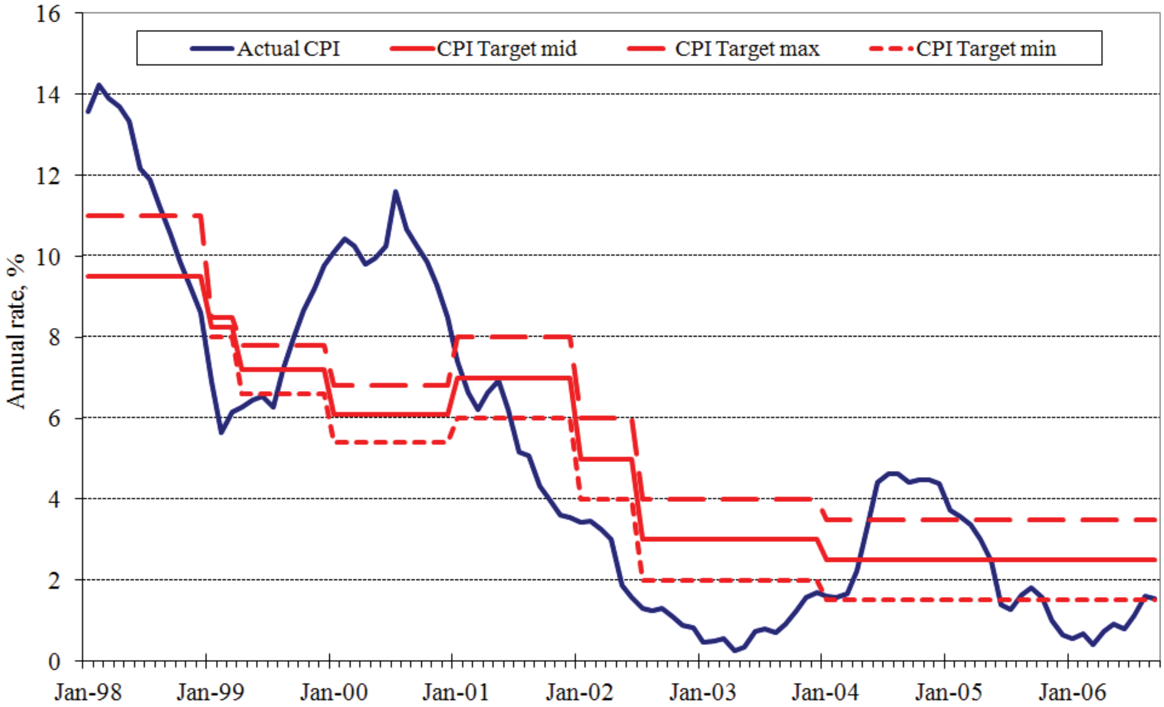
reactions since then.

- The systematic policy responses demonstrate remarkable structural differences prior to and since April 2002. In its reaction to the deviation of inflation from the target, the NBP has shifted from the backward- to forward-looking behavior.
- Prior to April 2002, in the period of fighting the high inflation the NBP reacted to the real activity measures far less, but to the exchange rate far more regular than since then, in the period of stabilizing the low inflation.
- The NBP reacts highly asymmetrically to the changes in inflationary expectations, depending on whether the expected inflation is above or below the inflation target.
- The policy rates appear to be driven by the key economic indicators without evidence for deliberate interest-rate smoothing by the central bank.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

1.9 Figures

Figure 1.1: Actual and target rates of inflation in Poland



Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
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Figure 1.2: Changes to NBP reference rate

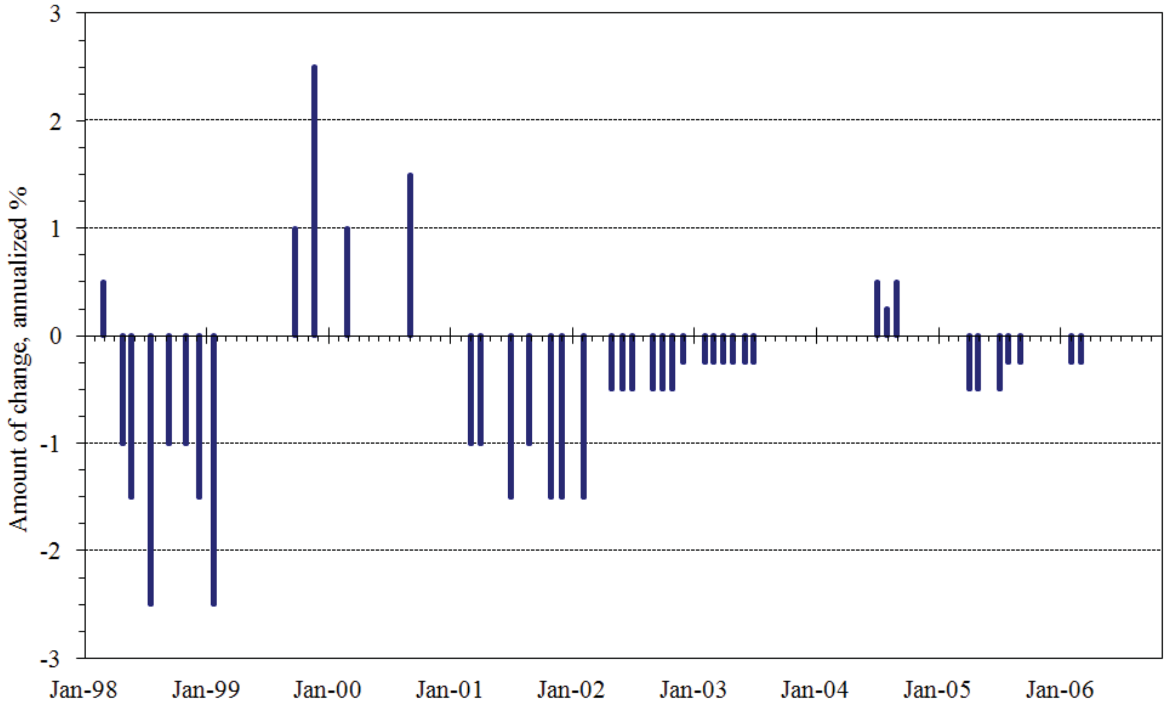
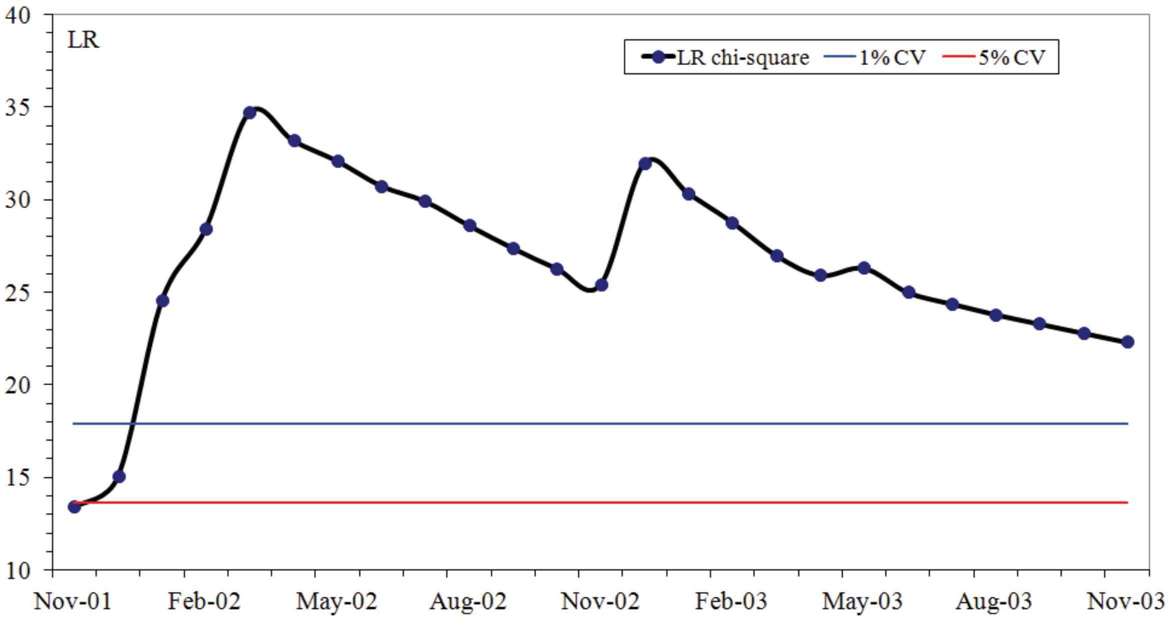


Figure 1.3: Andrews' sup-LR test for structural change with unknown change point



Notes:

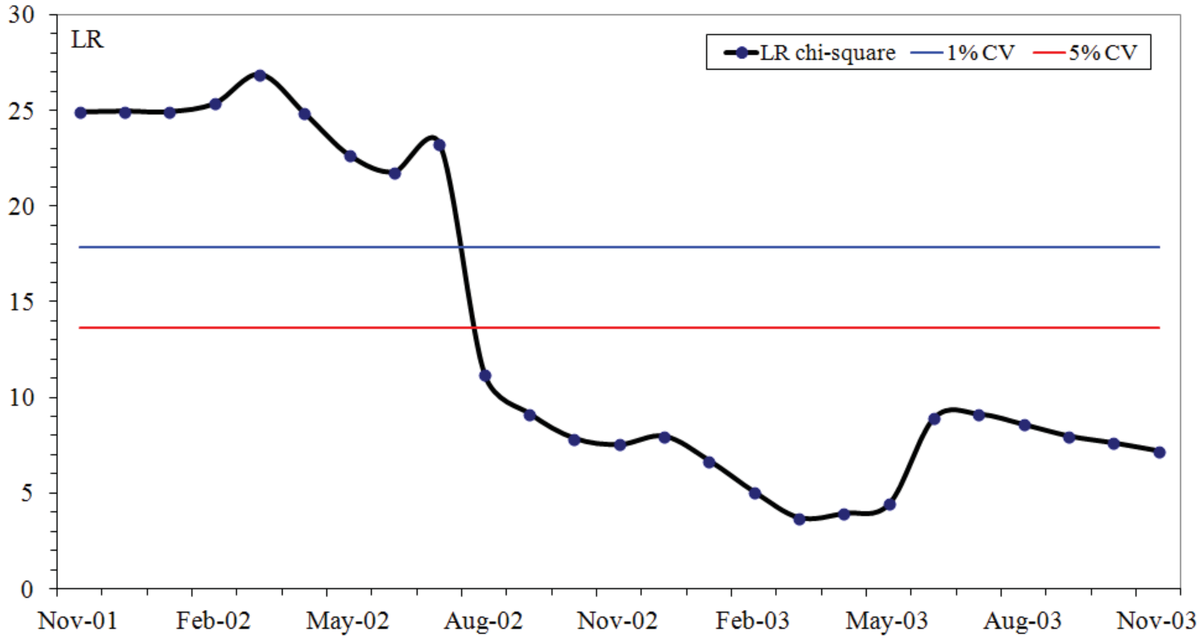
Dependent variable: ΔRR_t;

Independent variables: $GVARna\_Y$ and $ExInf\_T\_M$;

Model: Ordered probit with three categories: 'up', 'no change', 'down';

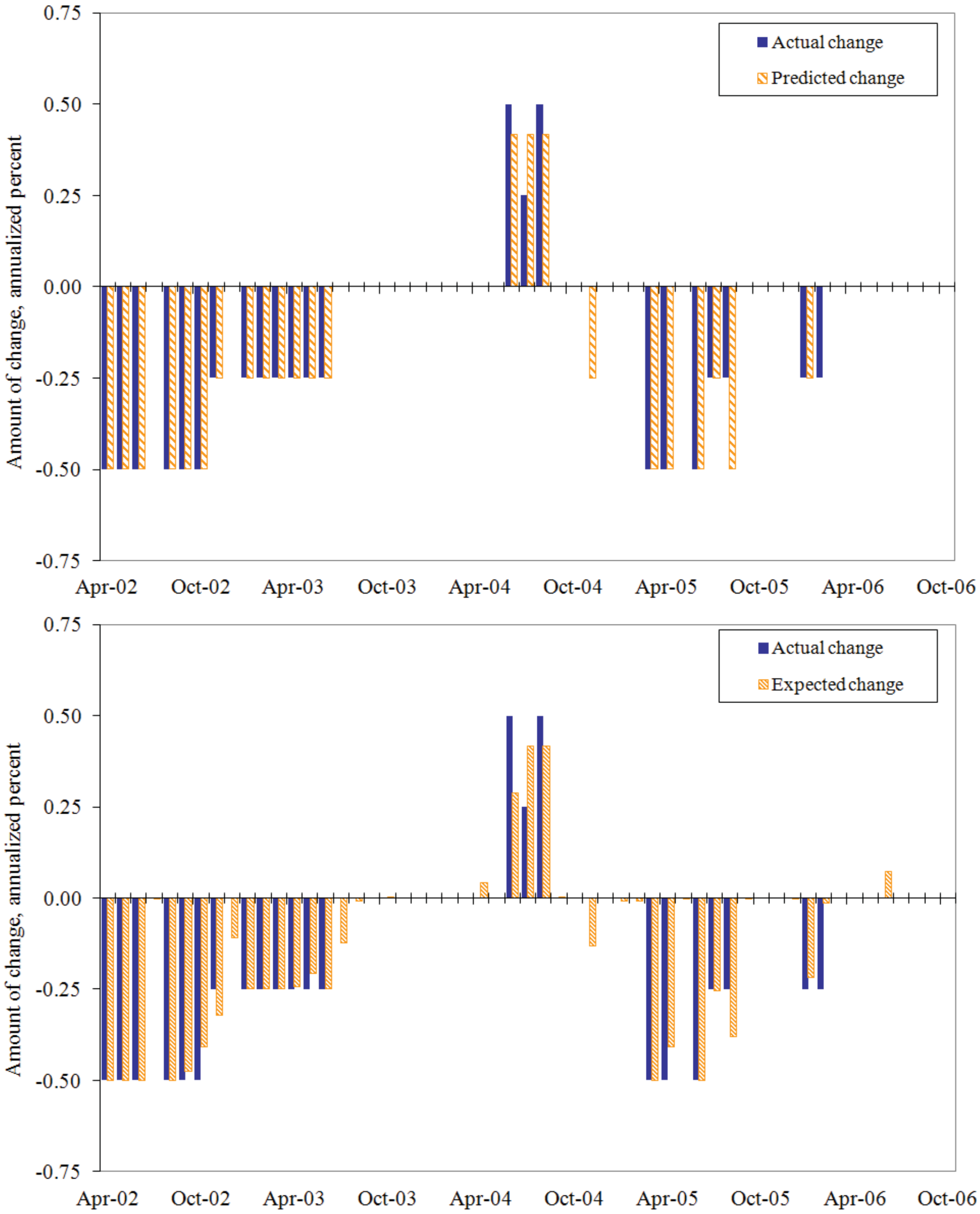
Sample: 1999/02 - 2006/10.

Figure 1.4: Andrews' sup-LR test for structural change with unknown change point



Notes:
Dependent variable: ΔRR_t;
Independent variables: $EReu$ and $CPIxac\_T\_YM$;
Model: Ordered probit with three categories: 'up', 'no change', 'down';
Sample: 1999/02 - 2006/10.

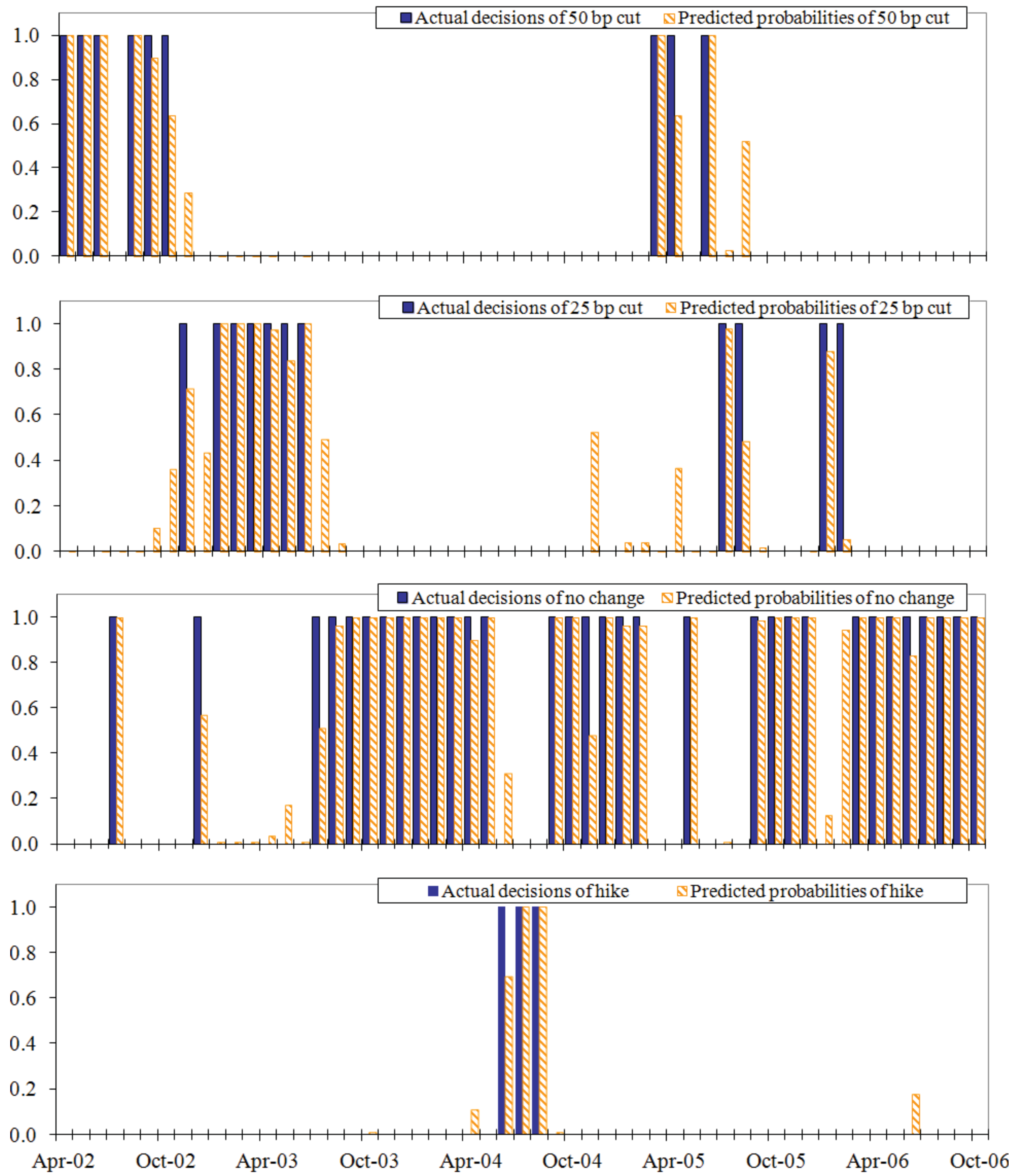
Figure 1.5: Actual, predicted and expected MPC decisions



Notes: The ordered probit estimations are performed for the specification 16.4 with four categories of dependent variable - change to the reference rate: 'hike', 'no change', '0.25% cut' and '0.50% cut'. A particular choice is predicted if its predicted probability exceeds the predicted probabilities of the alternatives. If a 'hike' is predicted, it is shown as a (0.5+0.5+0.25)/3 increase. The expected changes are computed using formula: E(Y|X) = P(Y=-0.5|X)*(-0.5) + P(Y=-0.25|X)*(-0.25) + P(Y=0|X)*(0) + P(Y>0|X)*(0.5+0.5+0.25)/3, where (0.5+0.5+0.25)/3 = E(Y|Y>0, X) – sample mean of "hike" category.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Figure 1.6: Estimated probabilities of MPC decisions



Notes: The ordered probit estimations are performed for the specification 16.4.

Figure 1.7: Correlograms of generalized residuals from ordered probit models

Model 16.2

Dependent variable: the reference rate change with four outcome categories: "increase", "no change", "0.25% decrease", and "0.50% decrease".

Independent variables: *ExInf_T_M, GDPnaiy, ExInf_T_M*Ind_ExInf_T, WIBOR12m_ZP*.

Sample: 2002/04 – 2006/10.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.057	0.057	0.1912	0.662
		2	-0.118	-0.122	1.0150	0.602
		3	-0.016	-0.002	1.0311	0.794
		4	0.012	-0.002	1.0394	0.904
		5	-0.033	-0.036	1.1061	0.954
		6	-0.195	-0.193	3.5419	0.738
		7	0.045	0.064	3.6731	0.817
		8	0.039	-0.015	3.7772	0.877
		9	-0.013	-0.007	3.7887	0.925
		10	0.053	0.060	3.9869	0.948
		11	0.053	0.035	4.1840	0.964
		12	0.009	-0.020	4.1900	0.980

Model 16.4

Dependent variable: the reference rate change with four outcome categories: "increase", "no change", "0.25% decrease", and "0.50 % decrease".

Independent variables: *ExInf_T_M, GVATnaiy, ExInf_T_M*Ind_ExInf_T, WIBOR12m_ZP*.

Sample: 2002/04 – 2006/10.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.101	0.101	0.5906	0.442
		2	-0.101	-0.112	1.1925	0.551
		3	-0.028	-0.006	1.2400	0.743
		4	0.008	0.000	1.2439	0.871
		5	-0.066	-0.072	1.5149	0.911
		6	-0.210	-0.200	4.3432	0.630
		7	0.071	0.106	4.6726	0.700
		8	0.071	0.007	5.0079	0.757
		9	0.026	0.028	5.0541	0.830
		10	0.061	0.069	5.3153	0.869
		11	0.050	0.022	5.4934	0.905
		12	-0.008	-0.040	5.4986	0.939

1.10 Tables

Table 1.1: Summary of empirical literature on Polish monetary policy rules

Study	Sample	Dependent variable	Estimation method	Data frequency	Interest rate equation specification	Notes
Brzozowski (2004)	1995-2003	Short-term market rate	OLS	quarterly	The CPI, the deviation of the real GDP from the potential one, the first difference and lagged level of the dependent variable	The output gap is significant (at 10%) only prior to 2000; real exchange rate is never significant
Golinelli, Rovelli (2005)	1991-2001	Difference b/w domestic & foreign short-term rates	VAR, 3-stage OLS	quarterly	The lagged dependent variable, and expected deviation of domestic inflation from the foreign one	The output gap (capacity utilization ratio) is not significant; stability tests fail to reject the parameters' constancy
Hristov (2005)	1993-2004	Treasury bill rate	Bayesian SVAR	monthly	The monetary aggregate M2, exchange rate, CPI, industrial production, money market rates reported by Frankfurt banks	
Kłos, Wróbel (2001)	1995-2000	The reference rate	SVAR, OLS	monthly	The inflation rate, and rate of growth of real credit to non-financial sector	
Kokoszczyński et al. (2006)	1995-2002	1-month WIBOR	SVAR, GMM	monthly	The log of price level, industrial output (deviation from the trend), and money aggregate M1	The policy is evaluated using Bernanke-Mihov index of monetary conditions
Kotłowski (2006)	2004-2005	Policy bias and reference rate	Ordered logit model	monthly	The deviations of CPI, industrial production and nominal exchange rate EUR/PLN from their expectations, and growth rate of real exchange rate EUR/PLN	The reaction functions are estimated individually for all MPC's members. The sample includes only 18 observations.
Maliszewski (2003)	1995-2002	Combination of 1-month WIBOR and exchange rate	Bayesian SVAR	monthly	The CPI, industrial production index and EMBI+	The model allows for a limited time-variation of parameters with the switch in February 1998
Mohanty, Klau (2004)	1995-2002	Short-term WIBOR	OLS	quarterly	The CPI, output gap, and lagged dependent variable	The real effective exchange rate is not significant; the response to negative inflation shock is stronger than to positive one (Poland is an outlier among the other countries)
	1998-2002		GMM	monthly	The expected CPI and output gap, and lagged dependent variable	
Wróbel, Pawłowska (2002)	1995-2002	1- and 3-month WIBOR	SVAR, OLS	monthly	The CPI (the only variable significant for the whole sample), broad money M2 (losing its role after 1997), lagged nominal effective exchange rate (gradually losing its role while becoming more and more freely floating), current account deficit with respect to GDP (strengthening its role after 1996), lagged credit to the non-financial sector or deposits of private individuals (having a primary role before 2000 and then gradually replaced by the industrial output gap)	

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
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Table 1.2: History of the NBP reference rate

Date of MPC meeting*	Reference rate, %	Amount of change, %	Date of MPC meeting*	Reference rate, %	Amount of change, %
1998-02-25	24.00	0.50	2002-07-19	8.50	0.00
1998-03-18	24.00	0.00	2002-08-28	8.00	-0.50
1998-04-22	23.00	-1.00	2002-09-25	7.50	-0.50
1998-05-20	21.50	-1.50	2002-10-23	7.00	-0.50
1998-06-17	21.50	0.00	2002-11-27	6.75	-0.25
1998-07-16	19.00	-2.50	2002-12-18	6.75	0.00
1998-08-19	19.00	0.00	2003-01-29	6.50	-0.25
1998-09-09	18.00	-1.00	2003-02-26	6.25	-0.25
1998-10-28	17.00	-1.00	2003-03-26	6.00	-0.25
1998-11-18	17.00	0.00	2003-04-24	5.75	-0.25
1998-12-09	15.50	-1.50	2003-05-28	5.50	-0.25
1999-01-20	13.00	-2.50	2003-06-25	5.25	-0.25
1999-02-17	13.00	0.00	2003-07-18	5.25	0.00
1999-03-24	13.00	0.00	2003-08-27	5.25	0.00
1999-04-21	13.00	0.00	2003-09-30	5.25	0.00
1999-05-27	13.00	0.00	2003-10-29	5.25	0.00
1999-06-16	13.00	0.00	2003-11-26	5.25	0.00
1999-07-21	13.00	0.00	2003-12-17	5.25	0.00
1999-08-18	13.00	0.00	2004-01-21	5.25	0.00
1999-09-22	14.00	1.00	2004-02-25	5.25	0.00
1999-10-20	14.00	0.00	2004-03-31	5.25	0.00
1999-11-17	16.50	2.50	2004-04-27	5.25	0.00
1999-12-15	16.50	0.00	2004-05-26	5.25	0.00
2000-01-26	16.50	0.00	2004-06-30	5.75	0.50
2000-02-23	17.50	1.00	2004-07-28	6.00	0.25
2000-03-29	17.50	0.00	2004-08-25	6.50	0.50
2000-04-26	17.50	0.00	2004-09-29	6.50	0.00
2000-05-24	17.50	0.00	2004-10-27	6.50	0.00
2000-06-21	17.50	0.00	2004-11-24	6.50	0.00
2000-07-19	17.50	0.00	2004-12-15	6.50	0.00
2000-08-30	19.00	1.50	2005-01-26	6.50	0.00
2000-09-19	19.00	0.00	2005-02-25	6.50	0.00
2000-10-25	19.00	0.00	2005-03-30	6.00	-0.50
2000-11-29	19.00	0.00	2005-04-27	5.50	-0.50
2000-12-20	19.00	0.00	2005-05-25	5.50	0.00
2001-01-22	19.00	0.00	2005-06-29	5.00	-0.50
2001-02-28	18.00	-1.00	2005-07-27	4.75	-0.25
2001-03-28	17.00	-1.00	2005-08-31	4.50	-0.25
2001-04-26	17.00	0.00	2005-09-28	4.50	0.00
2001-05-30	17.00	0.00	2005-10-26	4.50	0.00
2001-06-27	15.50	-1.50	2005-11-30	4.50	0.00
2001-07-20	15.50	0.00	2005-12-21	4.50	0.00
2001-08-22	14.50	-1.00	2006-01-31	4.25	-0.25
2001-09-26	14.50	0.00	2006-02-28	4.00	-0.25
2001-10-25	13.00	-1.50	2006-03-29	4.00	0.00
2001-11-28	11.50	-1.50	2006-04-26	4.00	0.00
2001-12-19	11.50	0.00	2006-05-31	4.00	0.00
2002-01-30	10.00	-1.50	2006-06-28	4.00	0.00
2002-02-27	10.00	0.00	2006-07-26	4.00	0.00
2002-03-27	10.00	0.00	2006-08-30	4.00	0.00
2002-04-26	9.50	-0.50	2006-09-27	4.00	0.00
2002-05-29	9.00	-0.50	2006-10-25	4.00	0.00
2002-06-26	8.50	-0.50			

Notes: * Dates of taking the policy decisions; Source: National Bank of Poland.

Table 1.3: Frequency distribution of NBP reference rate changes

Historical changes to NBP reference rate

Amount of change, %	Frequency		
	1998/02 to 2002/03	2002/04 to 2006/10	1998/02 to 2006/10
2.50	1		1
1.50	1		1
1.00	2		2
0.50	1	2	3
0.25		1	1
0.00	31	32	63
-0.25		11	11
-0.50		9	9
-1.00	6		6
-1.50	6		6
-2.50	2		2
Total:	50	55	105

NBP reference rate changes, consolidated into three and four categories

Outcome category	Frequency		
	1998/02 to 2002/03	2002/04 to 2006/10	1998/02 to 2006/10
Increase	5	3	8
No change	31	32	63
Decrease	14	20	34
Total:	50	55	105
Increase		3	
No change		32	
0.25% decrease		11	
0.50% decrease		9	
Total:		55	

Source: National Bank of Poland and author's compilations.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
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Table 1.4: Real-time MPC-meeting data set

Variable description	Mnemonics	Release frequency	Seasonal adjustment	Sourse	Release schedule
Price indexes					
Consumer price index	CPI	M	nsa	GUS	9
Consumer price index, excl. administratively controlled prices	CPIxac	M	nsa	GUS & NBP	8
Consumer price index, excl. the most volatile prices	CPIxmv	M	nsa	GUS & NBP	8
Consumer price index, excl. the most volatile and fuel prices	CPIxmvf	M	nsa	GUS & NBP	8
Consumer price index, excl. food and fuel prices	CPIxff	M	nsa	GUS & NBP	8
Consumer price index, 15% trimmed mean	CPItri	M	nsa	GUS & NBP	8
Business tendency survey in retail trade - Prices of sold goods	BTSRspr	M	nsa	GUS	11
Inflationary expectations					
Expected annual rate of CPI over next 12 months, percent	ExInf	M	nsa	Ipsos & NBP	4
CPI forecast by banking analysts by the end of the year, annual rate in percent	ReuCPI_Dec	M	nsa	Reuters	4
CPI forecast by banking analysts over next 11 months, annual rate in percent	ReuCPI_11m	M	nsa	Reuters	4
CPI forecast by banking analysts for the previous month, annual rate in percent	ReuCPI_prm	M	nsa	Reuters	4
CPI average annual rate forecast by banking analysts for the next year, percent	ReuCPI_nya	M	nsa	Reuters	4
PPI forecast by banking analysts for the previous month, annual rate in percent	ReuPPI_prm	M	nsa	Reuters	4
PPI forecast by banking analysts over next 11 months, annual rate in percent	ReuPPI_11m	M	nsa	Reuters	4
CPI central projection by NBP for the current quarter, annual rate in percent	NBP_CPI_cq	Q	nsa	CPI inflation projections, published in the NBP's Inflation Reports since August 2004. Since 2006 they are prepared for MPC's meetings in January, April, July and October	
CPI central projection by NBP for the next quarter, annual rate in percent	NBP_CPI_1q	Q	nsa		
CPI central projection by NBP over next two quarters, annual rate in percent	NBP_CPI_2q	Q	nsa		
CPI central projection by NBP over next three quarters, annual rate in percent	NBP_CPI_3q	Q	nsa		
CPI central projection by NBP over next four quarters, annual rate in percent	NBP_CPI_4q	Q	nsa		
CPI central projection by NBP over next five quarters, annual rate in percent	NBP_CPI_5q	Q	nsa		
CPI central projection by NBP over next six quarters, annual rate in percent	NBP_CPI_6q	Q	nsa		
CPI central projection by NBP over next seven quarters, annual rate in percent	NBP_CPI_7q	Q	nsa		
CPI central projection by NBP over next eight quarters, annual rate in percent	NBP_CPI_8q	Q	nsa		
Business tendency survey in industry - Expected selling prices of products	BTSIerpr	M	nsa	GUS	11
Business tendency survey in retail trade - Expected prices of goods	BTSRepr	M	nsa	GUS	11
Gross domestic product and main components					
Domestic demand, current prices, bln PLN	Demna	Q	nsa	GUS	3
Final consumption expenditure of households, current prices, bln PLN	FCEhna	Q	nsa	GUS	3
Gross domestic product, current prices, bln PLN	GDPna	Q	nsa	GUS	3
Gross fixed capital formation, current prices, bln PLN	GFCFna	Q	nsa	GUS	3
Gross value added, current prices, bln PLN	GVAna	Q	nsa	GUS	3
Index of domestic demand, growth rate in percent since corresponding period of previous year	Demnaiy	Q	nsa	GUS	3
Index of final consumption expenditure of households, growth rate in percent since corresponding period of previous year	FCEhnaiy	Q	nsa	GUS	3
Index of gross domestic product, growth rate in percent since corresponding period of previous year	GDPnaiy	Q	nsa	GUS	3
Index of gross fixed capital formation, growth rate in percent since corresponding period of previous year	GFCFnaiy	Q	nsa	GUS	3
Index of gross value added, total, growth rate in percent since corresponding period of previous year	GVATnaiy	Q	nsa	GUS	3
Annual growth rate of gross domestic product less annual growth rate of CPI, percent	GDPRna_Y	Q	nsa	GUS	3
Annual growth rate of gross value added less annual growth rate of CPI, percent	GVARna_Y	Q	nsa	GUS	3
Other measures of real activity					
Business tendency survey in construction - General economic situation	BTSCges	M	nsa	GUS	11
Business tendency survey in construction - Capacity utilization	BTSCcu	M	nsa	GUS	11
Business tendency survey in construction - Financial situation	BTSCfs	M	nsa	GUS	11
Business tendency survey in construction - General business tendency climate	BTSCcli	M	nsa	GUS	11
Business tendency survey in industry - General economic situation	BTSIges	M	nsa	GUS	11
Business tendency survey in industry - Current stocks of finished products	BTSIsfp	M	nsa	GUS	11
Business tendency survey in industry - General business tendency climate	BTSIcli	M	nsa	GUS	11
Business tendency survey in industry - Current volume of sold production	BTSIsold	M	nsa	GUS	11
Business tendency survey in retail trade - General economic situation	BTSRges	M	nsa	GUS	11
Business tendency survey in retail trade - Stocks of goods	BTSRsg	M	nsa	GUS	11
Business tendency survey in retail trade - General business tendency climate	BTSRcli	M	nsa	GUS	11
Business tendency survey in retail trade - Amount of goods sold	BTSRsold	M	nsa	GUS	11
Sold production of industry, total, current prices, bln PLN	IndProdT	M	nsa	GUS	7
Sold production of industry, manufacturing, bln PLN	IndProdM	M	nsa	GUS	7
Retail sale of goods, current prices	RetailS	M	nsa	GUS	8
Wholesale of goods by trade enterprises, current prices	WholeS	M	nsa	GUS	8
Investments newly started, number of tasks in thousands	InvStart	3Q	nsa	GUS	17
Real sector expectations					
Business tendency survey in construction - Expected general economic situation	BTSCeges	M	nsa	GUS	11
Business tendency survey in construction - Expected financial situation	BTSCefs	M	nsa	GUS	11
Business tendency survey in industry - Expected general economic situation	BTSIeges	M	nsa	GUS	11
Business tendency survey in industry - Expected volume of sold production	BTSIesold	M	nsa	GUS	11
Business tendency survey in industry - Expected domestic and foreign order-books	BTSIedfob	M	nsa	GUS	11
Business tendency survey in industry - Expected ability to pay the current debts	BTSIeabpay	M	nsa	GUS	11
Business tendency survey in retail trade - Expected general economic situation	BTSReges	M	nsa	GUS	11

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
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Variable description	Mnemonics	Release frequency	Seasonal adjustment	Sourse	Release schedule
Business tendency survey in retail trade - Expected orders placed with suppliers	BTSReo	M	nsa	GUS	11
Business tendency survey in retail trade - Expected ability to pay the current debts	BTSReabpay	M	nsa	GUS	11
Sold production of industry forecast by banking analysts for the previous month, annual rate in percent	ReuIndOut_prm	M	nsa	Reuters	4
Sold production of industry average annual rate forecast by banking analysts for the next year, percent	ReuIndOut_prm	M	nsa	Reuters	4
Gross domestic product annual rate forecast by banking analysts for the previous quarter, percent	ReuGDP_prq	M	nsa	Reuters	4
Gross domestic product annual rate forecast by banking analysts for the current quarter, percent	ReuGDP_cq	M	nsa	Reuters	4
Gross domestic product average annual rate forecast by banking analysts for the current year, percent	ReuGDP_cya	M	nsa	Reuters	4
Gross domestic product annual rate forecast by banking analysts for the next quarter, percent	ReuGDP_1q	M	nsa	Reuters	4
Gross domestic product annual rate forecast by banking analysts over the next 2 quarters, percent	ReuGDP_2q	M	nsa	Reuters	4
GDP central projection by NBP for the current quarter, annual rate in percent	NBP_GDP_cq	Q	nsa	GDP projections,	
GDP central projection by NBP for the next quarter, annual rate in percent	NBP_GDP_1q	Q	nsa	published in NBP	
GDP central projection by NBP over next two quarters, annual rate in percent	NBP_GDP_2q	Q	nsa	Inflation Reports	
GDP central projection by NBP over next three quarters, annual rate in percent	NBP_GDP_3q	Q	nsa	since May 2005.	
GDP central projection by NBP over next four quarters, annual rate in percent	NBP_GDP_4q	Q	nsa	Since 2006 they	
GDP central projection by NBP over next five quarters, annual rate in percent	NBP_GDP_5q	Q	nsa	are prepared for	
GDP central projection by NBP over next six quarters, annual rate in percent	NBP_GDP_6q	Q	nsa	MPC meetings in	
GDP central projection by NBP over next seven quarters, annual rate in percent	NBP_GDP_7q	Q	nsa	January, April,	
GDP central projection by NBP over next eight quarters, annual rate in percent	NBP_GDP_8q	Q	nsa	July and October	
Labour market and wages					
Unemployed persons, mln, LFS (BAEL)	UnemplLFS	Q	nsa	GUS	12
Unemployed persons, urban areas, mln, LFS (BAEL)	UnempluLFS	Q	nsa	GUS	12
Unemployment rate in %, total, LFS (BAEL)	URLFS	Q	nsa	GUS	12
Unemployment rate in %, males, LFS (BAEL)	URmLFS	Q	nsa	GUS	12
Unemployment rate in %, urban areas, LFS (BAEL)	URuLFS	Q	nsa	GUS	12
Unemployment rate in %, persons aged 15-24 years, LFS (BAEL)	UR1524LFS	Q	nsa	GUS	12
Economically inactive persons, mln, LFS (BAEL)	EcinactLFS	Q	nsa	GUS	13
Employed persons, mln, LFS (BAEL)	EmplLFS	Q	nsa	GUS	13
Activity rate, total, LFS (BAEL)	ARLFS	Q	nsa	GUS	13
Activity rate, urban areas, LFS (BAEL)	ARuLFS	Q	nsa	GUS	13
Employment rate, total, LFS (BAEL)	ERLFS	Q	nsa	GUS	13
Employment rate, urban areas, LFS (BAEL)	ERuLFS	Q	nsa	GUS	13
Registered unemployed persons, mln	Unempl	M	nsa	GUS	8
Number of employed, corporate sector, total, mln	EmplCS	M	nsa	GUS	8
Average employment, corporate sector, total, mln	EmplCSav	M	nsa	GUS	8
Average employee earnings (wages and salaries), total, corporate sector, thousands PLN	EarnCS	M	nsa	GUS	8
Average monthly gross wages and salaries, nominal, total, thousands PLN	Wagemav	Q	nsa	GUS	6
Employment expectations					
Business tendency survey in construction - Expected employment	BTSCeem	M	nsa	GUS	11
Business tendency survey in industry - Expected employment	BTSIeem	M	nsa	GUS	11
Business tendency survey in retail trade - Expected employment	BTSReem	M	nsa	GUS	11
Market interest rates					
Warsaw Interbank Offer Rate (WIBOR), 1-month, annualized percent	WIBOR1m	D	nsa	Reuters	D
Warsaw Interbank Offer Rate (WIBOR), 3-month, annualized percent	WIBOR3m	D	nsa	Reuters	D
Warsaw Interbank Offer Rate (WIBOR), 6-month, annualized percent	WIBOR6m	D	nsa	Reuters	D
Warsaw Interbank Offer Rate (WIBOR), 9-month, annualized percent	WIBOR9m	D	nsa	Reuters	D
Warsaw Interbank Offer Rate (WIBOR), 12-month, annualized percent	WIBOR12m	D	nsa	Reuters	D
52-week Treasury bill rate, average yield from the last auction prior to a MPC meeting, annualized percent	TB52w	IR	nsa	Ministry of Finance	n/a
Interest rates' expectations					
52-week Treasury bill yield forecast by banking analysts by the end of current month, annualized percent	Reu52w_cm	M	nsa	Reuters	4
52-week Treasury bill yield forecast by banking analysts over next 12 months, annualized percent	Reu52w_12m	M	nsa	Reuters	4
3-month WIBOR forecast by banking analysts by the end of current month, annualized percent	ReuWibor3M_cm	M	nsa	Reuters	4
3-month WIBOR forecast by banking analysts over next 12 months, annualized percent	ReuWibor3M_12m	M	nsa	Reuters	4
2-year Treasury bond yield forecast by banking analysts by the end of current month, annualized percent	Reu2y_cm	M	nsa	Reuters	4
2-year Treasury bond yield forecast by banking analysts over next 12 months, annualized percent	Reu2y_12m	M	nsa	Reuters	4
5-year Treasury bond yield forecast by banking analysts by the end of current month, annualized percent	Reu5y_cm	M	nsa	Reuters	4
5-year Treasury bond yield forecast by banking analysts over next 12 months, annualized percent	Reu5y_12m	M	nsa	Reuters	4

Variable description	Mnemonics	Release frequency	Seasonal adjustment	Sourse	Release schedule
10-year Treasury bond yield forecast by banking analysts by the end of current month, annualized percent	Reu10y_cm	M	nsa	Reuters	4
10-year Treasury bond yield forecast by banking analysts over next 12 months, annualized percent	Reu10y_12m	M	nsa	Reuters	4
Reference rate forecast by banking analysts by the end of current month, annualized percent	ReuRR_cm	M	nsa	Reuters	4
Reference rate forecast by banking analysts over next 12 months, annualized percent	ReuRR_12m	M	nsa	Reuters	4
Exchange rates					
Average monthly exchange rate, PLN/USD	ERUSm	M	nsa	NBP	19
Average monthly exchange rate, PLN/EUR	EREUm	M	nsa	NBP	19
Daily exchange rate, PLN/USD	ERUS	D	nsa	NBP	D
Daily exchange rate, PLN / (DM up to 31.12.1998 / EUR from 1.1.1999)	EREU	D	nsa	NBP	D
Exchange rates' expectations					
Exchange rate PLN/EUR forecast by banking analysts by the end of current month	ReuEReu_cm	M	nsa	Reuters	4
Exchange rate PLN/EUR forecast by banking analysts over next 12 months	ReuEReu_12m	M	nsa	Reuters	4
Exchange rate PLN/USD forecast by banking analysts by the end of current month	ReuERus_cm	M	nsa	Reuters	4
Exchange rate PLN/USD forecast by banking analysts over next 12 months	ReuERus_12m	M	nsa	Reuters	4
Foreign policy interest rates					
US Federal funds rate target, annualized percent	dFFR	D	nsa	US Federal Reserve	D
Main ECB target rate: minimum bid rate on the main refinancing operations of the Eurosystem, annualized percent	dECBR	D	nsa	European Central Bank	D
Lending and credit					
MFI's loans to private corporations, bln PLN	Loanpc	M	nsa	NBP	2
MFI's loans to private corporations, total, bln PLN	Loanpct	M	nsa	NBP	2
MFI's loans and other claims on households, bln PLN	Claimh	M	nsa	NBP	2
MFI's loans and other claims on households, total, bln PLN	Claimht	M	nsa	NBP	2
MFI's loans to households, bln PLN	Loanh	M	nsa	NBP	2
MFI's loans to households, total, bln PLN	Loanht	M	nsa	NBP	2
MFI's loans and other claims to non-financial corporations, bln PLN	Claimnfc	M	nsa	NBP	2
MFI's loans and other claims to non-financial corporations, total, bln PLN	Claimnfct	M	nsa	NBP	2
MFI's loans to non-financial corporations, bln PLN	Loannfc	M	nsa	NBP	2
MFI's loans to non-financial corporations, total, bln PLN	Loannfct	M	nsa	NBP	2
MFI's loans and other claims on non-financial sector, bln PLN	Claimnfs	M	nsa	NBP	2
MFI's loans and other claims on non-financial sector, total stocks, bln PLN	Claimnfst	M	nsa	NBP	2
MFI's credit to domestic residents, bln PLN	Cred	M	nsa	NBP	2
Deposits and other liabilities of MFIs to non-financial corporations, bln PLN	Depnfc	M	nsa	NBP	2
Deposits and other liabilities of MFIs to non-financial corporations, total stocks, bln PLN	Depnfct	M	nsa	NBP	2
Deposits and other liabilities of MFIs to non-financial sector, bln PLN	Depnfs	M	nsa	NBP	2
Deposits and other liabilities of MFIs to non-financial sector, total stocks, bln PLN	Depnfst	M	nsa	NBP	2
Deposits and other liabilities of MFIs to households, bln PLN	Deph	M	nsa	NBP	2
Deposits and other liabilities of MFIs to households, total, bln PLN	DepHT	M	nsa	NBP	2
Housing loans to households, bln PLN	Hloanh	M	nsa	NBP	2
Housing loans to households, total, bln PLN	HloanT	M	nsa	NBP	2
Deposits and other liabilities of MFIs to other domestic residents in zloty, bln PLN	DepDRes	M	nsa	NBP	2
Deposits and other liabilities of MFIs to other domestic residents in zloty and foreign currency, bln PLN	DepDResT	M	nsa	NBP	2
Deposits and other liabilities of MFIs to central government in zloty, bln PLN	DepGov	M	nsa	NBP	2
Deposits and other liabilities of MFIs to central government in zloty and foreign currency, bln PLN	DepGovT	M	nsa	NBP	2
Inter-MFI's liabilities in zloty, bln PLN	DepiMFI	M	nsa	NBP	2
Inter-MFI's liabilities in zloty and foreign currency, bln PLN	DepiMFIT	M	nsa	NBP	2
Loans and other claims of MFIs to other domestic residents in zloty, bln PLN	ClaimDRes	M	nsa	NBP	2
Loans and other claims of MFIs to other domestic residents in zloty and foreign currency, bln PLN	ClaimDResT	M	nsa	NBP	2
Loans and other claims of MFIs to central government in zloty, bln PLN	ClaimGov	M	nsa	NBP	2
Loans and other claims of MFIs to central government in zloty and foreign currency, bln PLN	ClaimGovT	M	nsa	NBP	2
Inter-MFI's claims in zloty, bln PLN	ClaimiMFI	M	nsa	NBP	2
Inter-MFI's claims in zloty and foreign currency, bln PLN	ClaimiMFIT	M	nsa	NBP	2

Notes: Release frequencies: D - daily, M - monthly, Q - quarterly, 3Q - second, third and fourth quarters, D – daily, IR – irregular.Release schedules: see Table 1.6 for the availability of statistical data at MPC's meetings for all release schedules. Seasonal adjustment: sa - seasonally adjusted, nsa - not seasonally adjusted.

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Table 1.5: Transformations of original data.

Transformation description	Mnemonics
(Percentage) change since the previous business day	_D
Five-day moving average	_5da
Three-week moving average	_3wa
(Percentage) change since the previous month	_M
(Percentage) change since the previous quarter	_Q
(Percentage) change since the corresponding period of previous year	_Y
Three-month moving average	_3ma
Four-quarter moving average of the (percentage) change since the corresponding period of previous year	_4qa
Change since the previous MPC's meeting	_Z
Change since the date of the last non-zero adjustment to the reference rate	_C
Deviation from the target rate (for CPI)	_T
Original value of variable if it is positive, and zero otherwise	_P
Original value of variable if it is negative, and zero otherwise	_N
Spread between some variable X and the reference rate	X_RR
First-order lagged variable	_L1
Indicator variable: one if X is equal to or above the inflation target, zero otherwise	Ind_X_T

Notes: The transformations can be combined, for example, _YM means the change since the previous month to (percentage) change since the corresponding period of previous year, or _YC means the change since the date of the last non-zero adjustment to the reference rate to (percentage) change since the corresponding period of previous year.

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Table 1.6: Availability of latest statistical data at MPC meetings

Date of MPC meeting	Release schedule											
	# 2	# 3	# 4	# 6	# 7	# 8	# 9	# 11	# 12	# 13	# 17	# 19
1998-02-25	01-98	Q3-97	02-98	Q4-97	01-98	01-98	01-98	01-98	Q4-97	Q4-97	Q3-97	01-98
1998-03-18	02-98	Q3-97	03-98	Q4-97	02-98	02-98	02-98	02-98	Q4-97	Q4-97	Q4-97	02-98
1998-04-22	03-98	Q4-97	04-98	Q4-97	03-98	03-98	03-98	03-98	Q4-97	Q4-97	Q4-97	03-98
1998-05-20	04-98	Q4-97	05-98	Q1-98	04-98	04-98	04-98	04-98	Q1-98	Q1-98	Q4-97	04-98
1998-06-17	05-98	Q4-97	06-98	Q1-98	05-98	05-98	05-98	05-98	Q1-98	Q1-98	Q4-97	05-98
1998-07-16	06-98	Q1-98	07-98	Q1-98	06-98	06-98	06-98	06-98	Q1-98	Q1-98	Q4-97	06-98
1998-08-19	07-98	Q1-98	08-98	Q2-98	07-98	07-98	07-98	07-98	Q2-98	Q2-98	Q2-98	07-98
1998-09-09	08-98	Q1-98	09-98	Q2-98	07-98	07-98	07-98	08-98	Q2-98	Q2-98	Q2-98	08-98
1998-10-28	09-98	Q2-98	10-98	Q2-98	09-98	09-98	09-98	09-98	Q3-98	Q2-98	Q2-98	09-98
1998-11-18	10-98	Q2-98	11-98	Q3-98	10-98	10-98	10-98	10-98	Q3-98	Q3-98	Q3-98	10-98
1998-12-09	11-98	Q2-98	12-98	Q3-98	10-98	10-98	10-98	11-98	Q3-98	Q3-98	Q3-98	11-98
1999-01-20	12-98	Q3-98	01-99	Q3-98	12-98	12-98	12-98	12-98	Q3-98	Q3-98	Q3-98	12-98
1999-02-17	01-99	Q3-98	02-99	Q4-98	01-99	01-99	01-99	01-99	Q4-98	Q4-98	Q3-98	01-99
1999-03-24	02-99	Q4-98	03-99	Q4-98	02-99	02-99	02-99	02-99	Q4-98	Q4-98	Q4-98	02-99
1999-04-21	03-99	Q4-98	04-99	Q4-98	03-99	03-99	03-99	03-99	Q4-98	Q4-98	Q4-98	03-99
1999-05-27	04-99	Q4-98	05-99	Q1-99	04-99	04-99	04-99	04-99	Q1-99	Q4-98	Q4-98	04-99
1999-06-16	05-99	Q4-98	06-99	Q1-99	05-99	05-99	05-99	05-99	Q1-99	Q1-99	Q4-98	05-99
1999-07-21	06-99	Q1-99	07-99	Q1-99	06-99	06-99	06-99	06-99	Q1-99	Q1-99	Q4-98	06-99
1999-08-18	07-99	Q1-99	08-99	Q2-99	07-99	07-99	07-99	07-99	Q1-99	Q1-99	Q2-99	07-99
1999-09-22	08-99	Q2-99	09-99	Q2-99	08-99	08-99	08-99	08-99	Q1-99	Q1-99	Q2-99	08-99
1999-10-20	09-99	Q2-99	10-99	Q2-99	09-99	09-99	09-99	09-99	Q1-99	Q1-99	Q2-99	09-99
1999-11-17	10-99	Q2-99	11-99	Q3-99	10-99	10-99	10-99	10-99	Q1-99	Q1-99	Q3-99	10-99
1999-12-15	11-99	Q2-99	12-99	Q3-99	11-99	11-99	11-99	11-99	Q1-99	Q1-99	Q3-99	11-99
2000-01-26	12-99	Q3-99	01-00	Q3-99	12-99	12-99	12-99	12-99	Q1-99	Q1-99	Q3-99	12-99
2000-02-23	01-00	Q3-99	02-00	Q4-99	01-00	01-00	01-00	01-00	Q1-99	Q1-99	Q3-99	01-00
2000-03-29	02-00	Q4-99	03-00	Q4-99	02-00	02-00	02-00	02-00	Q1-99	Q1-99	Q4-99	02-00
2000-04-26	03-00	Q4-99	04-00	Q4-99	03-00	03-00	03-00	03-00	Q1-99	Q1-99	Q4-99	03-00
2000-05-24	04-00	Q4-99	05-00	Q1-00	04-00	04-00	04-00	04-00	Q1-99	Q1-99	Q4-99	04-00
2000-06-21	05-00	Q1-00	06-00	Q1-00	05-00	05-00	05-00	05-00	Q1-00	Q1-00	Q4-99	05-00
2000-07-19	06-00	Q1-00	07-00	Q1-00	06-00	06-00	06-00	06-00	Q1-00	Q1-00	Q4-99	06-00
2000-08-30	07-00	Q1-00	08-00	Q2-00	07-00	07-00	07-00	07-00	Q1-00	Q1-00	Q2-00	07-00
2000-09-19	08-00	Q1-00	09-00	Q2-00	08-00	08-00	08-00	08-00	Q2-00	Q2-00	Q2-00	08-00
2000-10-25	09-00	Q2-00	10-00	Q2-00	09-00	09-00	09-00	09-00	Q2-00	Q2-00	Q2-00	09-00
2000-11-29	10-00	Q2-00	11-00	Q3-00	10-00	10-00	10-00	10-00	Q2-00	Q2-00	Q3-00	10-00
2000-12-20	11-00	Q3-00	12-00	Q3-00	11-00	11-00	11-00	11-00	Q3-00	Q3-00	Q3-00	11-00
2001-01-22	12-00	Q3-00	01-01	Q3-00	12-00	12-00	12-00	12-00	Q3-00	Q3-00	Q3-00	12-00
2001-02-28	01-01	Q3-00	02-01	Q4-00	01-01	01-01	01-01	01-01	Q4-00	Q3-00	Q3-00	01-01
2001-03-28	02-01	Q4-00	03-01	Q4-00	02-01	02-01	02-01	02-01	Q4-00	Q4-00	Q4-00	02-01
2001-04-26	03-01	Q4-00	04-01	Q4-00	03-01	03-01	03-01	03-01	Q4-00	Q4-00	Q4-00	03-01
2001-05-30	04-01	Q4-00	05-01	Q1-01	04-01	04-01	04-01	04-01	Q4-00	Q4-00	Q4-00	04-01
2001-06-27	05-01	Q1-01	06-01	Q1-01	05-01	05-01	05-01	05-01	Q4-00	Q4-00	Q4-00	05-01
2001-07-20	06-01	Q1-01	07-01	Q1-01	06-01	06-01	06-01	06-01	Q4-00	Q1-01	Q4-00	06-01
2001-08-22	07-01	Q1-01	08-01	Q2-01	07-01	07-01	07-01	07-01	Q1-01	Q1-01	Q2-01	07-01
2001-09-26	08-01	Q2-01	09-01	Q2-01	08-01	08-01	08-01	08-01	Q2-01	Q2-01	Q2-01	08-01
2001-10-25	09-01	Q2-01	10-01	Q2-01	09-01	09-01	09-01	09-01	Q2-01	Q2-01	Q2-01	09-01
2001-11-28	10-01	Q2-01	11-01	Q3-01	10-01	10-01	10-01	10-01	Q3-01	Q3-01	Q3-01	10-01
2001-12-19	11-01	Q3-01	12-01	Q3-01	11-01	11-01	11-01	11-01	Q3-01	Q3-01	Q3-01	11-01
2002-01-30	12-01	Q3-01	01-02	Q3-01	12-01	12-01	12-01	01-02	Q3-01	Q3-01	Q3-01	12-01
2002-02-27	01-02	Q3-01	02-02	Q4-01	01-02	01-02	01-02	02-02	Q4-01	Q3-01	Q3-01	01-02
2002-03-27	02-02	Q4-01	03-02	Q4-01	02-02	02-02	02-02	03-02	Q4-01	Q4-01	Q4-01	02-02
2002-04-26	03-02	Q4-01	04-02	Q4-01	03-02	03-02	03-02	04-02	Q4-01	Q4-01	Q4-01	03-02
2002-05-29	04-02	Q4-01	05-02	Q1-02	04-02	04-02	04-02	05-02	Q1-02	Q4-01	Q4-01	04-02
2002-06-26	05-02	Q1-02	06-02	Q1-02	05-02	05-02	05-02	06-02	Q1-02	Q1-02	Q4-01	05-02
2002-07-19	06-02	Q1-02	07-02	Q1-02	06-02	06-02	06-02	07-02	Q1-02	Q1-02	Q4-01	06-02
2002-08-28	07-02	Q1-02	08-02	Q2-02	07-02	07-02	07-02	08-02	Q2-02	Q1-02	Q2-02	07-02

Date of MPC meeting	Release schedule											
	# 2	# 3	# 4	# 6	# 7	# 8	# 9	# 11	# 12	# 13	# 17	# 19
2002-09-25	08-02	Q2-02	09-02	Q2-02	08-02	08-02	08-02	09-02	Q2-02	Q2-02	Q2-02	08-02
2002-10-23	09-02	Q2-02	10-02	Q2-02	09-02	09-02	09-02	10-02	Q2-02	Q2-02	Q2-02	09-02
2002-11-27	10-02	Q2-02	11-02	Q3-02	10-02	10-02	10-02	11-02	Q2-02	Q2-02	Q3-02	10-02
2002-12-18	11-02	Q2-02	12-02	Q3-02	11-02	11-02	11-02	11-02	Q3-02	Q2-02	Q3-02	11-02
2003-01-29	12-02	Q3-02	01-03	Q3-02	12-02	12-02	12-02	01-03	Q3-02	Q3-02	Q3-02	12-02
2003-02-26	01-03	Q3-02	02-03	Q4-02	01-03	01-03	01-03	02-03	Q4-02	Q3-02	Q3-02	01-03
2003-03-26	02-03	Q4-02	03-03	Q4-02	02-03	02-03	02-03	03-03	Q4-02	Q4-02	Q4-02	02-03
2003-04-24	03-03	Q4-02	04-03	Q4-02	03-03	03-03	03-03	04-03	Q4-02	Q4-02	Q4-02	03-03
2003-05-28	04-03	Q4-02	05-03	Q1-03	04-03	04-03	04-03	05-03	Q1-03	Q4-02	Q4-02	04-03
2003-06-25	05-03	Q1-03	06-03	Q1-03	05-03	05-03	05-03	06-03	Q1-03	Q1-03	Q4-02	05-03
2003-07-18	06-03	Q1-03	07-03	Q1-03	06-03	06-03	06-03	06-03	Q1-03	Q1-03	Q4-02	06-03
2003-08-27	07-03	Q1-03	08-03	Q2-03	07-03	07-03	07-03	08-03	Q1-03	Q1-03	Q2-03	07-03
2003-09-30	08-03	Q2-03	09-03	Q2-03	08-03	08-03	08-03	09-03	Q2-03	Q2-03	Q2-03	08-03
2003-10-29	09-03	Q2-03	10-03	Q2-03	09-03	09-03	09-03	10-03	Q2-03	Q2-03	Q2-03	09-03
2003-11-26	10-03	Q2-03	11-03	Q3-03	10-03	10-03	10-03	11-03	Q2-03	Q2-03	Q3-03	10-03
2003-12-17	11-03	Q2-03	11-03	Q3-03	10-03	10-03	11-03	11-03	Q2-03	Q2-03	Q3-03	11-03
2004-01-21	12-03	Q3-03	01-04	Q3-03	12-03	12-03	12-03	12-03	Q3-03	Q3-03	Q3-03	12-03
2004-02-25	01-04	Q4-03	02-04	Q4-03	01-04	01-04	01-04	02-04	Q4-03	Q3-03	Q3-03	01-04
2004-03-31	02-04	Q4-03	03-04	Q4-03	02-04	02-04	02-04	03-04	Q4-03	Q4-03	Q4-03	02-04
2004-04-27	03-04	Q4-03	04-04	Q4-03	03-04	03-04	03-04	04-04	Q4-03	Q4-03	Q4-03	03-04
2004-05-26	04-04	Q4-03	05-04	Q1-04	04-04	04-04	04-04	05-04	Q4-03	Q4-03	Q4-03	04-04
2004-06-30	05-04	Q1-04	06-04	Q1-04	05-04	05-04	05-04	06-04	Q1-04	Q1-04	Q4-03	05-04
2004-07-28	06-04	Q1-04	07-04	Q1-04	06-04	06-04	06-04	07-04	Q1-04	Q1-04	Q4-03	06-04
2004-08-25	07-04	Q1-04	08-04	Q2-04	07-04	07-04	07-04	08-04	Q1-04	Q1-04	Q4-03	07-04
2004-09-29	08-04	Q2-04	09-04	Q2-04	08-04	08-04	08-04	09-04	Q2-04	Q2-04	Q2-04	08-04
2004-10-27	09-04	Q2-04	10-04	Q2-04	09-04	09-04	09-04	10-04	Q2-04	Q2-04	Q2-04	09-04
2004-11-24	10-04	Q2-04	11-04	Q3-04	10-04	10-04	10-04	11-04	Q2-04	Q2-04	Q3-04	10-04
2004-12-15	11-04	Q3-04	12-04	Q3-04	10-04	11-04	11-04	11-04	Q2-04	Q2-04	Q3-04	11-04
2005-01-26	12-04	Q3-04	01-05	Q3-04	12-04	12-04	12-04	01-05	Q3-04	Q3-04	Q3-04	12-04
2005-02-25	01-05	Q3-04	02-05	Q4-04	01-05	01-05	01-05	02-05	Q3-04	Q3-04	Q3-04	01-05
2005-03-30	02-05	Q4-04	03-05	Q4-04	02-05	02-05	02-05	03-05	Q4-04	Q4-04	Q4-04	02-05
2005-04-27	03-05	Q4-04	04-05	Q4-04	03-05	03-05	03-05	04-05	Q4-04	Q4-04	Q4-04	03-05
2005-05-25	04-05	Q4-04	05-05	Q1-05	04-05	04-05	04-05	05-05	Q4-04	Q4-04	Q4-04	04-05
2005-06-29	05-05	Q1-05	06-05	Q1-05	05-05	05-05	05-05	06-05	Q1-05	Q1-05	Q4-04	05-05
2005-07-27	06-05	Q1-05	07-05	Q1-05	06-05	06-05	06-05	07-05	Q1-05	Q1-05	Q4-04	06-05
2005-08-31	07-05	Q2-05	08-05	Q2-05	07-05	07-05	07-05	08-05	Q1-05	Q1-05	Q2-05	07-05
2005-09-28	08-05	Q2-05	09-05	Q2-05	08-05	08-05	08-05	09-05	Q2-05	Q2-05	Q2-05	08-05
2005-10-26	09-05	Q2-05	10-05	Q2-05	09-05	09-05	09-05	10-05	Q2-05	Q2-05	Q2-05	09-05
2005-11-30	10-05	Q3-05	11-05	Q3-05	10-05	10-05	10-05	11-05	Q2-05	Q2-05	Q3-05	10-05
2005-12-21	11-05	Q3-05	12-05	Q3-05	11-05	11-05	11-05	11-05	Q2-05	Q2-05	Q3-05	11-05
2006-01-31	12-05	Q3-05	01-06	Q4-05	12-05	12-05	12-05	01-06	Q3-05	Q3-05	Q3-05	12-05
2006-02-28	01-06	Q3-05	02-06	Q4-05	01-06	01-06	01-06	02-06	Q3-05	Q3-05	Q3-05	01-06
2006-03-29	02-06	Q4-05	03-06	Q4-05	02-06	02-06	02-06	03-06	Q4-05	Q4-05	Q4-05	02-06
2006-04-26	03-06	Q4-05	04-06	Q4-05	03-06	03-06	03-06	04-06	Q4-05	Q4-05	Q4-05	03-06
2006-05-31	04-06	Q1-06	05-06	Q1-06	04-06	04-06	04-06	05-06	Q4-05	Q4-05	Q4-05	04-06
2006-06-28	05-06	Q1-06	06-06	Q1-06	05-06	05-06	05-06	06-06	Q1-06	Q1-06	Q4-05	05-06
2006-07-26	06-06	Q1-06	07-06	Q1-06	06-06	06-06	06-06	07-06	Q1-06	Q1-06	Q4-05	06-06
2006-08-30	07-06	Q2-06	08-06	Q2-06	07-06	07-06	07-06	08-06	Q1-06	Q1-06	Q2-06	07-06
2006-09-27	08-06	Q2-06	09-06	Q2-06	08-06	08-06	08-06	09-06	Q2-06	Q2-06	Q2-06	08-06
2006-10-25	09-06	Q2-06	10-06	Q2-06	09-06	09-06	09-06	10-06	Q2-06	Q2-06	Q2-06	09-06

Notes: See Table 1.4 to determine according to which schedule each variable has been released.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 1.7: Augmented Dickey-Fuller unit root tests

Variable	Augmented Dickey-Fuller (ADF) unit root tests					P-values of the Ljung-Box Q-statistic of 12-order serial correlation among residuals
	Testing period	Model*	Lag length	t-statistic	P-value**	
ΔRR	1998/04 - 2007/08		2	-3.07	0.002	0.718
ExInf_T_M	1998/05 - 2007/08		2	-4.70	0.000	0.287
GDPnaiy	1998/09 - 2007/08	C	6	-2.90	0.049	0.737
GDPRna_Y	1998/05 - 2007/08	C	2	-2.78	0.065	0.956
GVATnaiy	1998/10 - 2007/08	C	7	-2.81	0.060	0.783
GVARna_Y	1998/07 - 2007/08	C	4	-3.86	0.003	0.537
CPI_T_YM	1999/03 - 2007/08		12	-5.47	0.000	0.922
CPIxac_T_YC	1999/04 - 2007/08	C	12	-3.61	0.007	0.999
CPIxac_T_YM	1999/04 - 2007/08		12	-4.40	0.000	0.881
CPIxmvf_T_YM	1999/04 - 2007/08		12	-5.33	0.000	0.914
Ereu	1993/01 - 2007/08	C	8	-3.09	0.028	0.216
WIBOR12m_ZP	2001/04 - 2007/08	C	0	-6.31	0.000	0.891
WIBOR12m_RR	2001/03 - 2007/08	C	0	-2.82	0.005	0.084
WIBOR9m_RR	2001/04 - 2007/08	C	1	-2.40	0.017	0.312
WIBOR6m_RR	1998/03 - 2007/08	C	0	-3.93	0.003	0.171
WIBOR3m_RR	1998/03 - 2007/08	C	0	-4.84	0.000	0.401
WIBOR1m_RR	1998/03 - 2007/08	C	0	-5.61	0.000	0.878
WIBOR3m_C	1998/03 - 2007/08	C	0	-4.98	0.000	0.725

Notes:The null hypothesis in ADF test: a series has a unit root.
The null hypothesis of the Ljung-Box Q-test of serial correlation: there is no serial correlation in the residuals up to 12th order.
* C - constant; ** MacKinnon (1996) one-sided p-values.
All tests are performed using Eviews 5.0.

Table 1.8: Tests for structural change

Dependent variable - change to the reference rate	Model 8.1		Model 8.2		Model 8.3		Model 8.4	
	ExInf_T_M	*GDPnai_Y*	*ExInf_T_M*	*GDPRna_Y*	*ExInf_T_M*	*GVATnai_Y*	*ExInf_T_M*	*GVARna_Y*
Full sample: 1999/02 - 2006/10 (93 observations)								
Parameter estimate	0.62	0.48	0.49	0.44	0.60	0.47	0.53	0.38
Standard error	0.21	0.09	0.22	0.08	0.21	0.09	0.22	0.08
P-Value	0.004	<0.001	0.025	<0.001	0.004	<0.001	0.014	<0.001
Log likelihood	-56.21		-55.56		-57.84		-58.12	
Likelihood ratio	44.27		45.59		41.01		40.46	
Count R^2	0.68		0.69		0.66		0.69	
Adj. count R^2	0.12		0.15		0.06		0.15	
McKelvey & Zavoina R^2	0.51		0.52		0.48		0.48	
Sup-LR test for structural change with unknown change point								
Change point *	April 2002		April 2002		April 2002		April 2002	
Max LR **	37.43		45.53		40.40		34.72	
First sub-sample: 1999/02 - 2002/03 (38 observations)								
Parameter estimate	0.30	0.29	0.21	0.34	0.30	0.28	0.24	0.29
Standard error	0.22	0.13	0.24	0.13	0.22	0.13	0.23	0.12
P-Value	0.175	0.023	0.368	0.007	0.179	0.026	0.301	0.016
Log likelihood	-26.17		-24.09		-26.28		-25.79	
Likelihood ratio	7.81		11.97		7.59		8.56	
Count R^2	0.71		0.71		0.71		0.71	
Adj. count R^2	0.00		0.00		0.00		0.00	
McKelvey & Zavoina R^2	0.28		0.41		0.27		0.30	
Second sub-sample: 2002/04 - 2006/10 (55 observations)								
Parameter estimate	5.27	1.12	9.35	1.76	5.57	1.23	5.24	0.79
Standard error	1.54	0.27	3.13	0.52	1.61	0.30	1.56	0.20
P-Value	0.001	<0.001	0.003	0.001	0.001	<0.001	0.001	<0.001
Log likelihood	-11.33		-8.70		-11.36		-14.97	
Likelihood ratio	69.92		75.18		69.85		62.64	
Count R^2	0.91		0.98		0.93		0.87	
Adj. count R^2	0.78		0.96		0.83		0.70	
McKelvey & Zavoina R^2	0.91		0.97		0.92		0.90	

Notes: Tests are performed for ordered probit models with three outcome categories of dependent variable: "increase", "no change", "decrease". Two threshold estimates are not reported.

* Testing period: 2001/11 - 2003/11. ** Andrews' asymptotical critical values:

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 1.9: Responses to real activity and inflation

Dependent variable - change to the reference rate	Model 9.1		Model 9.2		Model 9.3		Model 9.4	
	GDPnai_Y	*ExInf_T_M*	*GDPnai_Y*	*CPIxmvf_T_YM*	*GDPnai_Y*	*CPI_T_YM*	*GDPnai_Y*	*CPIxac_T_YM*
First sub-sample: 1999/02 - 2002/03 (38 observations)								
Parameter estimate	0.29	0.30	0.28	1.45	0.41	1.41	0.37	1.70
Standard error	0.13	0.22	0.15	0.51	0.17	0.44	0.17	0.49
P-Value	0.023	0.175	0.063	0.004	0.016	0.001	0.031	0.001
Log likelihood	-26.17		-21.28		-18.80		-17.26	
Likelihood ratio	7.81		17.59		22.56		25.63	
AIC	60.34		50.55		45.59		42.52	
Count R^2	0.71		0.76		0.82		0.82	
Adj. count R^2	0.00		0.18		0.36		0.36	
McKelvey & Zavoina R^2	0.28		0.57		0.65		0.69	
Second sub-sample: 2002/04 - 2006/10 (55 observations)								
Parameter estimate	1.12	5.27	0.71	1.29	0.73	0.94	0.73	1.05
Standard error	0.27	1.54	0.16	0.50	0.15	0.48	0.16	0.45
P-Value	<0.001	0.001	<0.001	0.010	<0.001	0.049	<0.001	0.021
Log likelihood	-11.33		-22.95		-24.32		-23.39	
Likelihood ratio	69.92		46.68		43.93		45.79	
AIC	30.66		53.89		56.65		54.79	
Count R^2	0.91		0.86		0.82		0.84	
Adj. count R^2	0.69		0.53		0.36		0.43	
McKelvey & Zavoina R^2	0.91		0.73		0.70		0.72	

Notes: The ordered probit estimations are performed with three outcome categories of dependent variable: "increase", "no change", "decrease". Two threshold estimates are not reported.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 1.10: Tests for structural change

Dependent variable - change to the reference rate	Model 10.1		Model 10.2	
	Ereu	*CPIxac_T_YM*	*Ind_CPI_T*	*CPIxac_T_YC*
Full sample: 1999/02 - 2006/10 (93 observations)				
Log likelihood	-62.10		-50.84	
Count R²	0.63		0.72	
Adj. count R²	0.00		0.24	
McKelvey & Zavoina R²	0.40		0.63	
Test for structural change with unknown change point				
Change point *	April 2002		April 2002	
Max LR **	26.84		17.12	
First sub-sample: 1999/02 - 2002/03 (38 observations)				
Parameter estimate	10.73	4.60	8.10	2.65
Standard error	3.96	1.81	3.67	0.91
P-Value	0.007	0.011	0.027	0.004
Log likelihood	-9.97		-10.44	
Likelihood ratio	40.20		39.26	
Count R²	0.87		0.95	
Adj. count R²	0.55		0.82	
McKelvey & Zavoina R²	0.96		0.97	
Second sub-sample: 2002/04 - 2006/10 (55 observations)				
Parameter estimate	1.05	1.01	1.71	0.95
Standard error	0.63	0.37	0.51	0.24
P-Value	0.094	0.006	<0.001	<0.001
Log likelihood	-38.71		-31.84	
Likelihood ratio	15.17		28.91	
Count R²	0.62		0.73	
Adj. count R²	0.09		0.35	
McKelvey & Zavoina R²	0.32		0.57	
Sample: 1998/03 - 2002/03 (49 observations)				
Parameter estimate	2.36	1.70	0.63	0.80
Standard error	0.95	0.47	0.39	0.21
P-Value	0.013	<0.001	0.111	<0.001
Log likelihood	-26.24		-31.03	
Likelihood ratio	31.04		21.45	
Count R²	0.71		0.69	
Adj. count R²	0.22		0.17	
McKelvey & Zavoina R²	0.67		0.50	

Notes: Tests are performed for ordered probit models with three outcome categories of dependent variable: "increase", "no change", "decrease". Two threshold estimates are not reported.

* Testing period: 2001/03 - 2004/07; ** Andrews' asymptotical critical values: 'CV 1%' = 19.08, 'CV 5%' = 14.87.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 1.11: Tests for interest rate smoothing

First sub-sample: 1999/02 - 2002/03	Model 11.1.1	Model 11.1.2			Model 11.1.3		
	RRC_L1	*Ereu*	*CPIxac_T_YM*	*RRC_L1*	*Ind_CPI_T*	*CPIxac_T_YC*	*RRC_L1*
Parameter estimate	0.34	15.02	6.08	-1.04	8.53	2.70	-0.59
Standard error	0.36	6.42	2.79	0.82	3.86	0.94	0.71
P-Value	0.347	0.019	0.029	0.205	0.027	0.004	0.406
				Goodness-of-fit measures			
Log likelihood	-29.63		-9.02			-10.08	
Likelihood ratio	0.90		42.11			39.99	
AIC	65.25		28.04			30.16	
Count R²	0.71		0.84			0.89	
Adj. count R²	0.00		0.45			0.64	
McKelvey & Zavoina R²	0.03		0.98			0.97	
Second sub-sample: 2002/04 - 2006/10	Model 11.2.1	Model 11.2.2			Model 11.2.3		
	RRC_L1	*ExInf_T_M*	*GDPRna_Y*	*RRC_L1*	*ExInf_T_M*	*GVATnai_Y*	*RRC_L1*
Parameter estimate	1.59	8.66	1.59	0.48	5.48	1.14	0.42
Standard error	0.35	3.10	0.56	0.84	1.60	0.33	0.71
P-Value	<0.001	0.005	0.004	0.568	<0.001	<0.001	0.553
				Goodness-of-fit measures			
Log likelihood	-34.26		-8.54			-11.19	
Likelihood ratio	24.05		75.49			70.20	
AIC	74.53		27.09			32.38	
Count R²	0.73		0.96			0.93	
Adj. count R²	0.35		0.91			0.83	
McKelvey & Zavoina R²	0.45		0.97			0.92	

Notes: The ordered probit setimations are performed with three outcome categories of dependent variable: "increase", "no change", "decrease". Two threshold estimates are not reported.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 1.12: Market anticipation of policy decisions

Specification	*WIBOR1m_RR*	*WIBOR3m_RR*	*WIBOR6m_RR*	*WIBOR9m_RR*	*WIBOR12m_RR*
			First sub-sample: 1999/02 - 2002/03		
Parameter estimate	1.24	1.85	1.71		
Standard error	0.39	0.48	0.45		
P-Value	0.002	<0.001	<0.001		
			Goodness-of-fit measures		
Log likelihood	-23.55	-16.90	-14.45		
Likelihood ratio	13.04	26.35	31.25		
AIC	53.11	39.80	34.90		
Count R^2	0.71	0.79	0.82		
Adj. count R^2	0.00	0.27	0.36		
McKelvey & Zavoina R^2	0.42	0.72	0.77		
			Second sub-sample: 2002/04 - 2006/10		
Parameter estimate	6.77	8.12	5.78	4.42	3.49
Standard error	1.42	1.80	1.36	1.04	0.80
P-Value	<0.001	<0.001	<0.001	<0.001	<0.001
			Goodness-of-fit measures		
Log likelihood	-30.01	-17.61	-16.35	-17.47	-18.81
Likelihood ratio	32.55	57.36	59.89	57.64	54.97
AIC	66.03	41.22	38.69	40.94	43.61
Count R^2	0.80	0.87	0.85	0.84	0.82
Adj. count R^2	0.52	0.70	0.65	0.61	0.57
McKelvey & Zavoina R^2	0.59	0.84	0.87	0.86	0.84

Notes: The ordered probit estimations are performed with three outcome categories of dependent variable - change to the reference rate: "increase", "no change", and "decrease". Two threshold estimates are not reported.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician’s Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 1.13: Comparison with market anticipation

First sub-sample: 1999/02 - 2002/03	*WIBOR6m_RR*	Reuters survey	Model 10.2
Proportion of correct predictions	0.82	0.87	0.95
Average likelihood of observed rate changes	0.77	0.80	0.83
Second sub-sample: 2002/04 - 2006/10	*WIBOR6m_RR*	Reuters survey	Model 8.2
Proportion of correct predictions	0.85	0.89	0.98
Average likelihood of observed rate changes	0.81	0.82	0.90

Notes: The predictions are made in terms of three possible policy choices: "increase", "no change", or "decrease" in the reference rate. The predicted choice is one with the highest predicted probability.

Model 8.2: *ExInf_T_M* and *GDPRna_Y*. Model 10.2: *Ind_CPI_T* and *CPIxac_T_YC*.

Table 1.14: Market anticipation of policy decisions in 2002/04 - 2006/10

Specification	Model 14.1 *WIBOR1m_RR*	Model 14.2 *WIBOR3m_RR*	Model 14.3 *WIBOR6m_RR*	Model 14.4 *WIBOR9m_RR*	Model 14.5 *WIBOR12m_RR*
Parameter estimate	4.91	5.16	3.86	3.15	2.68
Standard error	1.07	0.94	0.72	0.61	0.53
P-Value	<0.001	<0.001	<0.001	<0.001	<0.001
			Goodness-of-fit measures		
Log likelihood	-48.02	-37.29	-34.53	-34.59	-35.04
Likelihood ratio	24.07	45.52	51.04	50.92	50.03
AIC	104.03	82.59	77.06	77.19	78.08
Count R^2	0.71	0.71	0.69	0.67	0.65
Adj. count R^2	0.30	0.30	0.26	0.22	0.17
McKelvey & Zavoina R^2	0.43	0.68	0.74	0.76	0.76
Score test for equal slopes assumption	17.91 P-Value: <0.001	11.85 P-Value: 0.003	7.16 P-Value: 0.028	4.28 P-Value: 0.117	2.91 P-Value: 0.234

Notes: The ordered probit estimations are performed with four outcome categories of dependent variable - change to the reference rate: "increase", "no change", "0.25% decrease", and "0.50 % decrease". Three threshold estimates are not reported.

Count R^2 is the proportion of correct predictions. The predicted choice is one with the highest predicted probability. Adj. count R^2 is the proportion of correct predictions beyond the number that would be correctly guessed by choosing the outcome category with the largest percentage of observed cases.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
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Table 1.15: Comparison with market anticipation

Forecast	*WIBOR6m_RR* (model 14.3)	Reuters survey	Model 16.1	Model 16.2
Proportion of correct predictions	0.69	0.84	0.91	0.96
Average likelihood of observed rate changes	0.63	0.78	0.84	0.92
MAE of E(Y|X), basis points	10.27	7.25	4.60	2.84

Notes: The predictions are made in terms of four possible policy choices: "increase", "no change", "decrease -0.25%", or "decrease -0.50%" in the reference rate. The predicted choice is one with the highest predicted probability.

"MAE of E(Y|X)" is a mean absolute error, calculated with respect to the actual observed (non-consolidated) reference rate changes, where E(Y|X) = P(Y=-0.5|X)*(-0.5) + P(Y=-0.25|X)*(-0.25) + P(Y=0|X)*(0) + P(Y>0|X)*(0.375).

Model 16.1: *ExInf_T_M, GDPnaiy, ExInf_T_M* Ind_ExInf_T*.

Model 16.2: *ExInf_T_M, GDPnaiy, ExInf_T_M* Ind_ExInf_T, and WIBOR12m_ZP*.

Table 1.16: Policy rules in 2002/04 - 2006/10

	Model 16.1			Model 16.2				Model 16.3			Model 16.4			
Specification	*ExInf_T_M*	*GDPnaiy*	*ExInf_T_M* Ind_ExInf_T*	*ExInf_T_M*	*GDPnaiy*	*ExInf_T_M* Ind_ExInf_T*	*WIBOR12m_ZP*	*ExInf_T_M*	*GVATnaiy*	*ExInf_T_M* Ind_ExInf_T*	*ExInf_T_M*	*GVATnaiy*	*ExInf_T_M* Ind_ExInf_T*	*WIBOR12m_ZP*
Parameter estimate	4.02	1.44	8.99	11.36	4.65	28.48	32.43	4.19	1.56	8.83	9.18	3.90	21.34	24.59
Standard error	1.20	0.29	2.80	5.04	1.92	11.51	14.65	1.23	0.32	2.68	3.68	1.47	8.11	10.56
P-Value	<0.001	<0.001	0.001	0.024	0.015	0.013	0.027	<0.001	<0.001	0.001	0.013	0.008	0.009	0.020
Thresholds	α_1	α_2	α_3	α_1	α_2	α_3		α_1	α_2	α_3	α_1	α_2	α_3	
Parameter estimate	0.74	3.16	12.42	2.96	12.25	43.83		0.94	3.34	12.63	2.95	9.68	34.12	
Standard error	0.55	0.76	2.75	1.44	5.37	18.16		0.59	0.78	2.74	1.37	3.90	12.94	
P-Value	0.182	<0.001	<0.001	0.040	0.023	0.016		0.107	<0.001	<0.001	0.031	0.013	0.008	
Goodness-of-fit measures														
Log likelihood		-15.51			-7.13				-15.49			-8.15		
Likelihood ratio		89.07			105.84				89.13			103.80		
AIC		43.03			28.26				42.97			30.31		
Count R^2		0.91			0.96				0.91			0.95		
Adj. count R^2		0.78			0.91				0.78			0.87		
McKelvey & Zavoina R^2		0.96			1.00				0.96			0.99		
Adjusted Estrella R^2		0.89			0.96				0.89			0.95		
Cragg-Uhler-2 R^2		0.90			0.96				0.90			0.96		
Score test for the equal slopes assumption		8.79 P-value: 0.185			8.64 P-value: 0.373				9.02 P-value: 0.173			9.24 P-value: 0.322		

Notes: The ordered probit estimations are performed with four outcome categories of dependent variable: "0.50% or 0.25% increase", "no change", "0.25% decrease", and "0.50% decrease".

Table 1.17: Tests for interest rate smoothing in 2002/04 - 2006/10

	Model 17.1				Model 17.2			
Specification	*ExInf_T_M*	*GDPnaiy*	*ExInf_T_M** *Ind_ExInf_T*	*RRC_L1*	*ExInf_T_M*	*GVATnaiy*	*ExInf_T_M** *Ind_ExInf_T*	*RRC_L1*
Parameter estimate	4.05	1.41	9.03	0.74	4.23	1.53	8.95	1.01
Standard error	1.20	0.30	2.79	1.49	1.26	0.32	2.70	1.53
P-Value	<0.001	<0.001	0.001	0.618	<0.001	<0.001	<0.001	0.509
	Goodness-of-fit measures							
Log likelihood	-15.39				-15.27			
Likelihood ratio	89.32				89.56			
AIC	44.78				44.54			
Count R^2	0.93				0.93			
Adj. count R^2	0.83				0.83			
McKelvey & Zavoina R^2	0.96				0.96			

Notes: The ordered probit estimations are performed with four outcome categories of dependent variable: "0.50% or 0.25% increase", "no change", "0.25% decrease", and "0.50% decrease". Three threshold estimates are not reported.

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Table 1.18: In-sample prediction of policy rate changes

Actual decision	Predicted decision					Total	Adjusted noise to signal ratio, %
	hike	no change	0.25% cut	0.50% cut	Correct		
hike	3	0	0	0	3	3	0
no change	0	31	1	0	31	32	4.5
0.25% cut	0	1	9	1	9	11	2.8
0.50% cut	0	0	0	9	9	9	2.2
Total	3	32	10	10	52	55	

Notes:

Sample period: 2002/04 - 2006/10.

The ordered probit estimations are performed for the specification 16.4.

A particular choice is predicted if its predicted probability exceeds the predicted probabilities of the alternatives.

An 'adjusted noise-to-signal ratio', introduced by Kaminsky and Reinhart (1999), is defined as follows. Let *A* denote the event that the decision is predicted and occurred; let *B* denote the event that the decision is predicted but not occurred; let *C* denote the event that the decision is not predicted but occurred; let *D* denote the event that the decision is not predicted and not occurred. The desirable outcomes fall into categories *A* and *D*, while noisy ones fall into categories *B* and *C*. A perfect prediction would have no entries in *B* and *C*, while a noisy prediction would have many entries in *B* and *C*, but few in *A* and *D*. The 'adjusted noise-to-signal' ratio is defined as $[B/(B+D)]/[A/(A+C)]$.

Table 1.19: Out-of-sample forecasting of next change to the reference rate

Period	03-2006	04-2006	05-2006	06-2006	07-2006	08-2006	09-2006	10-2006	11-2006	12-2006	01-2007	02-2007	03-2007	04-2007	05-2007	06-2007	07-2007	08-2007	09-2007	10-2007
Actual change, %	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.25**	**0**	**0.25**	**0**	**0.25**	**0**	**0**
Forecast by Model 16.3																				
Pr(y=-0.50%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pr(y=-0.25%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pr(y=0%)	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**0.99**	**0.99**	**1.00**	**1.00**	**0.94**	**1.00**	**0.84**	**0.97**	0.00	**0.75**	**0.94**	0.00	**1.00**	**1.00**
Pr(y>=0.25%)	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.06	0.00	0.16	0.03	**1.00**	0.25	0.06	**1.00**	0.00	0.00
Predicted change, %	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.25**	**0**	**0**	**0.25**	**0**	**0**
Forecast by Model 16.4																				
Pr(y=-0.50%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pr(y=-0.25%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pr(y=0%)	**1.00**	**1.00**	**1.00**	**0.64**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	0.00	0.03	**0.86**	0.00	**1.00**	**1.00**
Pr(y>=0.25%)	0.00	0.00	0.00	0.36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**1.00**	**0.97**	0.14	**1.00**	0.00	0.00
Predicted change, %	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.25**	**0.25**	**0**	**0.25**	**0**	**0**
Market anticipation (forecast from Reuters survey of banks' analysts)																				
Pr(y=-0.50%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pr(y=-0.25%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pr(y=0%)	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**0.95**	0.05	**1.00**	**0.90**	**1.00**	0.19	**1.00**	**0.89**
Pr(y>=0.25%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	**0.95**	0.00	0.10	0.00	**0.81**	0.00	0.11
Predicted change, %	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.25**	**0**	**0**	**0**	**0.25**	**0**	**0**

Notes: Model 16.3: ExInf_T_M, GVATnaiy, ExInf_T_M*Ind_ExInf_T; Model 16.4: ExInf_T_M, GVATnaiy, ExInf_T_M*Ind_ExInf_T, WIBOR12m_ZP.
The forecasting by models 16.3 and 16.4 is performed using ordered probit models estimated for the period 2002/04-2006/02 without rolling re-estimation.
The predicted choice is that with the highest probability.

Table 1.20: Policy rules in 2002/04 - 2006/10, based on revised data at monthly frequency

Specification	Model 16.1			Model 16.2				Model 16.3			Model 16.4			
	ExInf_T_M	*GDPnaiy*	*ExInf_T_M* Ind_ExInf_T*	*ExInf_T_M*	*GDPnaiy*	*ExInf_T_M* Ind_ExInf_T*	*WIBOR12m_ZP*	*ExInf_T_M*	*GVATnaiy*	*ExInf_T_M* Ind_ExInf_T*	*ExInf_T_M*	*GVATnaiy*	*ExInf_T_M* Ind_ExInf_T*	*WIBOR12m_ZP*
Parameter estimate	4.04	1.43	6.04	4.05	1.45	6.12	-0.06	4.07	1.66	8.33	4.05	1.67	8.43	-0.04
Standard error	1.20	0.30	1.92	1.21	0.31	1.96	0.16	1.25	0.35	2.28	1.25	0.36	2.34	0.18
P-Value	<0.001	<0.001	0.002	<0.001	<0.001	0.002	0.723	0.001	<0.001	<0.001	0.001	<0.001	<0.001	0.823
Thresholds	α_1	α_2	α_3	α_1	α_2	α_3		α_1	α_2	α_3	α_1	α_2	α_3	
Parameter estimate	1.34	3.52	11.94	1.36	3.54	12.05		1.55	3.77	13.58	1.56	3.79	13.67	
Standard error	0.64	0.83	2.48	0.65	0.84	2.53		0.70	0.88	2.87	0.70	0.88	2.92	
P-Value	0.037	<0.001	<0.001	0.036	<0.001	<0.001		0.026	<0.001	<0.001	0.025	<0.001	<0.001	
Goodness-of-fit measures														
Log likelihood	-18.20			-18.14				-17.24			-17.22			
AIC	48.40			50.27				46.48			48.44			
Count R^2	0.85			0.85				0.87			0.87			
Adj. count R^2	0.65			0.65				0.70			0.70			
McKelvey & Zavoina R^2	0.95			0.95				0.96			0.96			

Notes: The ordered probit estimations are performed with four outcome categories of dependent variable – monthly change to the reference rate: "0.50% or 0.25% increase", "no change", "0.25% decrease", and "0.50% decrease".

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
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Table 1.21: Comparison of policy rules, based on revised and real-time data

Specification	*ExInf_T_M*	*GDPRna_Y*	*ExInf_T_M* Ind_ExInf_T*
	Real-time data available at MPC meetings		
Parameter estimate	3.35	1.47	9.12
Standard error	1.03	0.36	2.81
P-Value	0.001	<0.001	0.001
Thresholds	α_1	α_2	α_3
Parameter estimate	0.81	2.72	12.12
Standard error	0.61	0.78	3.86
P-Value	0.187	<0.001	0.002
	Goodness-of-fit measures		
Log likelihood		-19.04	
AIC		50.07	
Count R^2		0.85	
Adj. count R^2		0.65	
McKelvey & Zavoina R^2		0.96	
	Revised data at monthly frequency		
Parameter estimate	3.74	0.80	5.77
Standard error	0.96	0.19	1.64
P-Value	<0.001	<0.001	<0.001
Thresholds	α_1	α_2	α_3
Parameter estimate	0.87	2.14	7.81
Standard error	0.60	0.64	1.59
P-Value	0.148	<0.001	<0.001
	Goodness-of-fit measures		
Log likelihood		-29.48	
AIC		70.96	
Count R^2		0.76	
Adj. count R^2		0.43	
McKelvey & Zavoina R^2		0.89	

Notes: The ordered probit estimations are performed with four outcome categories of dependent variable – change to the reference rate: "0.50% or 0.25% increase", "no change", "0.25% decrease", and "0.50% decrease" for the period 2002/04 - 2006/10.

Table 1.22: Policy rules, estimated using linear OLS regression

Specification	Intercept	*ExInf_T_M*	*GVATnai_Y*	*ExInf_T_M* Ind_ExInf_T*	
Model 16.3					
Parameter estimate	-0.380	0.203	0.080	0.115	
Standard error	0.040	0.058	0.011	0.097	
P-Value	<0.001	0.001	<0.001	0.241	
Goodness-of-fit measures					
F-Statistic	37.55				
Pr > F	<0.001				
Root MSE	0.1319				
R^2	0.688				
Adj. R^2	0.670				
Durbin-Watson D	1.881				
Model 16.4					
Specification	Intercept	*ExInf_T_M*	*GVATnai_Y*	*ExInf_T_M* Ind_ExInf_T*	*WIBOR12m_ZP*
Parameter estimate	-0.381	0.201	0.079	0.106	0.058
Standard error	0.041	0.058	0.011	0.099	0.115
P-Value	<0.001	0.001	<0.001	0.291	0.619
Goodness-of-fit measures					
F-Statistic	27.81				
Pr > F	<0.001				
Root MSE	0.1328				
R^2	0.690				
Adj. R^2	0.665				
Durbin-Watson D	1.959				

Notes: Sample: 2002/04 – 2006/10.

Dependent variable: historical (non-consolidated) change to the reference rate made at a policy meeting of the MPC.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
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Table 1.23: Comparison of linear, rounded linear, interval and ordered probit models.

Model:		LRM	RLRM				IRM		OPM
Model 16.3: *ExInf_T_M, GVATnaiy, ExInf_T_M*Ind_ExInf_T*									
	c_1		-0.50	-0.25	-0.375	-0.50	-0.375	-0.50	0.94
Cut points	c_2		-0.25	0.00	-0.125	-0.25	-0.125	-0.25	3.34
	c_3		0.00	0.25	0.125	0.25	0.125	0.25	12.63
Goodness-of-fit measures									
MAE of E(Y|X), bp		9.92	17.22	14.44	10.16	10.36	10.02	6.03	4.50
Count R^2			0.55	0.42	0.78	0.73	0.69	0.87	0.91
Adjusted count R^2			-0.09	-0.39	0.48	0.35	0.26	0.70	0.78
Average likelihood			0.46	0.46	0.56	0.66	0.65	0.79	0.84
Log likelihood			-55.25	-52.87	-36.45	-36.64	-30.94	-19.18	-15.49
Likelihood ratio chi-square tests									
# of constraints			6	6	6	6	3	3	
Chi-square statistic			79.53	74.76	41.92	42.31	30.90	7.39	
P-value			0.000	0.000	0.000	0.000	0.000	0.060	
Model 16.4: *ExInf_T_M, GVATnaiy, ExInf_T_M*Ind_ExInf_T, WIBOR12m_ZP*									
	c_1		-0.50	-0.25	-0.375	-0.50	-0.375	-0.50	2.95
Cut points	c_2		-0.25	0.00	-0.125	-0.25	-0.125	-0.25	9.68
	c_3		0.00	0.25	0.125	0.25	0.125	0.25	34.12
Goodness-of-fit measures									
MAE of E(Y|X), bp		9.87	17.26	14.36	10.07	10.31	9.96	5.38	3.10
Count R^2			0.55	0.44	0.78	0.73	0.71	0.87	0.95
Adjusted count R^2			-0.09	-0.35	0.48	0.35	0.30	0.70	0.87
Average likelihood			0.46	0.46	0.56	0.66	0.65	0.82	0.91
Log likelihood			-54.88	-52.36	-36.21	-36.16	-29.70	-15.58	-8.15
Likelihood ratio chi-square tests									
# of constraints			7	7	7	7	3	3	
Chi-square statistic			93.45	88.41	56.11	56.02	43.10	14.85	
P-value			0.000	0.000	0.000	0.000	0.000	0.002	

Notes: LRM - linear regression model estimated by OLS; RLRM – extended 'rounded linear regression' model, which is identical to the constrained interval regression model with all coefficients β and σ^2 restricted to be the same as in the LRM, estimated by OLS; IRM - interval regression model; OPM - ordered probit model.

Sample period: 2002/04 - 2006/10. The estimations are performed with four outcome categories of dependent variable - change to the reference rate: "0.50% or 0.25% increase", "no change", "0.25% decrease", and "0.50% decrease".

In the RLRM, IRM and OPM the E(Y|X) = P(Y=-0.5|X)*(-0.5) + P(Y=-0.25|X)*(-0.25) + P(Y=0|X)*(0) + P(Y>0|X)*(0.5+0.5+0.25)/3, where (0.5+0.5+0.25)/3 = E(Y|Y>0, X). In the LRM the E(Y|X) = X*b. "MAE of E(Y|X)" - mean absolute error - is calculated with respect to the actual observed (non-consolidated) reference rate changes.

1.11 References

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European University Institute DOI: 10.2870/60780

Chapter 2

Policymakers' votes and predictability of monetary policy

2.1 Introduction

> "By making itself more predictable to the markets, the central bank makes market reactions to monetary policy more predictable to itself. And that makes it possible to do a better job of managing the economy."
>
> - Alan Blinder[1]

> "While specifying a complete policy rule is infeasible, however, there is much that a central bank can do – both by its actions and its words – to improve the ability of financial markets to predict monetary policy actions."
>
> - Ben Bernanke[2]

Most academic economists and central bank practitioners seem to agree nowadays that more transparent and predictable behavior not only promotes the credibility and democratic accountability of an independent central bank but also creates a stable environment to manage private sector expectations, reduces the uncertainty in financial markets, and, eventually, enhances the transmission and effectiveness of monetary policy itself and leads to social benefits. Indeed, over the past two decades most central banks have radically increased the disclosure of internal information and methodology used in policymaking.

[1] See Blinder (1998).
[2] See Bernanke (2004).

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

The vast majority of central banks currently entrust the conduct of monetary policy to a committee, in some countries called the Monetary Policy Committee or Council (MPC). Typically, the MPC sets the policy interest rate by either consensus or by way of formal voting. There is, however, no consensus among either the scholars or the central bankers on whether and when the voting records of policymaking meetings should be disclosed (Geraats 2002 and 2006, Hahn 2002, Lambert 2004, Blinder 2007, Maier 2007, Gersbach and Hahn 2008). The US Federal Reserve System (Fed) and Sweden's Central Bank (Riksbank) release the voting records immediately together with an announcement on the policy action; the Bank of England (BOE) publishes them within two weeks after the policy meeting; the National Bank of Poland (NBP) discloses them after a six-week delay; while the European Central Bank (ECB) does not publish them at all.

The voting (if any) on the policy rate in the Governing Council of the ECB remains clouded. According to Article 10.2 of the Statute of the European System of Central Banks and of the European Central Bank, "the Governing Council shall act by a simple majority of the members having a voting right." (Statute of the ESCB 2008). At the same time, however, the ECB claims that the policy decisions are made by consensus and formal votes are not taken at all: "As you know, we do not vote and have never voted in the past." (Trichet 2008).[3]

The ECB argues against publishing the voting records and minutes because they are likely to: (i) emphasize the disagreements among nations (rather than the interests of the euro currency area as a whole); (ii) increase external pressure on the Governing Council members; (iii) force them to follow national interests; (iv) impose on them an extra task to demonstrate that their decisions are actually *not* driven by national considerations; (v) discourage them from expressing personal views; (vi) introduce short-term personal career concerns into their deliberations and voting behavior; (vii) replace the free-flowing discussions by more formal statements; and (viii) raise suspicion that crucial discussions took place before the meeting or off the record.

These arguments are not universally accepted even for a special case of the ECB supranational structure, and do not seem to apply fully to the other central banks. Moreover, the above issues do not arise, even in a particular case of the ECB, if only the *non-attributed* voting patterns (*without* the policymakers' names attached to each vote) are disclosed. Instead, many observers conclude that the disclosure of votes, both attributed and non-attributed: (i) provides important information about the diversity and balance of views among the pol-

[3]For a heated debate on the ECB practice of not releasing the minutes and voting records, see Buiter (1999), Issing (1999a and 1999b), de Haan and Eijffinger (2000), and Waisman (2003).

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

icymakers; (ii) allows the public to more accurately observe the current policy stance and assess the riskiness of economic conditions; (iii) enhances the understanding of central bank behavior; and (iv) improves the predictability of monetary policy. In addition to the above, as argued by the advocates, the publication of the *attributed* voting records and minutes has the following additional advantages: it might (i) actually weaken the incentives to express the regional biases; (ii) reduce free-riding, especially in the large committees such as the ECB Governing Council; (iii) strengthen the motives to conduct high quality policy discussions; (iv) promote the committee's credibility and individual accountability; (v) allow the dissenting members to publicly defend their choices; and (vi) facilitate the monitoring and evaluation of policymakers' competence.

Some studies also conclude that the desirability of disclosing the votes depends on the institutional background and (re)appointment procedure for the MPC. According to Blinder (2007 and 2009), for instance, the release of the voting records is desirable as soon as possible for an *individualistic* committee, where each member votes for his own preferred policy and decisions are taken by the majority; however, it might harm the "aura of collegiality", "undermine clarity and common understanding and create a cacophony instead" in a *collegial* committee, since its decisions are reached by consensus, with or without a formal vote.[4]

Some observers emphasize that clarity is a prerequisite for transparency and express concern that conflicting individual views on policy actions might confuse the market participants. This hypothesis, however, lacks empirical support. Moreover, "if a cacophony problem arises from the fact that an MPC has too many uncoordinated and inconsistent voices that confuse rather than enlighten the public, the appropriate remedy is greater clarity, not silence" (Blinder 2009).

Whatever the results of theory, they must be scrutinized for empirical soundness. The data on the central bankers' votes are growing, and are currently available in at least nine countries: Brazil, the Czech Republic, Hungary, Japan, Korea, Poland, Sweden, the UK and the USA. The impact of the voting records on market anticipation of policy decisions can now be tested empirically. However, the studies of monetary policy predictability usually do not take into account the informational value contained in the available records, but instead routinely focus on the final collective decisions made by majority vote. The papers that do use the individual voting records are primarily concerned with detecting the heterogeneity of policy preferences among the policymakers (e.g., see Besley *et al.* 2008, Riboni and Ruge-Murcia 2008 on the UK case, and Havrilesky and Gildea 1991, and Chappell *et al.* 2005 on

[4] See Blinder and Wyplosz (2004) and Blinder (2009) who proposed a classification of MPCs into *genuinely-collegial* (e.g., the ECB and the Fed under B. Bernanke), *autocratically-collegial* (e.g., the Fed under A. Greenspan and Norges Bank) and *individualistic* ones (e.g., the BOE and Swedish Riksbank).

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

the US case).

However, as shown by Gerlach-Kristen (2004), the voting records of the BOE's MPC are informative about the future policy: the dissenting views help in forecasting the next policy decision if controlling for the lagged policy rate change and either the interest rate futures or the slope of the term structure of money market rates, or both. Besides, she found that the market expectation of future policy reacts to the publication of voting records. Gerlach-Kristen (2009) added evidence that the *attributed* voting records can further enhance the policy predictability: in the BOE case the dissenting votes of *external* MPC members alone predict the future policy changes whereas the *internal* members' dissents contain less clear signal. Gerlach-Kristen and Meade (2010) also reported that the dissents in the US Federal Open Market Committee (FOMC) help to forecast the future changes in the Federal funds rate in the context of an autoregression with the two lags of the rate change.

The timely release of information that provides precise policy signals is beneficial. The central banks that disclose the voting records differ in their timing: either immediately following the rate-setting meeting (in the Czech Republic, Japan, Korea, Sweden, and USA), or within two to three weeks (in Brazil, Hungary, and the UK), or with a six-week delay (in Poland).

According to "The Act on the National Bank of Poland", the positions taken by Council members during votes should be announced in the *Monitor Polski*, the official gazette of the Republic of Poland, after a period of six weeks but no later than three months from the date the resolution is adopted. The more detailed voting records, including all submitted propositions (even those not voted for) are released later in the NBP's *Inflation Report*, which has recently begun to be published three times per year. Therefore, in Poland, unlike in the other countries, the voting records are *not* available to the public before the subsequent policymaking meeting.

This delay in the disclosure of votes diminishes the relevance of such disclosure. If released only after the next meeting, the MPC minutes (even if they are very detailed) are known to receive little media coverage and minor market reaction. The empirical studies, using high-frequency data from financial markets, documented that the expedited release of the minutes by the BOE and the Fed significantly increased the market reaction to them (Reinhart and Sack 2006, Reeves and Sawicki 2007, Sellon 2008).

This paper provides empirical evidence on whether the (non-attributed) voting records of the last MPC meeting could improve the predictability and private sector anticipation of the next policy rate decision in Poland. The case of Poland, where the voting records become available only *after* the subsequent MPC meeting, provides an interesting opportunity to

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

investigate whether the disclosure of votes could create news for the private sector as late as one day before a policy meeting, when information on the state of the economy that is available to the public is as close as possible to that available to the policymakers at their meeting the next morning. If the voting records add information, they can improve the public's understanding of the systematic policy responses and decision-making process of the central bank.

This paper not only extends the scarce empirical literature (limited to the UK and US cases), but also makes a contribution in the following directions. First, do voting records (in addition to relevant economic data) help to forecast the next policy rate decision? Second, could dissenting votes, if they were available, add information to the market expectations of upcoming policy decisions? Third, do voting records enhance the policy predictability beyond the private sector anticipation? And fourth, can the direction of dissents and dispersion of votes explain the direction of bias and uncertainty of private sector forecasts?

The rest of the paper is structured as follows. The next section provides institutional background, discusses the MPC voting records and introduces a measure of dissent among the MPC members, used to predict the policy decisions. Section 2.3 describes the data, the discreteness of the policy rate and the econometric approach employed for estimations and testing. Section 2.4 presents the econometric evidence. Section 2.5 concludes and makes policy suggestions.

2.2 Votes and dissent among policymakers

The available central bankers' voting records reveal that the fraction of unanimous decisions ranges from 0.38 to 0.76, with a median of 0.56, suggesting that the policymaking by consensus might suppress the dissent or, at least, not reveal it.[5] As pointed out by Blinder (2007), "the formal vote may be a poor indicator of the actual amount of disagreement on a collegial MPC, one that prizes - or, in the limit, forces - consensus. According to longstanding FOMC tradition, for example, a member is expected to vote in favor of the chairman's policy proposal unless he or she disagrees with it fundamentally - which is a much sterner test than merely preferring an alternative". Thus, "... the number of dissenting votes clearly underestimates the amount of disagreement".

The informational content of disagreement among the policymakers is also indirectly assessed by growing empirical evidence that the central bankers' press conferences, statements

[5] The unanimity rates for the NBP and BOE are calculated by the author, using the voting records up to December 2009 taken from the central banks' websites. The rates for the central banks of Brazil, the Czech Republic, Hungary, Japan, Sweden and the USA are taken from Geraats *et al.* (2008).

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

and minutes move financial markets and help in predicting the policy interest rates (Blinder *et al.* 2008, de Haan 2008, Blinder 2009, Jansen and de Haan 2009, and Hayo and Neuenkirch 2010). Financial media and market participants closely monitor the central banks' communication in order to extract any signals concerning future policy, learn about the dynamics of opinions and guess what majority is likely to prevail at the next policy meeting. However, the interpretation of central bank 'talk' suffers from subjectivity, because it is difficult to quantify sometimes incoherent and ambiguous rhetoric signals. Besides, the correspondence between what central bankers say and how they actually vote on policy decisions is not always perfect.

On the contrary, the amount of dissent among policymakers derived from the voting records is an objective quantitative measure, a direct and explicit policy signal: "Casting a minority vote appears to be a bigger step, and therefore carries more information, than merely expressing a personal dissenting view in public" (Blinder 2009).

The delay in releasing the voting records in Poland can not be shortened at the discretion of the MPC itself, because it has been embodied in "The Act on the National Bank of Poland" since its original version of August 29, 1997. At that time the BOE, which has been used as an example by many other central banks, had just recently begun publishing the voting records (since June of the same year). The NBP was following the UK practice of the time: the voting records were not published until after the subsequent MPC meeting (with a six-week delay) and they did not indicate numerically which interest rates the dissenting members preferred (although the voting records of the BOE did indicate whether the dissenting members favored a higher or lower interest rate than the majority). This practice was changed by the BOE shortly thereafter. As of October 1998 in the UK, the voting records are released with only a two-week lag and reveal the interest rates proposed by all dissenting members. Several years later, in January 2002, the Fed also decided to include the preferred policy choice of all dissenters, and since March 2002 it has been releasing the voting records together with the announcement of policy action (previously they were disclosed only after the subsequent meeting). In Poland, however, there have been *no* changes in this regard since 1997.

The MPC of the NBP, established in February 1998, consists of the Chair (the President of the NBP), appointed by the President of Poland, and nine other members, appointed in equal proportions by the President of Poland, the Sejm (lower house) and the Senate (upper house) of the Parliament. Members of the Council are appointed for a non-renewable term of six years, but the Chair may serve for two consecutive terms. The first term of office of the MPC lasted from February 1998 through January 2004. However, one member was replaced before the policy meeting in January 2004, and another passed away, so his seat was filled

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

midterm in August 2003. The second term lasted from February 2004 through January 2010. Because the first MPC Chair had resigned three years earlier in December 2000, the Chair since then has been appointed with a three-year lag with respect to the other members.

This paper analyzes the two samples with 71 observations in each: from March 1998 to January 2004 and from February 2004 to December 2009, matching the first and second terms of the MPC.

Policy interest rate decisions are made at the MPC meetings during the second half (usually at the end) of each month by majority vote: "The Council shall rule in the form of resolutions adopted by a majority vote, when at least five members are present, including the Chairperson of the Council. In the event of a tied vote, the Chairperson of the Council shall have a casting vote" (Act on the NBP 2010, Article 16.3). Each MPC member can express his or her preferred policy rate adjustment and make a motion to be voted on. If no proposal is made, there is no voting at all and the rate remains unchanged; otherwise, the Chair selects a proposition (as a rule of thumb, the largest proposed move) and the members vote on it. If the first voted proposal commands a majority, then the others are not voted on; otherwise, the members vote on an alternative one. Historically, the second voted proposal has always been passed (when the first was not).

The available voting records, unfortunately, do not provide complete information on individual policy rate preferences. They contain the description of all proposals submitted during a meeting and the list of members who voted yes and no at each voting round. The preferred interest rate of a member who voted against the winning proposal is *not* generally recorded. Moreover, the NBP does not disclose such information on request, despite its declared pursuit of transparency: "The Council will use its best efforts to ensure transparency of the monetary policy" (NBP, 2007). Therefore, it is not always possible to infer with certainty the favored interest rate of those members who disagreed with the majority. In the case of such uncertainty I assumed that the dissenting members favored the *status quo*, i.e. no change to the rate, if no alternative proposition was submitted. In the case where more than one proposal was put to vote on a meeting and a member supported different motions I used the proposition that the member supported the first. For instance, if a member voted yes for a defeated motion to cut the rate by 0.50% and then also voted "yes" for a motion to cut the rate by 0.25%, I recorded the member's preferred change to the rate at this meeting as a 0.50% cut, treating his support for 0.25% cut as a compromise decision.

Of course, the incomplete voting records require some subjectivity to recover the policy preferences of dissenting members. As the Dutch say, better half an egg than an empty shell. Nevertheless, the above assumptions seem to be quite realistic. The most significant

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

measurement error could potentially arise if a dissenting member who voted against a winning proposal, say, to cut the rate by 0.50%, was actually in favor of a 0.25% cut or perhaps even a 0.25% hike (rather than the *status quo* as I assumed in such a case), but did *not* submit any proposal (perhaps because the member realized that his proposal would not receive the majority support). Such a situation does not, however, seem to happen often, given the *individualistic* nature of the Polish MPC. There were actually 19 meetings when the MPC voted for a proposal to change the rate but it was defeated, and 23 meetings when two proposals were put to a vote because the first proposal voted on did not pass. In fact, the voting records *do* sometimes contain the proposals that were submitted but *not* put to a vote, because another proposal had already received the majority of votes.

In sum, the voting records of the Polish MPC do not provide full information on the expressed individual policy preferences in contrast to, for example, the records of the BOE or the Riksbank. However, they do provide far more accurate information on the balance of opinions among policymakers than the voting records of the *collegial* committees, such as the FOMC of the Fed. In terms of Blinder's (2007) taxonomy, the Polish MPC is clearly an example of an *individualistic* committee, founded on the principle of individual accountability and composed of a heterogeneous group of members who do not insist on achieving consensus and often dissent. In fact, the policy rate was set unanimously at only 80 out of 143 meetings, mostly (68 times) when the rate was not changed. The MPC Chair was actually voted down 13 times and had a casting vote 12 times (because of a tied vote).

Following Gerlach-Kristen (2004), I measure the dissent among MPC members by a variable $skew_{t-1}$, calculated from available voting records as the difference between the average of adjustments proposed by all MPC members and officially announced adjustment to the policy interest rate at the last MPC meeting. Figure 2.1 plots such differences for all MPC meetings: *skew* ranges from -80 to 75 basis points, taking a positive (negative) value if the average proposed change is above (below) the announced one. Table 2.1 reports the average and maximum absolute values of *skew* separately for the 1998/2–2004/1 and 2004/2–2009/12 periods as well as separately for the decisions to cut, leave unchanged or hike the interest rate. The absolute value of *skew* was on average higher in the first Council than in the second one (9.5 vs. 3.9 basis points), but the policy rate itself was more volatile during the first MPC term. The rate of dissent, calculated as the fraction of dissenting members at the final voting round, was on average roughly the same in both periods, and actually slightly lower in the first Council than in the second one (0.14 vs. 0.16, respectively). Interestingly, in both Councils the decisions to cut the rate caused on average a much stronger disagreement than the decisions to hike it, whereas the decisions to leave the rate unchanged were, on

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

average, accompanied by a lower degree of dissent than the decisions to change the rate.

2.3 Data and econometric model

The NBP, one of the pioneers of direct inflation targeting (DIT) in Central and Eastern Europe, has followed the DIT strategy with short-term interest rates as a principal policy tool since 1998. The reference rate of the NBP, introduced in February 1998, determines the yield obtainable on the main open market operations and sets the path of monetary policy. The reference rate is the rate on 28-day (from 1998 to 2003), 14-day (from 2003 to 2005), and 7-day (since 2005 to the present) NBP money market bills.

The dates of the last and next policy rate decision are denoted as $t-1$ and $t+1$; the date of forecasting the next policy decision is denoted as t. Throughout this paper the forecasts are made using information truly available to the public one day before each policymaking meeting. The level of the reference rate set by the MPC at the date $t+1$ is denoted as r_{t+1}. The predicted variable in this study is $\Delta r_{t+1} = r_{t+1} - r_{t-1}$, a change to the reference rate made at the meeting $t+1$. As Table 2.2 shows, the NBP has always altered its policy rate in discrete adjustments – the multiples of 25 basis points (a quarter of one percent): all 142 historical changes for the period 1998/03 - 2009/12 took only twelve values, between -250 and 250 basis points. The policy rate adjustments are distributed heterogeneously: 120 out of 142 observations fall into 4 out of 12 observed discrete values. I merged all observed changes into four categories: large cut (50 basis points or more), small cut (25 basis points), no change and hike. Table 2.2 reports the frequency distribution of consolidated changes to the rate. This quadruple classification is definitely able to represent the essence of the NBP operating policy and closely reflects the most recent historical policy moves. Indeed, since February 2002, only four (out of 95) observations were combined with an adjacent category: there were two 0.50% hikes (merged with the 0.25% hikes) and two 0.75% cuts (merged with the 0.50% cuts).

To address the discreteness of the dependent variable, the paper employs an ordered probit approach, which forms a probabilistic forecast of the discrete change to the policy rate Δr_t as a nonlinear function of explanatory variables X_t.[6] This approach assumes an underlying level of the reference rate r^*_{t+1} that would have been observed had the MPC been willing to make the continuous (rather than discrete) changes to the rate. At every policy-setting meeting $t+1$ the MPC determines the change $\Delta r^*_{t+1} = r^*_{t+1} - r^*_{t-1}$ in this latent rate

[6] I also tried the ordered logit model - the results were similar.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

according to the following formula:

$$\Delta r_{t+1}^{*} = X_t\beta + \varepsilon_t,$$

where $\varepsilon_t|X_t \sim$ i.i.d. $N(0,\sigma^2)$, and X_t is a matrix that may incorporate any data relevant for the policymakers and available at date t.

Although Δr_{t+1}^{*} is unobserved, the MPC announces the official (i.e. observed) adjustments to the reference rate Δr_{t+1} according to the following rule:

$$\Delta r_{t+1} = \begin{cases} \text{"large cut"} & \text{if} \quad \Delta r_{t+1}^{*} \leq \gamma_1 \\ \text{"small cut"} & \text{if} \quad \gamma_1 < \Delta r_{t+1}^{*} \leq \gamma_2 \\ \text{"no change"} & \text{if} \quad \gamma_2 < \Delta r_{t+1}^{*} \leq \gamma_3 \\ \text{"hike"} & \text{if} \quad \gamma_3 < \Delta r_{t+1}^{*} \end{cases},$$

where $-\infty < \gamma_1 < \gamma_2 < \gamma_3 < \infty$ are unknown thresholds to be estimated.

Assuming Gaussian cumulative distribution function Φ of ε_t, it follows that the probabilities of observing each possible outcome of Δr_{t+1} are

$$\Pr(\Delta r_{t+1}|X_t) = \begin{cases} \Pr(\Delta r_{t+1} = \text{"large cut"}|X_t) & = \Phi(\gamma_1 - X_t\beta) \\ \Pr(\Delta r_{t+1} = \text{"small cut"}|X_t) & = \Phi(\gamma_2 - X_t\beta) - \Phi(\gamma_1 - X_t\beta) \\ \Pr(\Delta r_{t+1} = \text{"no change"}|X_t) & = \Phi(\gamma_3 - X_t\beta) - \Phi(\gamma_2 - X_t\beta) \\ \Pr(\Delta r_{t+1} = \text{"hike"}|X_t) & = 1 - \Phi(\gamma_3 - X_t\beta) \end{cases}.$$

The estimates of β and γ were obtained by making the usual identifying assumptions (that the variance of latent disturbance term ε_t is one and the intercept β_0 is zero) and maximizing the logarithm of likelihood function L with respect to the vector of parameters $\theta = (\beta, \gamma)$:

$$\ln L(\theta) = \sum_{t=1}^{T}\sum_{i=1}^{4} I_{ti} \ln[\Pr(\Delta r_{t+1} = d_i|X_t)],$$

where T is the sample size, d_1 is a "large cut", d_2 is a "small cut", d_3 is a "no change", d_4 is a "hike", and I_{ti} is an indicator function such that $I_{ti} = 1$ if $\Delta r_t = d_i$ and 0 otherwise. All reported ordered probit estimations were performed using Huber(1967)–White(1980) heteroskedasticity-robust standard errors.

The latest versions of time series commonly used in the empirical literature may differ from the *real-time* ones because of revisions. To avoid the distortion of information, I compiled the novel Polish real-time dataset, which consists of the historical vintages of time series truly available to the public one day before each decision-making MPC meeting. The dataset

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

contains the measures of current inflation (headline and core consumer price indexes (CPI) and prices of sold goods from Business Tendency Survey (BTS) of the Central Statistical Office), inflationary expectations (from BTS, Ipsos–Demoskop survey of consumers, Reuters survey of market analysts and NBP projections), gross domestic product (GDP) and its main components, industrial production and other measures of real activity from BTS, expectations of real sector activity (from BTS, Reuters survey and NBP projections), labor market and wages, employment expectations (from BTS), market interest rates (52-week treasury bill rate and various Warsaw interbank offer rates (WIBOR) and spreads between the longer- and shorter-term rates), market interest rates' expectations (from Reuters survey), exchange rates, exchange rates' expectations (from Reuters survey), foreign policy interest rates, and measures of credit and lending.

The full list, descriptions and modifications of right-hand-side variables used in reported estimations are presented in the Appendix. It constitutes a small sub-set of the dataset used in the specification search. All the time series employed were checked for stationarity using the augmented Dickey–Fuller (ADF) unit root tests. The lag order of lagged first differences of the dependent variable in the tests was chosen according to a criterion of no serial correlation among residuals up to the twelfth order, checked using the Ljung–Box Q-statistic. The ADF tests of all employed series failed to detect non-stationarity at the 1% significance level.[7]

2.4 Do voting records matter? The econometric evidence

> "Most economic decisions depend, directly or indirectly, on the predictability of monetary policy."
>
> - William Poole[8]
>
> "[R]evealing the monetary policy committee's vote may carry a strong hint about where interest rates might head in the future. A 5-4 vote [...] conveys rather different information than a 9-0 vote."
>
> -Alan Blinder[9]

[7] The results of the ADF tests are available upon request.
[8] See Poole (2005).

[9] See Blinder (2004).

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

How can the disagreement among the MPC members improve predictions of the next policy decision? Suppose that in one case the policy rate was unanimously left unchanged at the last meeting, while in the second case it was still left unchanged, but not as a result of a unanimous decision: a minority favored a higher rate. Naturally, in the latter case, one can expect an additional pressure to increase the rate at the next meeting. The direction of dissenting votes indicates the policy inclination, while the degree of dissent suggests the likelihood of policy adjustment. A rationale behind this, suggested by Gerlach-Kristen (2004), might be due to the *discreteness* of interest rates and uncertainty. The discreteness of announced policy rates is a human-made phenomenon; there is no reason to believe that the optimal underlying interest rate is also a discrete-valued variable. One can assume a latent continuous policy rate that, however, is not observed by the MPC members with certainty. Suppose the optimal rate change is 15 basis points, observed by the policymakers with errors in the range of ± 10 basis points. One should then expect the majority of the MPC members to vote for a 25-basis-point hike and the minority for a no-change decision. If the voting records are released it becomes evident that the optimal interest rate is below the announced one; hence, the probability of a future rate cut increases.

As noted by Geraats (2006), the voting records may correctly indicate the existing policy inclination only if the distribution of the preferred policy rates among the MPC members is sufficiently wide and symmetric. Suppose that in the above case, the optimal 15-basis-point rate change is observed by the policymakers with errors in the range of ± 2 or, alternatively, $-2...+20$ basis points. Then all the members in both cases would vote for a 25-basis-point increase and the voting patterns would *not* reveal the negative policy tilt.

In this section, I present the econometric evidence on whether the (non-attributed) voting records of the last MPC meeting could enhance the predictability and improve the private sector anticipation of the next policy rate decision. I employed both the market-based and survey-based measures of private sector anticipations. The policy predictability, according to the widely-established practice in the academic literature, was analyzed in the context of monetary policy reaction functions or rules. However, the monetary policy rules were estimated in differences (rather than in levels), using a discrete ordered choice approach, *without* and *with* the variable $skew_{t-1}$. The advantage of a difference specification is that it is more operational, more transparent for the public, and robust to mismeasurement of unobservable variables such as a 'neutral' interest rate (see Orphanides and Williams 2006 for a comparison of the level- and difference-rule approaches under the framework of imperfect knowledge). All the data used in the empirical estimations, except the voting records, were available to the public in real time at the latest one day before each policymaking meeting.

More specifically, I have analyzed the following four questions.

2.4.1 Do voting records (in addition to relevant economic data) help to predict the next policy rate decision?

The relation between the measure of dissent at the last MPC meeting $skew_{t-1}$ and historical (unconsolidated) change to the rate at the subsequent meeting is itself rather weak: Pearson correlation coefficients are 0.129 and -0.028 for the first (1998/3–2004/1) and the second (2004/2–2009/12) periods, respectively. In the ordinary least squares (OLS) regression of historical change to the rate at the subsequent meeting on $skew_{t-1}$ the latter is not significant at the 5% level, using White's heteroskedasticity-consistent standard errors, in either period: the p-values of the coefficient of $skew_{t-1}$ are 0.096 and 0.823, and adjusted R^2s are 0.002 and -0.014 for the first and second periods, respectively. In the ordered probit regression $skew_{t-1}$ as a single explanatory variable demonstrates weak predictive power for Δr_{t+1}, especially in the second period (see Model 1 in Table 2.3): whereas the p-values of the coefficient of $skew_{t-1}$ are 0.005 and 0.684, the p-values of the likelihood-ratio (LR) test of the redundancy of $skew_{t-1}$ are 0.088 and 0.680 for the first and second periods, respectively.

Definitely, the dissent on the last meeting is not a factor that *solely* drives the next policy decision. The further results show that $skew_{t-1}$ has, however, a strong and robust predictive power as a *supplementary* factor when controlling for other determinants relevant for the interest rate setting.

In this sub-section, I present the following alternative models of policy interest rate, estimated separately for both MPC terms with and without the variable $skew_{t-1}$: (1) naïve "no change" rules (see Table 2.3); (2) pure interest-rate smoothing rules (see Table 2.3); (3) backward-looking Taylor-type rules with interest-rate smoothing (see Table 2.4); (4) forward-looking Taylor-type rules with interest-rate smoothing (see Table 2.4); (5) Taylor-type rules augmented with exchange rates, financial market interest rates and spreads, and indicator of policy bias (see Table 2.5); and (6) favored empirical policy rules (see Table 2.6).

Monetary policy reaction functions specified by Models (2) to (5) are widely used in both theoretical and empirical literature. The pure interest-rate smoothing rules were estimated with one lag of dependent variable. The lag length was chosen according to the Schwarz information criterion. The coefficient of the second lag is not statistically significant at the 5% level in either period. The choice of right-hand-side variables in the *reported* Taylor-type rules was motivated by the best fit and availability of data for both periods.[10] In fact, the

[10]For example, the 15% trimmed mean core CPI is the only core index that was not redefined in August

impact of $skew_{t-1}$ is strikingly robust to both various specifications and alternative measures of economic indicators, such as different measures of current and expected inflation, exchange rates and real activity (the estimation details are available upon request).

The same specifications of the Taylor-type rules, estimated separately for both terms of the MPC, reveal structural breaks in policy responses according to the LR-tests.[11] In the first period, contrary to the second one, the MPC did not systematically react to the real activity, but did react to the exchange rate. Therefore, the augmented Taylor-type rules, reported in Table 2.5, were estimated using different specifications, containing inflation, exchange rate and financial market information in the first period, but inflation, real activity, financial market information and indicator of policy bias in the second period. The lagged dependent variable became insignificant in both periods. The responses to (un)employment and industrial production either are not statistically significant or have an unexpected sign.

The favored empirical Models (6) are data-driven and were selected by an extensive search among numerous possible specifications and hundreds of explanatory variables, including financial market indicators, (un)employment and wages, measures of money supply, credit and lending in addition to various measures of current and expected inflation, real sector activity, and exchange rates. The NBP looks at everything and monitors hundreds of data series: "While making decisions it is necessary to take into account all available information, rather than just the inflation projection" (NBP, 2007). The variables employed in the specification search are frequently mentioned in the MPC press releases and *Inflation Reports*. The estimated reaction functions become more regular if the first twelve MPC meetings, from February 1998 through January 1999, are omitted. The year of 1998 was a period of gradual transition to a new framework of DIT, an "interim" year, additionally affected by the Russian crisis in August (Polański 2004, Sirchenko 2008). The reported favored empirical policy rules in Table 2.6 are actually the extended versions of the Taylor-type rule, and include current and expected CPI, exchange rate and market interest rates and spreads in the first period, and expected CPI, expected GDP, market interest rates and spreads, deposits of non-financial sector and indicator of policy bias in the second period.

The estimations of Models (1) through (6) are summarized in Table 2.7. The inclusion of $skew_{t-1}$ improves the ability of all models to explain the next policy decision in both periods, the only exception being the naïve 'no change' model (1) in the second period. In all Models

2007; GDP forecasts from Reuters surveys are available only since November 2000; CPI forecasts by the NBP are available since August 2004; 9- and 12-month WIBOR are available since January 2001; the policy bias is available since February 2000.

[11] The null hypothesis of equality of coefficients in Models (1)–(4) is rejected by the LR-tests at the 1% (mostly) or 5% significance level in both sub-periods, except in Model (3a) with $skew_{t-1}$, where it is rejected at the 8% level (see Tables 3 and 4).

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

(2) through (6) $skew_{t-1}$ is a statistically significant variable at the 1% level (except Model (3a), where it is significant at the 5% level), and likelihood-based measures of fit, McFadden's and McKelvey-Zavoina's pseudo-R^2s, are higher by 3–19 percentage points.[12] The 'hit rate', the fraction of correctly predicted discrete outcomes or count R^2, is the same or higher by up to 17 percentage points.[13] It is worth noting that maximum likelihood estimation is *not* optimized with respect to this measure of fit. A significant increase in the likelihood function, i.e. a tightening of estimated distribution around actual distribution of choices, does not necessarily result in more accurate prediction of a particular choice, including a realized one.

The positive value of the coefficient of $skew_{t-1}$ suggests that a positive (negative) value of $skew_{t-1}$ increases (reduces) the probability of the rate hike and reduces (increases) the probability of the large rate cut. The impacts on the probabilities of small cut and no change are not univocal and depend on the values of all independent variables, including the value of $skew_{t-1}$ itself.

Interestingly, not only does $skew_{t-1}$ reveal the strong predictive power in the context of both the backward- and forward-looking Taylor-type rules, augmented by exchange rate and financial market expectation of future policy interest rate (as reflected in the movements and spreads between various market interest rates), but also it remains statistically significant after the inclusion of policy bias indicator. The policy bias statement was used by the MPC in its monthly press-releases since February 2000 through December 2005 to *explicitly* signal the likely stance of future monetary policy: it could be "mild", "neutral" or "restrictive". The interpretation was straightforward: the "mild" bias meant that the future interest rate cuts were more likely than hikes, while the "restrictive" bias indicated a tighter monetary policy. In January 2006, the policy bias was replaced by a balance of risks assessment with respect to the inflationary pressure and economic growth in the foreseeable future, with less straightforward, but in most cases still univocal interpretation. Based on the reading of the MPC press releases, I constructed the indicator variable $bias_{t-1}$ coded as -1 if policy bias is "mild", 0 if "neutral" and 1 if "restrictive". The variable $bias_{t-1}$, included into Models (5) and (6) in the second period, has an expected positive coefficient and adds predictive information: it is statistically significant at the 1% level, if $skew_{t-1}$ is not included, and remains significant at the 1% level after the inclusion of $skew_{t-1}$, which is significant at the

[12] McFadden's pseudo-$R^2 = R/U$, where $R = 2 * (\ln L - \ln L_0)$ is the likelihood ratio, $U = -2 * \ln L_o$ is the upper bound of R, L is the likelihood of the full model, and L_o is the likelihood of the model without regressors. McKelvey-Zavoina's pseudo-$R^2 = \frac{\beta' Var(X)\beta}{\beta' Var(X)\beta + 1}$.

[13] The predicted discrete policy decision is computed as a discrete change (out of four choices) closest to the expected change calculated using estimated probabilities from the ordered probit model.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

1% level as well (see Models (5c), (5d) from Table 2.5, and (6c) and (6d) from Table 2.6).

The strong and robust predictive power of $skew_{t-1}$ is again strongly confirmed when it is included in the favored empirical models with high measures of fit. In Models (6a) and (6b) for the 1999/2–2004/1 period and Models (6c) and (6d) for the 2004/2–2009/12 period McKelvey-Zavoina's R^2s are 0.93, 0.93, 0.95 and 0.97, while the hit rates are 0.73, 0.72, 0.90 and 0.89, respectively, if $skew_{t-1}$ is not included. The inclusion of $skew_{t-1}$, which is significant at the 1% level in all specifications, increases McFadden's and McKelvey-Zavoina's pseudo-R^2s by 3–12 and hit rate by 0–10 percentage points.

All favored models were checked for the equality of coefficients across response categories (parallel regression assumption). All of them passed the test with p-value 0.22, at least, if $skew_{t-1}$ is included. Thus, it seems superfluous here to employ the generalized ordered or multinomial probit/logit models, which are too richly parameterized for our small sample size.

To make the further regression diagnostics, I tested for serial correlation among residuals from Models (6a)–(6d). The null of no serial correlation among residuals up to the twelfth order is overwhelmingly accepted - all p-values are greater than 0.05 for all models. Figure 2.2 shows the correlograms of generalized residuals (see Chesher and Irish 1987 and Gourieroux *et al.* 1987 for details) from Models (6a) and (6d). It seems unnecessary to use the far more computationally demanding dynamic ordered probit approach that accounts for the serial correlation among residuals, but cannot be directly estimated by maximizing the likelihood function.

To test for possible asymmetry in the impacts of positive and negative values of $skew_{t-1}$ I constructed two variables, $skew^p_{t-1}$ and $skew^n_{t-1}$, defined as follows: $skew^p_{t-1}$ ($skew^n_{t-1}$) is equal to $skew_{t-1}$, if $skew_{t-1}$ is positive (negative), and equal to zero otherwise. Thus, by definition, $skew^p_{t-1} + skew^n_{t-1} = skew_{t-1}$. I re-estimated Models (6a)–(6d) with variables $skew^p_{t-1}$ and $skew^n_{t-1}$ in place of $skew_{t-1}$, and tested for equality of coefficients of $skew^p_{t-1}$ and $skew^n_{t-1}$ using both the LR and Wald tests. In the 2004/2–2009/12 period both tests overwhelmingly failed to reject the null hypothesis of equality of coefficients of $skew^p_{t-1}$ and $skew^n_{t-1}$: the LR (Wald) tests' p-values are 0.995 (0.978) and 1.000 (0.930) for Models (6c) and (6d), respectively. The coefficients of both $skew^p_{t-1}$ and $skew^n_{t-1}$ are statistically significant at the 1% level in both models. In the 1999/2–2004/1 period both tests also failed to reject the null hypothesis of equality of coefficients, although not so overwhelmingly: the LR (Wald) tests' p-values are 0.081 (0.049) and 0.075 (0.051) for Models (6a) and (6b), respectively. However, while the coefficient of $skew^n_{t-1}$ is statistically significant at 2% level, the coefficient of $skew^p_{t-1}$ is not significant at 9% level in either model.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

To test whether there are statistical differences in the predictive content of the votes of the MPC members appointed by the President of Poland, or the Senate, or the Sejm of the Parliament, I decomposed $skew_{t-1}$ into three components: $skew_{t-1}^{pre}$, $skew_{t-1}^{sen}$ and $skew_{t-1}^{sej}$, respectively. Both the LR and Wald tests failed to reject the null hypothesis of equality of coefficients of $skew_{t-1}^{pre}$, $skew_{t-1}^{sen}$ and $skew_{t-1}^{sej}$ at the 5% significance level in both periods: both tests' p-values are greater than 0.65 and 0.07 in the 1999/2–2004/1 and 2004/2–2009/12 periods, respectively. Interestingly, for the second Council $skew_{t-1}^{sen}$ is the most informative component of $skew_{t-1}$ and alone, without $skew_{t-1}^{sen}$ and $skew_{t-1}^{sej}$, has virtually the same predictive power as $skew_{t-1}$. For Model (6d) with $skew_{t-1}^{sen}$ McFadden's R^2 is 0.882 vs. 0.882 with $skew_{t-1}$, McKelvey-Zavoina's R^2 is 0.994 vs. 0.998, and hit rate is 0.972 vs. 0.944, while for Model (6c) they are 0.832 vs. 0.827, 0.984 vs. 0.988 and 0.944 vs. 0.901, respectively.

2.4.2 Could voting records add information to private sector anticipation?

In this sub-section, I directly test whether the voting records, if they were released before the subsequent policy meeting, could add information to the private sector anticipation of the next policy decision. I used both the market-based (as measured by the movements in the market interest rates and spreads between the longer- and shorter-term rates a day before each policymaking meeting) and survey-based measures of private sector anticipation (as measured using the original disaggregated quantitative data taken from Reuters surveys of commercial bank analysts, made one or two days before each policymaking meeting). If the voting records do contain news for the private sector then the coefficient of $skew_{t-1}$ should be statistically significant when added to the regression of the next policy decision on the private sector expectation.

Table 2.8 reports the estimations of the specification $\Delta r_{t+1}^{*} = b_1(X_{1t} - X_{2t}) + b_2 X_{3t} + b_3 skew_{t-1} + \varepsilon_t$, where $X_{1t} - X_{2t}$ is the spread either between the longer- and shorter-term WIBORs or between the long-term WIBOR and the policy rate, and X_{3t} is the change in either 1- or 3-month WIBOR since the next day after the last MPC meeting. The coefficient of $skew_{t-1}$ is significant in all specifications at the 1% level in the 1999/2–2004/1 period and at the 5% or 10% level in the 2004/2–2009/12 period. The inclusion of $skew_{t-1}$ raises McFadden's and McKelvey-Zavoina's pseudo-R^2s by up to 9 percentage points. Thus, the voting records appear to add information to financial market anticipation of monetary policy.

However, the movements and spreads among market interest rates react mostly to the expectations of future inflation, which depends on the future policy rate, so the above financial instruments can be used only as *implicit* market expectations of the next policy action. Now I focus on the *explicit* private sector forecasts of the next policy decision taken from Reuters surveys.

Reuters has conducted its poll in Poland monthly since 1994. Up to 30 bank analysts participate in the surveys. The respondents predict the major economic and financial indicators. These forecasts are widely cited in the Polish press as well as in the NBP *Inflation Reports* and MPC press releases. Since April 1998 the market analysts have also predicted the policy interest rate with steadily improving forecasting performance. From April 1998 through January 1999, during the period of transition to a new monetary policy framework of the DIT, the market analysts predicted correctly only three out of ten, i.e., 30% of policy actions (again, in the context of four possible policy choices). From February 1999 through January 2004, when the monetary policy became more transparent and regular, while the interest rate itself less volatile, the private sector learned a lot about the central bank responses to economic environment and managed to correctly predict 80% of policy decisions. Finally, in the 2004/2–2009/12 period, the hit rate of the Reuters polls reached 87%.

Table 2.9 reports the ordered probit estimations of the specification $\Delta r^*_{t+1} = b_1 \Delta r^e_t + b_2 skew_{t-1} + e_t$, where Δr^e_t is the average of individual forecasts of the next policy decision from Reuters surveys. The coefficient of $skew_{t-1}$ is significant at the the 1% level in the 2004/2–2009/12 period (see the second column). The inclusion of $skew_{t-1}$ raises McFadden's and McKelvey-Zavoina's pseudo-R^2s by 3–4 percentage points; and according to the LR-test, the null hypothesis of the redundancy of $skew_{t-1}$ is rejected with the p-value 0.029. In the 1998/4—2004/1 period I employed a slightly modified version of $skew_{t-1}$, calculated as above but disregarding the votes of one MPC member, Marek Dabrowski. The reason for this exclusion is that Dabrowski was the most dissenting member and a clear outlier: he voted against the adopted resolution at 26 out of 33 meetings, when the voting took place, and at eight meetings was the only dissenting member. As explained in Section 2.2, his preferred policy preferences at the above 26 meetings are not reported in the available voting records. The omission of this outlying member might reduce the noise in the measure of dissent among the MPC members. As shown in the first column of Table 2.9, the coefficient of the modified version of $skew_{t-1}$ is statistically significant at the 5% level: the p-value is 0.047, whereas the coefficient of original $skew_{t-1}$ has p-value 0.330. However, the inclusion of modified $skew_{t-1}$ raises McFadden's and McKelvey-Zavoina's pseudo-R^2s by 1 percentage point only, and the LR-test failed to reject the null hypothesis of the redundancy of $skew_{t-1}$ with the p-value 0.238.

If $bias_{t-1}$ is also added to the regression for the 2004/2–2009/12 sample (see the third column in Table 2.9), it is not significant at the 5% level and redundant with the p-value 0.199 according to the LR-test, whereas $skew_{t-1}$ remains significant at the 1% level and the p-value of the LR-test is 0.025. This is of no surprise: the policy bias statement has been released to the public immediately with the policy decision and its informational content has already been embedded into market analysts' forecasts.

To sum up, the dissenting votes *do* add supplementary information survey-based anticipations, especially in the 2004/2–2009/12 period, when the participants of Reuters polls were more successful in anticipating the monetary policy.

2.4.3 Do voting records enhance policy predictability beyond the private sector anticipation?

In this sub-section I compare the predictions implied by the favored empirical policy rules with the survey-based measures of private sector anticipation. The participants of Reuters polls have correctly foreseen 80% and 87% of the next policy actions with the average likelihood of observed outcomes 0.77 and 0.82 for the 1999/02–2004/1 and 2004/2–2009/12 periods, respectively (see Table 2.10). This forecasting performance is clearly inferior compared to the fit of favored empirical models, although the model-implied predictions are not optimized with respect to the percentage of correct predictions. The favored empirical Models (6a) and (6d) correctly predict, using information available to the participants of Reuters polls, 73% and 89% of the next policy actions with the average likelihood of observed outcomes 0.70 and 0.85, respectively for the first and second periods. The inclusion of voting records increases the hit rate by 10 and 6 percentage points, making it possible to correctly forecast 83% and 94% of the next policy decisions with the average likelihood of observed outcomes 0.77 and 0.92, respectively for the first and second periods.

The estimated policy rules, including the impact of dissenting votes (not available to the market analysts at the dates of forecasting), do enhance the short-term predictability of monetary policy beyond the historical anticipation of the private sector.

2.4.4 Can the direction of dissent and dispersion of votes explain the direction of bias and uncertainty of private sector forecasts?

The use of original disaggregated data from Reuters surveys makes it possible to examine the association between the voting dispersion and private sector uncertainty. In this sub-section

DOI: 10.2870/60780

I analyzed only the period of the second term of the MPC.

First, I tested whether the absolute forecast error, the fraction of wrong predictions and the dispersion of individual forecasts from Reuters surveys of bank analysts is positively related to a variable $disp_{t-1}$, defined as the dispersion of individual votes at the last MPC meeting. The dispersion was calculated as the average absolute deviation of data points from their mean. The (absolute) forecast error was computed as the (absolute) difference between the average of individual forecasts Δr_t^e and the announced change to the policy rate Δr_{t+1}^*. The fraction of wrong predictions was calculated as a ratio of wrong individual (original unconsolidated) forecasts to the total number of forecasts. All three aforementioned variables of interest are limited – they can take only the positive values; besides, the fraction of wrong predictions is additionally limited from above by one. Therefore, I used the censored normal (Tobit) regressions.

The Tobit estimations shown in Table 2.11 suggest that the dispersion of individual forecasts, the absolute forecast error and the fraction of wrong predictions are significantly (at the 1% level) and positively related to the dispersion of votes at the last meeting: a one-basis-point increase in $disp_{t-1}$ is associated on average with a 0.47-basis-point increase in the dispersion of individual forecasts, a 0.96-basis-point increase in the absolute error of forecast and a 0.032 increase in the fraction of wrong predictions. Furthermore, the explanatory power of $disp_{t-1}$ is robust to the inclusion of $disp_{t+1}$, the dispersion of votes at the upcoming meeting: the former remains significant at the 10% or 5% level, while the latter is significant at the 5% or 1% level in all three regressions. In this context a one-basis-point increase in $disp_{t-1}$ and/or $disp_{t+1}$ is associated on average with a 0.30- and/or 0.41-basis-point increase in the dispersion of individual forecasts, a 0.64- and/or 0.78-basis-point increase in the absolute forecast error, and a 0.018 and/or 0.028 increase in the fraction of wrong predictions.

These findings, however, cannot explain whether the dissents inside the MPC move the private forecast errors in a particular direction, and how the expedited disclosure of votes would influence the bias and uncertainty of private forecasts. If the dispersion of votes is seen to represent a degree of uncertainty about economic prospects, then one might expect the voting records, revealing a higher dispersion of votes, to induce more volatility in financial markets. On the other hand, if the dispersion of votes is taken to indicate the heterogeneity of policy preferences, then disclosure of voting records might enhance the public's understanding of collective policymaking process and, hence, reduce the uncertainty of private sector anticipation. Reeves and Sawicki (2007) found that the expedited release of the BOE's MPC minutes (containing the voting records) made the market reaction to them statistically significant. However, the higher degree of dissent is *not* significantly associated with any more volatility above that usually associated with publication.

I turn now to the more interesting part of the question: whether there is a relationship between the direction of forecast bias and the direction of dissent. The first and the second columns of Table 2.12 show the regressions of the four-category forecast error on the dissent at the last MPC meeting $skew_{t-1}$ only, and on both $skew_{t-1}$ and the dissent at the upcoming meeting $skew_{t+1}$, respectively. The four-category forecast error was computed as the deviation of discrete change to the policy rate (out of four choices) closest to the average of individual forecasts Δr_t^e from the implemented policy rate change Δr_{t+1}^*. The coefficient of $skew_{t-1}$ is statistically significant at the 5% level and remains significant at the 5% level after the inclusion of $skew_{t+1}$, which is significant at the 10% level.

Both $skew_{t-1}$ and $skew_{t+1}$ have the expected sign, negative and positive, respectively. If the dissenting members at the *upcoming* meeting prefer a higher rate than does the majority, i.e., if $skew_{t+1}$ is positive, then the forecasters also tend to overpredict the rate; therefore, the forecast error is also positive. However, if the dissenting members at the *last* meeting preferred a higher rate than the majority did, i.e., if $skew_{t-1}$ is positive, then the MPC is likely to set a higher interest rate at the upcoming meeting than the market analysts, who are not aware of the voting records, would normally expect. Therefore, they tend to under-predict, and the forecast error is negative.

As a robustness check, the third column in Table 2.12 reports the regression of non-consolidated forecast error (computed as the deviation of unconsolidated discrete change to the policy rate closest to the average of individual forecasts from Δr_{t+1}^*) on both $skew_{t-1}$ and $skew_{t+1}$: a one-basis-point positive dissent at the *upcoming* meeting $skew_{t+1}$ is related to a 0.60-basis-point over-forecast, while a one-basis-point positive dissent at the *last* meeting $skew_{t-1}$ is related to a 0.32-basis-point underforecast.

Overall, these findings suggest that timely disclosure of voting records before the subsequent MPC meeting could reduce the bias and uncertainty of private sector anticipation of the next policy rate decision.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

2.5 Conclusions

> "The positions taken by [the NBP's Monetary Policy] Council members during votes shall be announced [...] after a period of six weeks, but not later than three months."
>
> - From the Act on the NBP.[14]

> "MPC [of the BOE] concluded that there was no compelling reason why publication of the minutes should not be brought forward to a date prior to the next monthly monetary meeting."
>
> - Eddie George[15]

This paper provides empirical evidence in favor of a prompter release of the MPC voting records, which are currently published in Poland with a six-week delay and thus not available to the public before the subsequent policymaking meeting. It is shown using real-time data that if the voting records were available, they could improve the predictability of upcoming policy decisions. More specifically, if the dissenters preferred a higher policy rate, the MPC is more likely to hike the rate than cut it. This despite the fact that the dissent at the last t a factor that *solely* predicts the next policy decision: the correlation between upcoming policy rate change and the dissent among the policymakers at the last MPC meeting is quite low.

However, the dissenters' votes have a strong predictive content as supplementary statistics when controlling for relevant economic and financial determinants driving the interest rate. The empirical policy rules, augmented by the measure of dissent among the MPC members, correctly predict about 90% of discrete adjustments to the interest rate, and surpass the private sector forecasts made before each policy meeting. The results suggest that the publication of voting records could reduce the informational asymmetry and refine the public's understanding of systematic policy responses and decision-making process.

The dissenting votes contain predictive power not embedded in various Taylor type rules, market anticipations of future policy as revealed by market interest rates and spreads, and the MPC statements on policy bias and balance of risks. The informational value added by the voting records is shown to be robust not only to the alternative measures of economic indicators employed, but also to different specifications of estimated policy reaction functions.

Moreover, the dissenting votes add information even to the explicit forecasts of the next policy decision made by market analysts in Reuters polls just before each policymaking

[14] See Act on the NBP (2010).

[15] See George (1998).

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

meeting. The direction of dissent and dispersion of votes explain the direction of bias and uncertainty of private sector forecasts. The econometric evidence suggests that the observed dissenting votes inside the MPC could significantly reduce the bias and uncertainty of private sector anticipation of monetary policy.

All of the above findings are based on the voting *patterns* only, without the knowledge of the MPC members' names attached to each vote. Therefore, they might be of interest to the central banks that currently do not publish the voting records because of the reluctance to disclose the individual members' votes (e.g., the European Central Bank).

Over the last twelve years the National Bank of Poland has radically increased the disclosure of internal information on its policymaking process. One thing, however, has remained unchanged since 1998: the six-week lag in the release of the MPC voting records. There seems to be no clear argument in favor of this delay. Since April 2007, the minutes of the MPC meetings have been published within three weeks after each policy decision. In the context of central bank transparency, the finding that the voting patterns help in predicting the policy rate implies that their expedited release is beneficial. All the other central banks that disclose their voting records do so either immediately following the rate-setting meeting (in the Czech Republic, Japan, Korea, Sweden, and the USA) or within two to three weeks (in Brazil, Hungary, and the UK). *Only* in Poland are the voting records released *after* the subsequent policy meeting and *without* revealing the policy actions proposed by *all* dissenting members.

This paper provides clear policy messages. First, the NBP can further improve the predictability and public understanding of its monetary policy by publishing the MPC voting records as soon as possible, preferably in its press releases immediately after a policy meeting. Second, the voting records should include the proposed policy choice of each dissenting member.

Because the delay in releasing the voting records has been embodied in "The Act on the National Bank of Poland" and may not be shortened at the discretion of the MPC itself, it is probably time to change the law. In the meantime, the NBP might report the balance of votes in its press releases, without the policymakers' names attached. In fact, in the minutes of the MPC meeting held in September 2010, when the policy rate was left unchanged, the NBP broke the ice, for the first time mentioning that an alternative motion (to raise the interest rate) had been put forward at the meeting (but did not pass).

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

2.6 Figures

Figure 2.1: Announced and average proposed changes to the NBP reference rate

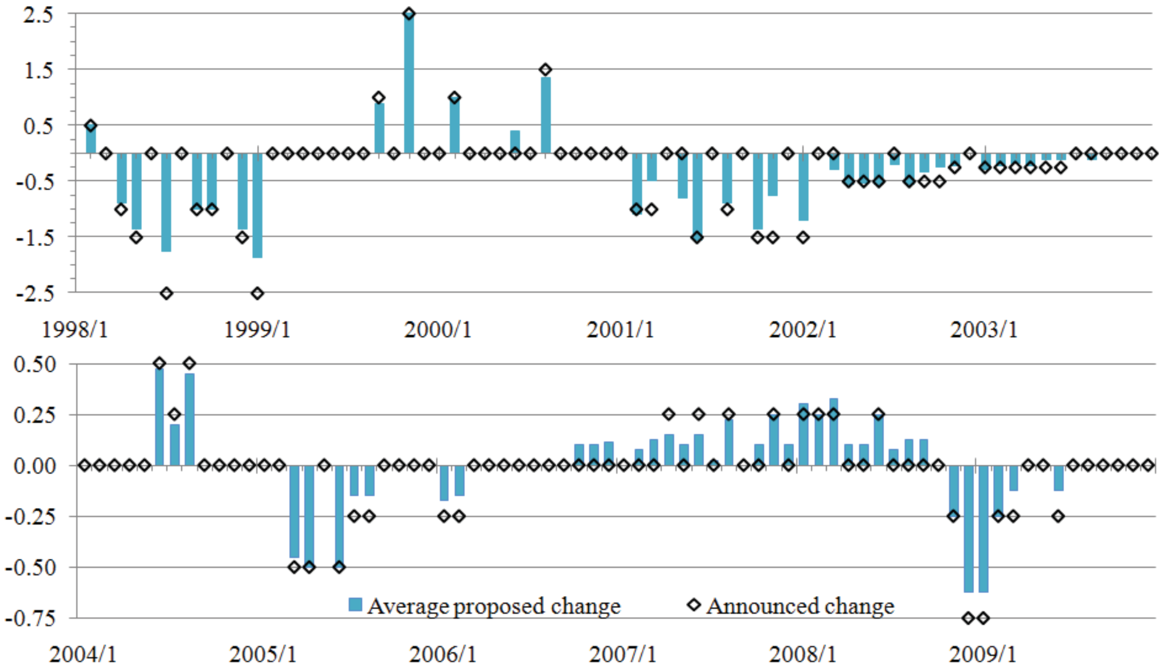
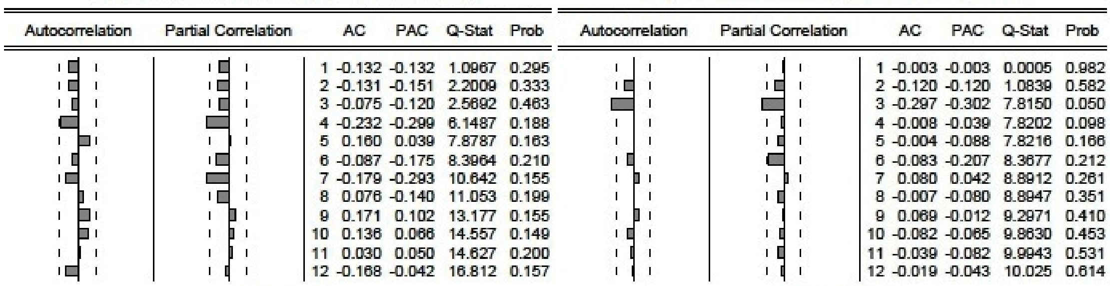


Figure 2.2: Correlograms of generalized residuals



Model 6a

Sample: 1999M02 2004M01 Included observations: 60

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.132	-0.132	1.0967	0.295
		2	-0.131	-0.151	2.2009	0.333
		3	-0.075	-0.120	2.5692	0.463
		4	-0.232	-0.299	6.1487	0.188
		5	0.160	0.039	7.8787	0.163
		6	-0.087	-0.175	8.3964	0.210
		7	-0.179	-0.293	10.642	0.155
		8	0.076	-0.140	11.053	0.199
		9	0.171	0.102	13.177	0.155
		10	0.136	0.066	14.557	0.149
		11	0.030	0.050	14.627	0.200
		12	-0.168	-0.042	16.812	0.157

Model 6d

Sample: 2004M02 2009M12 Included observations: 71

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.003	-0.003	0.0005	0.982
		2	-0.120	-0.120	1.0839	0.582
		3	-0.297	-0.302	7.8150	0.050
		4	-0.008	-0.039	7.8202	0.098
		5	-0.004	-0.088	7.8216	0.166
		6	-0.083	-0.207	8.3677	0.212
		7	0.080	0.042	8.8912	0.261
		8	-0.007	-0.080	8.8947	0.351
		9	0.069	-0.012	9.2971	0.410
		10	-0.082	-0.065	9.8630	0.453
		11	-0.039	-0.082	9.9943	0.531
		12	-0.019	-0.043	10.025	0.614

2.7 Tables

Table 2.1: Rate and degree of dissent inside the MPC

Policy rate decision	Average rate of dissent		Average (maximum) absolute value of *skew*, basis points	
	1998/02-2004/01	2004/02-2009/12	1998/02-2004/01	2004/02-2009/12
Cut	0.30	0.31	17.7 (75.0)	7.1 (12.5)
No change	0.05	0.12	4.5 (80.0)	2.9 (12.5)
Hike	0.04	0.18	5.2 (15.0)	4.3 (10.0)
All	0.14	0.16	9.5 (80.0)	3.9 (12.5)

Table 2.2: Frequency distribution of changes to the NBP reference rate.

Sample	Historical changes to reference rate, percentage points												
	-2.50	-1.50	-1.00	-0.75	-0.50	-0.25	0.00	0.25	0.50	1.00	1.50	2.50	All
1998/03-2004/01	2	6	6		6	7	40			2	1	1	71
2004/02-2009/12				2	3	8	47	9	2				71
	Consolidated categories of reference rate changes												
			Large cut			Small cut	No change			Hike			All
1998/03-2004/01			20			7	40			4			71
2004/02-2009/12			5			8	47			11			71

Table 2.3: Do voting records matter if included in naive and interest-rate smoothing rules?

(1): $\Delta r^*_{t+1} = b_1 skew_{t-1} + \varepsilon_t$ (2): $\Delta r^*_{t+1} = b_1 skew_{t-1} + b_2 \Delta r_{t-1} + \varepsilon_t$

Sample	1998/03-2004/01 (71 observations)		2004/02-2009/12 (71 observations)	
Model	(1)	(2)	(1)	(2)
b_1	1.18 (0.42)***	2.76 (0.59)***	1.01 (2.48)	8.92 (3.02)***
b_2		2.51 (0.68)***		5.13 (1.17)***
Goodness-of-fit pseudo-R^2 measures with (without) $skew_{t-1}$				
McFadden	0.02 (0.00)	0.11 (0.04)	0.00 (0.00)	0.21 (0.15)
McKelvey-Zavoina	0.06 (0.00)	0.28 (0.10)	0.00 (0.00)	0.42 (0.32)
Hit rate	0.58 (0.56)	0.61 (0.44)	0.66 (0.66)	0.69 (0.68)
LR test (Prob > χ^2) of equality of coefficients in 1998/3-2004/1 and 2004/2-2009/12 periods with (without) $skew_{t-1}$			0.007 (0.003)	0.029 (0.009)

Notes: The ordered probit estimations with Huber(1967)/White(1980) robust standard in parentheses. ***/**/* denote significance at 1/5/10 % level, respectively. The cutpoints are estimated, but not reported here.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
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Table 2.4: Do voting records matter if included in Taylor-type rules?

$$(3a):\ \Delta r^*_{t+1} = b_1 \Delta r_{t-1} + b_2 \Delta(cpi_t - it_t) + b_3 \Delta_q gdp_t + b_4 skew_{t-1} + \varepsilon_t$$
$$(3b):\ \Delta r^*_{t+1} = b_1 \Delta r_{t-1} + b_2 \Delta cpit_t + b_3 \Delta_a cli_t + b_4 skew_{t-1} + \varepsilon_t$$
$$(4a):\ \Delta r^*_{t+1} = b_1 \Delta r_{t-1} + b_2 \Delta_a p^e_t + b_3 \Delta_a sale^e_t + b_4 skew_{t-1} + \varepsilon_t$$
$$(4b):\ \Delta r^*_{t+1} = b_1 \Delta r_{t-1} + b_2 \Delta(cpi^{e(i)}_t - it_t) + b_3 \Delta_a sale^e_t + b_4 skew_{t-1} + \varepsilon_t$$

Sample	1998/03-2004/01 (71 observations)				2004/02-2009/12 (71 observations)			
Model	(3a)	(3b)	(4a)	(4b)	(3a)	(3b)	(4a)	(4b)
b_1	2.23***	1.87**	1.36*	2.35***	4.13***	3.16**	2.65*	3.36***
	(0.78)	(0.80)	(0.82)	(0.69)	(1.34)	(1.36)	(1.42)	(1.16)
b_2	0.85**	1.57***	0.05***	0.23	1.24***	3.47***	0.06***	1.63***
	(0.34)	(0.57)	(0.01)	(0.21)	(0.43)	(0.78)	(0.02)	(0.42)
b_3	0.09	-0.00	-0.02	-0.00	0.23	0.05***	0.05***	0.05***
	(0.12)	(0.01)	(0.01)	(0.01)	(0.14)	(0.02)	(0.01)	(0.01)
b_4	3.01***	2.99***	2.90***	2.95***	7.68**	10.81***	9.72***	10.70***
	(0.69)	(0.82)	(0.79)	(0.60)	(3.18)	(3.27)	(3.50)	(3.01)
Goodness-of-fit pseudo-R^2 measures with (without) $skew_{t-1}$								
McFadden	0.21(0.13)	0.19(0.11)	0.20(0.13)	0.12(0.04)	0.31(0.27)	0.44(0.37)	0.39(0.33)	0.38(0.31)
McKelvey-Zavoina	0.46(0.31)	0.44(0.27)	0.45(0.31)	0.30(0.11)	0.54(0.50)	0.71(0.64)	0.69(0.63)	0.65(0.56)
Hit rate	0.61(0.48)	0.58(0.49)	0.61(0.54)	0.62(0.45)	0.72(0.69)	0.79(0.72)	0.68(0.68)	0.70(0.70)
LR test (Prob > χ^2) of equality of coefficients in 1998/3-2004/1 and 2004/2-2009/12 periods with (without) $skew_{t-1}$					0.075 (0.011)	0.002 (0.001)	0.008 (0.008)	0.000 (0.000)

Notes: The ordered probit estimations with Huber(1967)/White(1980) robust standard in parentheses. ***/**/* denote significance at 1/5/10 % level, respectively. The cutpoints are estimated, but not reported here.

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Table 2.5: Do voting records matter if included in augmented Taylor-type rules?

$$\text{(5a): } \Delta r^*_{t+1} = b_1 \Delta cpix_t + b_2 \Delta_c usd_t + b_3(wibor6m_t - r_{t-1}) + b_4 skew_{t-1} + \varepsilon_t$$
$$\text{(5b): } \Delta r^*_{t+1} = b_1 \Delta cpix_t + b_2 \Delta_c usd^e_t + b_3(wibor6m_t - r_{t-1}) + b_4 skew_{t-1} + \varepsilon_t$$
$$\text{(5c): } \Delta r^*_{t+1} = b_1 \Delta cpit_t + b_2 \Delta_a cli_t + b_3 \Delta_m wibor1m_t + b_4 bias_{t-1} + b_5 skew_{t-1} + \varepsilon_t$$
$$\text{(5d): } \Delta r^*_{t+1} = b_1(\Delta cpi^{e(i)}_t - it_t) + b_2 \Delta gdp^e_t + b_3 \Delta_m wibor1m_t + b_4 bias_{t-1} + b_5 skew_{t-1} + \varepsilon_t$$

Sample	1998/03-2004/01 (71 observations)		2004/02-2009/12 (71 observations)	
Model	(5a)	(5b)	(5c)	(5d)
b_1	1.47 (0.39)***	1.67 (0.42)***	3.64 (1.00)***	2.64 (0.62)***
b_2	0.09 (0.04)**	0.23 (0.06)***	0.03 (0.01)**	2.74 (0.67)***
b_3	0.87 (0.23)***	0.87 (0.24)***	7.18 (2.18)***	10.21 (2.01)***
b_4	2.57 (0.67)***	2.65 (0.68)***	1.14 (0.34)***	1.30 (0.30)***
b_5			11.02 (3.82)***	10.63 (3.72)***
Goodness-of-fit pseudo-R^2 measures with (without) $skew_{t-1}$				
McFadden	0.41 (0.35)	0.45 (0.39)	0.59 (0.53)	0.66 (0.61)
McKelvey-Zavoina	0.73 (0.69)	0.78 (0.75)	0.88 (0.82)	0.91 (0.88)
Hit rate	0.72 (0.69)	0.77 (0.72)	0.83 (0.77)	0.80 (0.77)

Notes: The ordered probit estimations with Huber(1967)/White(1980) robust standard errors in parantheses. ***/** denote significance at 1/5 % level, respectively. The cutpoints are estimated, but not reported. Data on $\Delta_a wibor12m_t$ are available since 2002/01, the observations before 2002/01 are set to zero. $\Delta_c usd_t$ is used in the form of 30-day average.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 2.6: Do voting records matter if included in favored empirical policy rules?

$$(6a):\ \Delta r^*_{t+1} = b_1\Delta cpix_t + b_2(\Delta cpi^{e(r)}_t - it_t) + b_3\Delta_c usd_t + b_4(wibor6m_t - r_{t-1}) + b_5\Delta_a wibor12m_t + b_6 skew_{t-1} + \varepsilon_t$$

$$(6b):\ \Delta r^*_{t+1} = b_1\Delta cpix_t + b_2(\Delta cpi^{e(r)}_t - it_t) + b_3\Delta_c usd^e_t + b_4(wibor6m_t - r_{t-1}) + b_5\Delta_a wibor12m_t + b_6 skew_{t-1} + \varepsilon_t$$

$$(6c):\ \Delta r^*_{t+1} = b_1(\Delta cpi^{e(i)}_t - it_t) + b_2\Delta gdp^e_t + b_3\Delta_m wibor1m_t + b_4(wibor12m_t - wibor1m_t) + b_5 dep_t + b_6 bias_{t-1} + b_7 skew_{t-1} + \varepsilon_t$$

$$(6d):\ \Delta r^*_{t+1} = b_1(\Delta cpi^{e(i)}_t - it_t) + b_2\Delta gdp^e_t + b_3\Delta_m wibor1m_t + b_4(wibor12m_t - wibor1m_t) + b_5 dep_t + b_6 bias_{t-1} + b_7 skew_{t-1} + b_8 I[cpi^{e(i)}_t > it_t] + \varepsilon_t$$

Sample	1999/02-2004/01 (60 observations)		2004/02-2009/12 (71 observations)	
Model	(6a)	(6b)	(6c)	(6d)
b_1	3.16 (0.84)***	3.16 (0.86)***	4.97 (1.87)***	7.69 (2.31)***
b_2	2.04 (0.63)***	1.91 (0.61)***	7.43 (2.19)***	12.87 (3.12)***
b_3	0.11 (0.05)**	0.18 (0.08)**	25.67 (8.14)***	46.96 (12.29)***
b_4	1.76 (0.52)***	1.91 (0.49)***	4.54 (1.31)***	15.60 (4.21)***
b_5	0.61 (0.15)***	0.56 (0.14)***	-1.07 (0.34)***	-2.06 (0.69)***
b_6	3.87 (0.94)***	3.82 (0.99)***	3.76 (0.90)***	9.46 (2.37)***
b_7			29.91 (9.94)***	59.74 (13.69)***
b_8				7.49 (2.13)***
Goodness-of-fit pseudo-R^2 measures with (without) $skew_{t-1}$				
McFadden	0.64 (0.54)	0.64 (0.54)	0.83 (0.72)	0.88 (0.76)
McKelvey-Zavoina	0.96 (0.93)	0.96 (0.93)	0.99 (0.95)	1.00 (0.97)
Hit rate	0.83 (0.73)	0.82 (0.72)	0.90 (0.90)	0.94 (0.89)
LR test of equality of coefficients across response categories with (without) $skew_{t-1}$				
Prob > χ^2	0.223(0.054)	0.257(0.078)	0.480(0.039)	0.404(0.020)

Notes: The ordered probit estimations with Huber(1967)/White(1980) robust standard errors in parantheses. ***/** denote significance at 1/5 % level, respectively. The cutpoints are estimated, but not reported. Data on $\Delta_a wibor12m_t$ are available since 2002/01, the observations before 2002/01 are set to zero. $\Delta_a wibor12m_t$ and $\Delta_c usd_t$ are used in the form of 30-day average; $wibor12m_t$-$wibor1m_t$ is in the form of five-business-day average.

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Table 2.7: Do voting records improve policy predictability?

Ordered probit's latent equation (forecasting model)		Pseudo-R^2 measures of fit with (without) $skew_{t-1}$ McFadden	McKelvey-Zavoina	Hit rate	P-value of $skew_{t-1}$
Sample: 1998/03 - 2004/01 (71 observations)					
Naïve "no change" rule	(1)	0.02 (0.00)	0.06 (0.00)	0.58 (0.56)	0.005
Interest rate smoothing rule	(2)	0.11 (0.04)	0.28 (0.10)	0.61 (0.44)	0.000
Backward-looking Taylor rule	(3a)	0.21 (0.13)	0.46 (0.31)	0.61 (0.48)	0.000
Forward-looking Taylor rule	(4a)	0.20 (0.13)	0.45 (0.31)	0.61 (0.54)	0.000
Augmented Taylor rule	(5b)	0.45 (0.39)	0.78 (0.75)	0.77 (0.72)	0.000
Sample: 1999/02 - 2004/01 (60 observations)					
Favored empirical rule	(6a)	0.64 (0.54)	0.96 (0.93)	0.83 (0.73)	0.000
Sample: 2004/02 - 2009/12 (71 observations)					
Naïve "no change" rule	(1)	0.00 (0.00)	0.00 (0.00)	0.66 (0.66)	0.684
Interest rate smoothing rule	(2)	0.21 (0.15)	0.42 (0.32)	0.69 (0.68)	0.003
Backward-looking Taylor rule	(3b)	0.44 (0.37)	0.71 (0.64)	0.79 (0.72)	0.001
Forward-looking Taylor rule	(4a)	0.39 (0.33)	0.69 (0.63)	0.68 (0.68)	0.006
Augmented Taylor rule	(5d)	0.66 (0.61)	0.91 (0.88)	0.80 (0.77)	0.004
Favored empirical rule	(6d)	0.88 (0.76)	1.00 (0.97)	0.94 (0.89)	0.000

Notes: The ordered probit estimations with Huber(1967)/White(1980) robust standard errors.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 2.8: Do voting records add information to market-based expectations?

$$\Delta r^*_{t+1} = b_1(X_{1t} - X_{2t}) + b_2 X_{3t} + b_3 skew_{t-1} + \varepsilon_t$$

X_{1t}	$wibor12m_t$	$wibor12m_t$	$wibor12m_t$	$wibor6m_t$	$wibor6m_t$
X_{2t}	r_{t-1}	$wibor1m_t$	$wibor3m_t$	r_{t-1}	$wibor1m_t$
X_{3t}	$\Delta_m\, wibor1m_t$	$\Delta_m\, wibor1m_t$	$\Delta_m\, wibor3m_t$	$\Delta_m\, wibor1m_t$	$\Delta_m\, wibor1m_t$
Sample: 1999/02 - 2004/01 (60 observations)					
b_1	1.52 (0.32)***	1.57 (0.45)***	2.50 (0.69)***	1.52 (0.36)***	1.25 (0.30)***
b_2	0.84 (0.39)**	0.87 (0.40)**	1.58 (0.48)***	0.16 (0.34)	0.78 (0.35)**
b_3	2.15 (0.68)***	2.07 (0.69)***	2.72 (0.74)***	2.77 (1.00)***	2.66 (0.76)***
Goodness-of-fit pseudo-R^2 measures with (without) $skew_{t-1}$					
McFadden	0.23 (0.18)	0.24 (0.19)	0.31 (0.25)	0.37 (0.32)	0.28 (0.22)
McKelvey-Zavoina	0.51 (0.42)	0.53 (0.45)	0.63 (0.54)	0.77 (0.70)	0.59 (0.50)
Hit rate	0.68 (0.65)	0.70 (0.60)	0.67 (0.63)	0.73 (0.68)	0.65 (0.55)
Sample: 2004/02 - 2009/12 (71 observations)					
b_1	0.88 (0.42)**	1.00 (0.46)**	2.36 (0.92)**	0.87 (0.52)*	0.99 (0.57)*
b_2	6.69 (1.94)***	7.28 (1.83)***	6.30 (1.27)***	6.94 (1.95)***	7.56 (1.79)***
b_3	4.81 (2.48)*	5.57 (2.41)**	5.72 (2.72)**	4.32 (2.61)*	4.99 (2.49)**
Goodness-of-fit pseudo-R^2 measures with (without) $skew_{t-1}$					
McFadden	0.39 (0.37)	0.38 (0.36)	0.41 (0.39)	0.37 (0.35)	0.36 (0.34)
McKelvey-Zavoina	0.65 (0.63)	0.65 (0.62)	0.70 (0.67)	0.63 (0.62)	0.62 (0.60)
Hit rate	0.69 (0.76)	0.70 (0.76)	0.72 (0.73)	0.70 (0.75)	0.73 (0.77)

Notes: The ordered probit estimations with Huber(1967)/White(1980) robust standard errors in parantheses. ***/**/* denote significance at 1/5/10 % level, respectively. The cutpoints are estimated, but not reported here. The data on $wibor12m_t$ are available since 2002/1 only, the observations before 2002/1 are set to zero.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 2.9: Do voting records add information to survey-based anticipations?

$$\Delta r^*_{t+1} = b_1 \Delta r^e_t + b_2 skew_{t-1} + (b_3 bias_{t-1}) + \varepsilon_t$$

Sample	1998/04-2004/01 (70 observations)	2004/02-2009/12 (71 observations)	
b_1	4.64 (1.17)***	13.00 (2.22)***	12.03 (2.33)***
b_2	1.13 (0.57)**	7.96 (2.96)***	8.51 (3.22)***
b_3			00.44 (0.26) *
	Goodness-of-fit pseudo-R^2 measures with (without) $skew_{t-1}$		
McFadden	0.28 (0.27)	0.60 (0.57)	0.62 (0.58)
McKelvey-Zavoina	0.70 (0.69)	0.81 (0.77)	0.83 (0.78)
Hit rate	0.77 (0.76)	0.83 (0.86)	0.82 (0.87)

Notes: The ordered probit estimations with Huber(1967)/White(1980) robust standard errors in parantheses. ***/**/* denote significance at 1/5/10 % level, respectively. The cutpoints are estimated, but not reported here. The values of $skew_{t-1}$ in the 1998/4-2004/1 period are calculated disregarding the votes of Dabrowski.

Table 2.10: Comparison with private sector anticipation

	Hit rate		Average likelihood	
Forecast	1999/2-2004/1	2004/2-2009/12	1999/2-2004/1	2004/2-2009/12
Forecast from Reuters surveys	0.80	0.87	0.77	0.82
Empirical policy rule without $skew_{t-1}$	0.73	0.89	0.70	0.85
Empirical policy rule with $skew_{t-1}$	0.83	0.94	0.77	0.92

Notes: The estimated policy rules are given by Models (6a) and (6d) from Table 6, respectively for 1999/2-2004/1 and 2004/2-2009/12 periods. The predicted discrete policy decision from Reuters surveys is computed as a discrete change (out of the four choices) closest to the average of individual forecasts. The model-based predicted discrete policy decision is computed analogously as a discrete change closest to the expected change calculated using probabilities from ordered probit model.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 2.11: Can the dispersion of votes explain the uncertainty of private sector forecasts?

$$y_{t+1} = b_0 + b_1 disp_{t-1} + (b_2 disp_{t+1}) + \varepsilon_t$$

y_{t+1}	Forecasts' dispersion		Absolute forecast error		Fraction of wrong predictions	
b_1	0.47 (0.14)***	0.30 (0.17)*	0.96 (0.31)***	0.64 (0.31)**	3.22 (1.04)***	1.98 (1.10)*
b_2		0.41 (0.18)**		0.78 (0.33)**		2.92 (1.07)***
Adj. R^2	0.08	0.10	0.07	0.09	0.08	0.12

Notes: Sample: 2004/2-2009/12 (71 observations). The Tobit estimations with Huber(1967)/White(1980) robust standard errors in parantheses. ***/**/* denote significance at 1/5/10 % level, respectively. The constant term b_0 and variance of e_t are estimated, but not reported.

Table 2.12: Can the direction of dissent explain the direction of private sector forecast errors?

$$y_{t+1} = b_0 + b_1 skew_{t-1} + (b_2 skew_{t+1}) + \varepsilon_t$$

y_{t+1}	Four-category forecast error		Unconsolidated forecast error
b_1	-0.41 (0.20)**	-0.44 (0.21)**	-0.32 (0.19)*
b_2		0.32 (0.18)*	0.60 (0.33)*
Durbin-Watson statistics	1.65	1.71	1.71
Adjusted R^2	0.05	0.08	0.08

Notes: Sample 2004/2 - 2009/12 (71 observations). The OLS estimations with Newey-West (1987) robust standard errors in parantheses. **/* denote significance at 5/10 % level, respectively. The constant term b_0 and variance of e_t are estimated, but not reported.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician’s Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

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Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

2.9 Appendix: Description of data

Mnemonics	Variable description (source of data)
bias	Indicator of "policy bias" or "balance of risks" (since 2006/1): -1 if "mild", 0 if "neutral", and 1 if "restrictive" (NBP & AC)
cli	General business tendency climate in industry from the Business Tendency Survey (GUS)
cpi	Consumer price index (CPI) (GUS)
cpit	CPI, 15% trimmed mean (GUS and NBP)
cpix	CPI, excluding administratively controlled prices (GUS and NBP)
$cpi^{e(i)}$	Expected CPI over next 12 months from the survey of consumers (Ipsos-Demoskop and NBP)
$cpi^{e(n)}$	Central projection of CPI over the next eight quarters (NBP)
$cpi^{e(r)}$	Expected CPI over next 11 months from the survey of bank analysts (Reuters)
dep	Deposits and other liabilities to non-financial sector (NBP)
disp	Average absolute deviation of changes to the reference rate proposed by MPC members from their mean (NBP & AC)
gdp	Index of gross domestic product (GDP) (GUS)
gdp^{e}	Expected GDP over the next 2 quarters from the survey of bank analysts (Reuters)
$i[x>it]$	Indicator variable: one if x is equal to or above the inflation target, zero otherwise
p^{e}	Expected prices of goods in retail trade from the Business Tendency Survey (GUS)
r	NBP reference rate (NBP)
Δr^{e}	The average of individual forecasts of the next change to the reference rate from the survey of bank analysts (Reuters)
$sale^{e}$	Expected volume of sold production in industry from the Business Tendency Survey (GUS)
skew	Difference between average proposed and announced change to the reference rate (NBP & AC)
it	Official NBP target for CPI (NBP)
usd	Exchange rate PLN/USD (NBP)
usd^{e}	Expected exchange rate PLN/USD over next 12 months from survey of bank analysts (Reuters)
wiborNm	N-month Warsaw interbank offer rate (Datastream)
	Transformation description
Δ	Change since the previous month
Δ_a	Change since the corresponding period of previous year
Δ_c	Change since the date of the last non-zero adjustment to the reference rate
Δ_m	Change since the next day after the last MPC meeting
Δ_q	Change since the previous quarter

Notes: All data are not adjusted seasonally. GUS is the Central Statistical Office of Poland. AC stands for author's calculations. Data on $cpi^{e(n)}$ are available only since August 2004; from February to July 2004 data on $cpi^{e(i)}$ were used.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Chapter 3

A model for ordinal responses with an application to policy interest rate

3.1 Introduction

Ordinal dependent variables, taking on negative, zero and positive values, are often characterized by the abundant observations in the middle (neutral or zero) category. For instance, most central banks adjust policy rates by discrete increments - namely multiples of 25 basis points - and no-change decisions commonly constitute an absolute majority[1]. Such excessive "zeros" can be generated by different decision-making processes. In addition, the positive and negative changes may be also driven by distinct factors. This definitely poses a problem for a single-equation standard ordered probit (OP) model. In such situations, it would be a misspecification to disregard the heterogeneity of zeros, to treat all the observations (the zeros and non-zeros) as coming from the same data-generating process (d.g.p.), and to apply a standard ordered-response model, based on a single equation. This paper develops a latent-class three-equation model for such types of ordinal outcomes, and illustrates the model in the context of policy interest rate decisions.

Suppose that an ordinal dependent variable, for example, a discrete change to policy rate, can be in three latent regimes (loose, neutral or tight), where it can take on only nonpositive, zero or nonnegative values, respectively. Figure 3.1 shows the decision tree. The first stage, a policy *inclination* decision, sets the regime, i.e. monetary policy stance. The inclination decision is driven by direct reaction to the economic conditions, particularly

[1] For example, 76, 79, 63 and 66 percent in the Bank of England, European Central Bank, US Federal Reserve and National Bank of Poland, respectively, during the 6/1997-10/2012, 1/1999-10/2012, 10/1982-10/2012 and 3/1998-10/2012 periods.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

to the developments since the last policy meeting. At the second stage, if the stance is neutral, no further policy actions are taken and the rate is maintained. If the stance is loose (tight), the policymakers can cut (hike) the rate by certain amount or may leave it unchanged. These two *amount* decisions, conditional on either loose or tight policy stances, fine-tune the rate and are more of a tactical and institutional nature. Under this interpretation, we can define and classify three kinds of zeros and describe how they arise: the "always" or "neutral" zeros, generated directly by neutral policy reaction to economic conditions; and two kinds of "not-always" or "offset" zeros, the "loose" and "tight" zeros, generated by loose or tight policy stance, offset by the tactical and institutional reasons.

For example, despite a loose policy stance, the policymakers can maintain the rate due to the following reasons. First, the recent "policy bias" statement of the central bank, which indicates the most likely policy direction in the immediate future, was neutral or even tightening (this addresses the policymakers' concerns about the competence and credibility of the central bank's communication). Second, the dissenting policymakers at the last meeting preferred the higher rate, creating an upward pressure to the rate at the current meeting (this accounts for the fact that the monetary policy is commonly conducted by a committee, often composed of heterogeneous members)[2]. Third, the rate was already lowered at the last meeting (this reflects the general reluctance to move the rate frequently). Fourth, the cumulative changes to the economic indicators since the date of the last non-zero policy rate adjustment do not suggest the policy easing (the policymakers, who face uncertainty about the economy and incur the costs in the case of the subsequent rate reversal, prefer to wait and to react to more accumulated economic information in order to minimize the risk of the reversals). Finally, the policy rate has already reached the lower zero bound.

The proposed middle-category-inflated ordered probit (MIOP) model assumes three separate parts: one decision sets policy stance (loose, neutral or tight), while the two others determine the amount of change.

The existence of different types of no-change decisions is justified by the very nature of monetary policymaking that involves processing huge amount of data, meeting different and sometimes conflicting goals, and is often conducted by a committee composed of heterogeneous members as well as by the discrete nature of the interest rate changes themselves.

Many central banks are reluctant to engage in frequent changes and reversals of policy rate. As Figure 3.2 shows, the policy rate of the National Bank of Poland (NBP) remained unchanged during three different circumstances: namely, during policy tightening; during

[2] See, for example, Gerlach-Kristen (2004) and Sirchenko (2010), who documented that the dissenting views of policymakers at the last policy meeting help predict the next policy decision of the Bank of England and National Bank of Poland, respectively.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

maintaining (between the reversals); and during periods of easing. Many zeros, clustered between the reversals during the maintaining periods, are likely to be driven by different forces than many of those that are situated between the changes in the same direction during periods of policy tightening or easing. To illustrate this Table 3.1 reports the average values of macroeconomic indicators observed separately only during the NBP policy decisions to either increase, reduce or leave the rate unchanged; in the no-change scenario, these values are reported separately for policy tightening, maintaining and easing periods. The economic conditions, observed when the rates were not changed during the tightening/easing periods, are much closer, on average, to those observed when the rates were increased/reduced, than to those that prevailed when the rates were maintained between the reversals. On the other hand, as Figure 3.3 shows, during some decisions to hike, leave unchanged or cut the rates, the observed inflation developments were actually similar. The same situation was observed for other economic indicators too.

The next section provides a brief overview of the related literature. The MIOP econometric framework (including its extended version, the MIOP(c) model, where the mechanisms determining the inclination and amount decisions are dependent) is introduced in Section 3.3. The proposed middle-category-inflated models are able to identify the driving factors of each decision. As a practical matter, this allows certain variables to affect the inclination and amount decisions differently, as well as the probabilities of three types of zeros, and the positive and negative outcomes to be driven by different sources. The models estimate the proportion of zeros coming from each regime and shed additional light on monetary policy inertia. As we shall observe, such models are fairly easy to estimate. Section 3.4 reports the results of Monte Carlo simulations to assess and compare the finite sample performance of the OP, NOP, NOP(c), MIOP and MIOP(c) models as well as the performance of the *LR* and *Vuong* tests and model selection criteria. In Section 3.5 the five alternative models - the OP, multinomial probit, ZIOP, MIOP and MIOP(c) - are applied to explain policy interest rate decisions of the NBP, using a panel of the individual votes of the Monetary Policy Council (MPC) members and *real-time* macroeconomic data available at policy meetings. Both the empirical applications and simulations demonstrate the superiority of the three-part middle-inflated models with respect to the conventional single-equation and two-part models. Section 3.6 concludes.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

3.2 Relation to existing literature

The proposed MIOP model is related to three strands of econometric literature. On the one hand, it can be described as a two-level cross-nested ordered probit model, an extension of a two-level nested ordered probit (NOP) model with three nests (see Figure 3.1). At the upper level of the NOP model the policymakers decide whether to increase, maintain, or decrease the rate. This trilemma is modelled by a trichotomous OP model. In case of a no-change decision, no further policy actions are taken, and the rate remains unchanged. If the policymakers decide to hike or to cut the rate, they have to choose the amount of the change. This fine-tuning lower level, conditional on the decision to increase or decrease the rate at the upper level, is modeled by two distinct OP models. Overall, the NOP model combines three equations with, in general, different sets of covariates. Therefore, in contrast to a standard single-equation OP model, in the NOP model, one set of explanatory variables may be relevant for the rate cuts, while another set may be relevant for the hikes. The third set of covariates would affect the no-change decisions. In the MIOP model the three nests overlap - they all contain the zero outcomes. It creates three distinct d.g.p., generating zero observations; hence, the probability of zeros is "inflated".

Notice also another key difference between the NOP and MIOP models: in the former both levels' decisions are observable, whereas in the latter they are observed partially, only when the outcome is nonzero. In the MIOP model the outcomes in the inflated zero category are observationally equivalent. We never know from which of the three regimes the zeros arise, while in the NOP model we always know to which of the three nests the observed outcome belongs. In this sense the three regimes in the MIOP model are latent.

In case of the unordered categorical data that are naturally clustered (e.g., schools within districts, classes within schools, students within classes), the nested (or *hierarchical*, or *multi-level*) multinomial logit model is used widely (see Greene 2012). Several kinds of multinomial logit models with overlapping nests have been also proposed. Wen and Koppelman (2001) introduced a generalized nested logit model, which contains the other cross-nested logit models as special cases. The hierarchical ordinal data are usually analyzed in the context of the generalized linear models (proposed by Agresti 1977), based on the cumulative logit, complementary log-log or probit link (for a survey, see Agresti and Natarajan 2001). The cross-nested models, specifically designed for the hierarchical ordinal data, are not so well developed[3].

On the other hand, the MIOP model can be perceived as a zero-inflated three-part

[3]Small (1987) proposed a model for ordered outcomes, called ordered generalized extreme value model, that has overlapping nests, but each nest contains only two alternatives.

mixture model. The mixture models, developed to deal with both the abundant zeros and unobserved heterogeneity, include the zero-inflated Poisson (Lambert 1992) and negative binomial (Greene 1994) models for count outcomes, as well as the zero-inflated ordered probit (ZIOP) model (Harris and Zhao 2007) and zero-inflated proportional odds model (Kelley and Anderson 2008) for ordinal variables. These zero-inflated models are the natural extensions of the two-part (or *hurdle*, or *split-population*) models, first proposed by Cragg (1971) for non-negative continuous data, and then developed for the count data (Mullahy 1986) survival time data (Schmidt and Witte 1989) and discrete ordered time-series data (the autoregressive conditional hazard (ACH) model of Hamilton and Jorda 2002). A two-part model basically represents a two-level hierarchical model with two nests. It combines a binary outcome model for the probability of crossing the hurdle (the upper-level *participation* decision) with a truncated-at-zero model for the outcomes above the hurdle (the lower-level *amount* decision). The difference between the two-part ACH and ZIOP models (see Figure 3.1) is that in the former the two parts are estimated separately, the zero observations are excluded from the second part, and, hence, the discrimination among different kinds of zeros is not accommodated, whereas the latter assumes two types of zeros and is able to identify their different d.g.p.[4]. Hamilton and Jorda (2002) applied the ACH model to the US Federal funds rate target; Brooks et al. (2007) applied the ZIOP model to the voting preferences of the Bank of England's MPC members.

The three-part MIOP model is a natural generalization of the two-part ZIOP model. A trichotomous participation decision (increase versus no change versus decrease) seems to be more realistic than a binary one (change versus no change) if applied to such types of ordinal data: the policymakers, who are willing to adjust the rate, have naturally already decided in which direction they want to move it. Besides, the MIOP model allows the probabilities and magnitudes of the positive changes to the rate to be affected by different determinants than those of the negative changes. Combining these two distinct decisions at the upper hurdle into one category, as done in the ZIOP model, may seriously distort the inference. The ZIOP model is more suitable if applied to explain such decisions as, for example, the levels of consumption, when the upper hurdle is naturally binary (to consume or not to consume).

Finally, the two-part model is similar by structure to a discrete version of the sample selection model[5]. However, in the sample selection model the first hurdle, the *selection* decision, determines whether the outcome variable is *observed*, rather than whether the activity is *undertaken*, as in the two-part model, where *all* the outcomes are actually *observed*.

[4] On the other hand, the ZIOP model assumes no serial correlation among the latent residuals, whereas the ACH model accounts for the serial dependence in discrete-valued time series.

[5] The early contributions are Gronau (1974) and Heckman (1976 and 1979), among others.

In many applications, in the absence of the sample selection problem, there is no need in modeling the latent potential, as opposed to the observed actual outcomes, but there is a need to model the "corner solution" outcomes or address the heterogeneity instead[6].

3.3 The econometric framework

The MIOP model allows for any number of the ordered discrete categories of the dependent variable greater than two, while the NOP model degenerates to the standard OP model in case of three outcome categories. For ease of exposition and without loss of generality, the observed dependent variable is assumed to take on a finite number of discrete values j coded as $\{-J, ..., -1, 0, 1, ..., J\}$, and the inflated neutral outcome is coded as zero[7].

The proposed models are suitable for the large survey data, both cross-sectional and longitudinal, though the sufficiently long discrete-valued time-series data are also applicable. Since in this paper the models are applied to the panel data with a small number of cross-sectional units and a relatively large number of time periods, the econometric framework is presented in the panel context using double subscript, where the index i denotes one of N cross-sectional units and index t denotes one of T time periods. The application to the pure cross-sectional or time-series data is straightforward by setting N or T to one.

Each observation is treated as an independent draw from the population both along the cross-sectional and time-series dimensions. Thus, it is assumed that the cross-sectional units are independent, that the model specification is dynamically complete, and that there is no serial correlation among the latent errors[8]. The advantage of this assumption is that even an unbalanced panel with some missing (at random) observations can be easily estimated by a pooled maximum likelihood (ML) estimator.

3.3.1 The middle-inflated ordered probit (MIOP) model

Let $r_{it} = \{-1, 0, 1\}$ be a trichotomous latent variable that determines whether the individual policy stance is loose, neutral or tight, and let m_{it}^{-} and m_{it}^{+} be the discrete nonpositive and nonnegative latent variables that set the magnitude of Δy_{it}, conditional on $r_{it} = -1$ and $r_{it} = 1$, respectively. Then assume that the observed vote for change to policy rate Δy_{it} is generated as

[6] For a debate between the sample selection and two part-models see Leung and Yu (1996), Jones (2000), Dow and Norton (2003), Madden (2008).

[7] Of course, the inflated outcome does not have to be in the *very* middle of ordered categories.

[8] The treatments of quite reasonably expected in the panel with small N spatial effects and serial auto-correlation of the disturbamce terms are among the possible extentions of the model.

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$$\Delta y_{it} = \frac{|r_{it}|}{2}\left\{(1-r_{it})\, m_{it}^{-} + (1+r_{it})m_{it}^{+}\right\} = \begin{cases} m_{it}^{-} & \text{if} \quad r_{it} = -1, \\ 0 & \text{if} \quad r_{it} = 0, \\ m_{it}^{+} & \text{if} \quad r_{it} = 1. \end{cases}$$

Notice that r_{it} is observed only if $\Delta y_{it} \neq 0$, whereas m_{it}^{-} and m_{it}^{+} are observed only if $\Delta y_{it} < 0$ or $\Delta y_{it} > 0$, respectively. Conditional on a set of explanatory variables, we will assume further that the mechanisms generating r_{it}, m_{it}^{-} and m_{it}^{+} are either independent or dependent.

The model assumes two stages and three regimes, and includes three OP latent equations. At the first stage (the upper level of the decision tree - see Figure 3.1) there is a continuous latent variable r_{it}^{*}, representing the magnitude of the policymaker i's policy stance and set at a meeting t in response to the observed data according to policy *inclination* equation

$$r_{it}^{*} = \mathbf{x}_{it}'\boldsymbol{\beta} + \nu_{it}, \tag{3.1}$$

where $\mathbf{x}_{it}$ is the t^{th} row of an observed $T_i \times K_\beta$ data matrix $\mathbf{X}_i$, T_i is the number of observations available for the individual i, $\boldsymbol{\beta}$ is a $K_\beta \times 1$ vector of unknown coefficients, and ν_{it} is an error term, independently and identically distributed (i.i.d.) across i and t.

The regime-setting decision r_{it} is coded as -1, 0, or 1, if the policymaker i's policy stance is loose, neutral or tight, respectively. The correspondence between r_{it}^{*} and r_{it} is given by the matching rule

$$r_{it} = \begin{cases} -1 & \text{if} \quad r_{it}^{*} \leq \alpha_1, \\ 0 & \text{if} \quad \alpha_1 < r_{it}^{*} \leq \alpha_2, \\ 1 & \text{if} \quad \alpha_2 < r_{it}^{*}, \end{cases}$$

where $-\infty < \alpha_1 \leq \alpha_2 < \infty$ are unknown threshold parameters to be estimated.

Under the assumption that the disturbance term ν_{it} is distributed with the c.d.f. F, the probabilities of each possible outcome of r_{it} are:

$$\begin{aligned} \Pr(r_{it} = -1|\mathbf{x}_{it}) &= \Pr(r_{it}^{*} \leq \alpha_1|\mathbf{x}_{it}) &&= F(\alpha_1 - \mathbf{x}_{it}'\boldsymbol{\beta}), \\ \Pr(r_{it} = 0|\mathbf{x}_{it}) &= \Pr(\alpha_1 < r_{it}^{*} \leq \alpha_2|\mathbf{x}_{it}) &&= F(\alpha_2 - \mathbf{x}_{it}'\boldsymbol{\beta}) - F(\alpha_1 - \mathbf{x}_{it}'\boldsymbol{\beta}), \\ \Pr(r_{it} = 1|\mathbf{x}_{it}) &= \Pr(\alpha_2 < r_{it}^{*}|\mathbf{x}_{it}) &&= 1 - F(\alpha_2 - \mathbf{x}_{it}'\boldsymbol{\beta}). \end{aligned} \tag{3.2}$$

At the second stage (the lower level of the decision tree) there are three regimes and two latent *amount* equations.

- *Regime* $r_{it} = -1$ *(loose policy stance).*

Conditional on being in regime $r_{it} = -1$ the continious latent variable m_{it}^{-*}, representing the desired change to the rate, is determined by the *amount* equation

$$m_{it}^{-*} = \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma} + \varepsilon_{it}^{-}, \tag{3.3}$$

where $\boldsymbol{\gamma}$ is a $K_\gamma \times 1$ vector of unknown coefficients, $\mathbf{z}_{it}^{-}$ is the t^{th} row of an observed $T_i \times K_\gamma$ data matrix $\mathbf{Z}_i^{-}$, and ε_{it}^{-} is an i.i.d. error term with the c.d.f. F^{-}.

The discrete change to the rate m_{it}^{-} is determined according to the rule:

$$m_{it}^{-} = j \text{ if } \mu_{j-1}^{-} < y_{it}^{-*} \leq \mu_j^{-} \text{ for } j = -J \text{ to } 0,$$

where $-\infty = \mu_{-J-1}^{-} \leq \mu_{-J}^{-} \leq ... \leq \mu_{-1}^{-} \leq \mu_0^{-} = \infty$ are J unknown thresholds to be estimated.

The conditional probability of a particular outcome j is given by

$$\Pr(m_{it}^{-} = j|\mathbf{z}_{it}^{-}, r_{it} = -1) = \begin{cases} F^{-}(\mu_{-J}^{-} - \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma}) & \text{for} \quad j = -J, \\ F^{-}(\mu_j^{-} - \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma}) - F^{-}(\mu_{j-1}^{-} - \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma}) & \text{for} \quad -J < j < 0, \\ 1 - F^{-}(\mu_{-1}^{-} - \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma}) & \text{for} \quad j = 0, \\ 0 & \text{for} \quad 0 < j \leq J, \end{cases}$$

which can be written more compactly, given that $-\infty = \mu_{-J-1}^{-}$ and $\mu_0^{-} = \infty$, as

$$\Pr(m_{it}^{-} = j|\mathbf{z}_{it}^{-}, r_{it} = -1) = \begin{cases} F^{-}(\mu_j^{-} - \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma}) - F^{-}(\mu_{j-1}^{-} - \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma}) & \text{for} \quad -J \leq j \leq 0, \\ 0 & \text{for} \quad 0 < j \leq J. \end{cases} \tag{3.4}$$

- *Regime $r_{it} = 0$ (neutral policy stance).*

Conditional on being in regime $r_{it} = 0$ no further policy actions are taken - the rate remains unchanged:

$$\Delta y_{it}|(r_{it} = 0) = 0.$$

Therefore, the conditional probability of a particular outcome j is given by

$$\Pr(\Delta y_{it} = j|\mathbf{x}_{it}, r_{it} = 0) = \begin{cases} 0 & \text{for} \quad j \neq 0, \\ 1 & \text{for} \quad j = 0. \end{cases} \tag{3.5}$$

- *Regime $r_{it} = 1$ (tight policy stance).*

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
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Conditional on being in regime $r_{it} = 1$ the continious latent variable m_{it}^{+*}, representing the desired change to the rate, is set by the other *amount* equation

$$m_{it}^{+*} = \mathbf{z}_{it}^{+\prime}\boldsymbol{\delta} + \varepsilon_{it}^{+}, \tag{3.6}$$

where $\boldsymbol{\delta}$ is a $K_\delta \times 1$ vector of unknown coefficients, $\mathbf{z}_{it}^{+}$ is the t^{th} row of an observed $T_i \times K_\delta$ data matrix $\mathbf{Z}_i^{+}$, and ε_{it}^{+} is an i.i.d. error term with the c.d.f. F^{+}.

The discrete change to the rate m_{it}^{+} is determined by

$$m_{it}^{+} = j \text{ if } \mu_{j-1}^{+} < y_{it}^{+*} \leq \mu_{j}^{+} \text{ for } j = 0 \text{ to } J,$$

where $-\infty = \mu_{-1}^{+} \leq \mu_{0}^{+} \leq ... \leq \mu_{J-1}^{+} \leq \mu_{J}^{+} = \infty$ are J unknown thresholds to be estimated.

The conditional probability of a particular outcome j is given by

$$\Pr(m_{it}^{+} = j|\mathbf{z}_{it}^{+}, r_{it} = 1) = \begin{cases} 0 & \text{for } \; -J \leq j < 0, \\ F^{+}(\mu_{j}^{+} - \mathbf{z}_{it}^{+\prime}\boldsymbol{\delta}) - F^{+}(\mu_{j-1}^{+} - \mathbf{z}_{it}^{+\prime}\boldsymbol{\delta}) & \text{for } \; 0 \leq j \leq J. \end{cases} \tag{3.7}$$

Assuming that ν_{it}, ε_{it}^{-} and ε_{it}^{+} are independent, the full unconditional probabilities to observe the outcome j are given by combining the probabilities in (2), (4), (5) and (7):

$$\Pr(\Delta y_{it} = j|\mathbf{x}_{it}, \mathbf{z}_{it}^{-}, \mathbf{z}_{it}^{+}) = \begin{cases} I_{j=0}\Pr(r_{it} = 0|\mathbf{x}_{it}) \\ +I_{j\geq 0}\Pr(r_{it} = 1|\mathbf{x}_{it})\Pr(m_{it}^{+} = j|\mathbf{z}_{it}^{+}, r_{it} = 1) \\ +I_{j\leq 0}\Pr(r_{it} = -1|\mathbf{x}_{it})\Pr(m_{it}^{-} = j|\mathbf{z}_{it}^{-}, r_{it} = -1) \end{cases}$$

$$= \begin{cases} I_{j=0}[F(\alpha_2 - \mathbf{x}_{it}'\boldsymbol{\beta}) - F(\alpha_1 - \mathbf{x}_{it}'\boldsymbol{\beta})] \\ +I_{j\geq 0}[1 - F(\alpha_2 - \mathbf{x}_{it}'\boldsymbol{\beta})][F^{+}(\mu_{j}^{+} - \mathbf{z}_{it}^{+\prime}\boldsymbol{\delta}) - F^{+}(\mu_{j-1}^{+} - \mathbf{z}_{it}^{+\prime}\boldsymbol{\delta})] \\ +I_{j\leq 0}F(\alpha_1 - \mathbf{x}_{it}'\boldsymbol{\beta})[F^{-}(\mu_{j}^{-} - \mathbf{z}_{it}^{-\prime}\boldsymbol{\delta}) - F^{-}(\mu_{j-1}^{-} - \mathbf{z}_{it}^{-\prime}\boldsymbol{\delta})], \end{cases} \tag{3.8}$$

where $I_{j\geq 0}$ is an indicator function such that $I_{j\geq 0} = 1$ if $j \geq 0$ and $I_{j\geq 0} = 0$ otherwise (analogously for $I_{j=0}$ and $I_{j\leq 0}$).

The proposed model, as any model with a latent variable, is not identified without some (arbitrary) assumptions. Let us assume the standard normal form[9] of the error distributions F, F^{-} and F^{+}, and also that the intercept components of $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ and $\boldsymbol{\delta}$ are all equal to zero. However, the above probabilities are absolutely *estimable* functions, i.e. they are i*nvariant*

[9] Employing the ordered logit and complementary log-log versions of the model is left for future research.

to the identifying assumptions. They can be estimated by using the pooled ML estimator of the vector of parameters $\boldsymbol{\theta} = (\boldsymbol{\alpha}', \boldsymbol{\beta}', \boldsymbol{\mu}^{-\prime}, \boldsymbol{\gamma}', \boldsymbol{\mu}^{+\prime}, \boldsymbol{\delta}')'$ that solves

$$\max_{\boldsymbol{\theta}\epsilon\boldsymbol{\Theta}} \sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{j=-J}^{J} q_{itj} \ln[\Pr(\Delta y_{it} = j|\mathbf{x}_{it}, \mathbf{z}_{it}^{-}, \mathbf{z}_{it}^{+}, \boldsymbol{\theta})], \tag{3.9}$$

where q_{itj} is an indicator function such that $q_{itj} = 1$ if $\Delta y_{it} = j$ and 0 otherwise.

The typical panels contain data covering a short timespan for each individual. In this case, the asymptotic arguments rely on N tending to infinity. With T fixed and $N \to \infty$, this estimator is consistent and $\sqrt{N}$-asymptotically normal without any assumptions other than the standard identification assumptions and regularity conditions. However, the usual asymptotic standard errors and test statistics obtained from pooled estimation are valid only under the assumption of no serial correlation among ν_{it}, ε_{it}^{-} and ε_{it}^{+}. Without dynamic completeness, they must be adjusted for serial dependence, for example, by using a robust to density misspecification quasi-ML sandwich estimator of asymptotic variance of $\boldsymbol{\theta}$

$$\widehat{Avar}(\widehat{\boldsymbol{\theta}}) = \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{H}_{it}(\widehat{\boldsymbol{\theta}})\right)^{-1} \left(\sum_{i=1}^{N}\mathbf{s}_i(\widehat{\boldsymbol{\theta}})\mathbf{s}_i(\widehat{\boldsymbol{\theta}})'\right) \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{H}_{it}(\widehat{\boldsymbol{\theta}})\right)^{-1}, \tag{3.10}$$

where $\mathbf{s}_i(\widehat{\boldsymbol{\theta}})$ is the score vector and $\mathbf{H}_i(\widehat{\boldsymbol{\theta}})$ is the Hessian (see Wooldridge 2010). The asymptotic standard errors of $\widehat{\boldsymbol{\theta}}$ are the square roots of the diagonal elements of (10).

For our type of panel with small N and relatively large T, we are basically in the realm of time-series analysis, and the asymptotic arguments rely on T tending towards infinity, standard identification assumptions and stability conditions. For both types of panel data, the above pooled ML estimator is consistent and asymptotically normal even if the error terms are arbitrarily serially correlated, the dynamics are not correctly specified, and $\mathbf{X}_i$, $\mathbf{Z}_i^{-}$ and $\mathbf{Z}_i^{+}$ contain not strictly exogenous covariates, lags of covariates and lagged Δy_{it} (see Wooldridge 2010).

3.3.2 The nested ordered probit (NOP) model

The only difference between the NOP and MIOP models is that all three nests of the NOP model do not overlap, i.e. regimes $r_{it} = -1$ and $r_{it} = 1$ do not allow for 'no change' response (see Figure 3.1). Therefore, in the NOP model the full unconditional probabilities to observe an outcome j (again, assuming that the disturbance terms of three latent equations are independent) are given by

$$\Pr(\Delta y_{it} = j|\mathbf{z}_{it}^-, \mathbf{z}_{it}^+, \mathbf{x}_{it}) = \begin{cases} I_{j=0}\Pr(r_{it} = 0|\mathbf{x}_{it}) + \\ I_{j>0}\Pr(r_{it} = 1|\mathbf{x}_{it})\Pr(w_{it}^+ = j|\mathbf{z}_{it}^+, r_{it} = 1) \\ +I_{j<0}\Pr(r_{it} = -1|\mathbf{x}_{it})\Pr(w_{it}^- = j|\mathbf{z}_{it}^-, r_{it} = -1) \end{cases}$$

$$= \begin{cases} I_{j=0}[F(\alpha_2 - \mathbf{x}_{it}'\boldsymbol{\beta}) - F(\alpha_1 - \mathbf{x}_{it}'\boldsymbol{\beta})] \\ +I_{j>0}[1 - F(\alpha_2 - \mathbf{x}_{it}'\boldsymbol{\beta})][F^+(\mu_j^+ - \mathbf{z}_{it}^{+\prime}\boldsymbol{\delta}) - F^+(\mu_{j-1}^+ - \mathbf{z}_{it}^{+\prime}\boldsymbol{\delta})] \\ +I_{j<0}F(\alpha_1 - \mathbf{x}_{it}'\boldsymbol{\beta})[F^-(\mu_j^- - \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma}) - F^-(\mu_{j-1}^- - \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma})], \end{cases} \tag{3.11}$$

where now $-\infty = \mu_{-J-1}^- \leq \mu_{-J}^- \leq ... \leq \mu_{-1}^- = \infty$ and $-\infty = \mu_0^+ \leq ... \leq \mu_{J-1}^+ \leq \mu_J^+ = \infty$ are $2(J-1)$ unknown thresholds to be estimated at the lower level (instead of $2J$ in the MIOP model), and the other parameters and assumptions are analogous to those in the MIOP model.

To estimate the NOP model one can employ the ML estimator from (9), using the probabilities from (11). The loglikelihood function of the NOP model, in contrast to that of the MIOP one, is separable with respect to the parameters in three latent equations. Thus, solving (9) is equivalent to maximizing separately the likelihoods of three OP models, corresponding to the above three latent equations (1), (3) and (6), where the data matrices $\mathbf{Z}_i^+$ and $\mathbf{Z}_i^-$ are truncated to contain only the rows with $\Delta y_{it} > 0$ and $\Delta y_{it} < 0$, respectively.

3.3.3 Relaxing assumption of independent disturbances

The NOP and MIOP models can be further extended by relaxing the assumption that the error terms $\boldsymbol{\nu}$, $\boldsymbol{\varepsilon}^-$ and $\boldsymbol{\varepsilon}^+$ are uncorrelated, and introducing the correlated versions of the models, NOP(c) and MIOP(c) ones. I now assume that $(\boldsymbol{\nu}, \boldsymbol{\varepsilon}^-)$ and $(\boldsymbol{\nu}, \boldsymbol{\varepsilon}^+)$ follow a standardized bivariate normal distribution with the correlation coefficients ρ^- and ρ^+, respectively. The full unconditional probabilities to observe an outcome j for the MIOP(c) model can be written now as

$$\begin{aligned} &\Pr(\Delta y_{it} = j) = I_{j=0}[F(\alpha_2 - \mathbf{x}_{it}'\boldsymbol{\beta}) - F(\alpha_1 - \mathbf{x}_{it}'\boldsymbol{\beta})] \\ &+I_{j\geq 0}[F_2(\mathbf{x}_{it}'\boldsymbol{\beta} - \alpha_2;\mu_j^+ - \mathbf{z}_{it}^{+\prime}\boldsymbol{\delta}; -\rho^+) - F_2(\mathbf{x}_{it}'\boldsymbol{\beta} - \alpha_2;\mu_{j-1}^+ - \mathbf{z}_{it}^{+\prime}\boldsymbol{\delta}; -\rho^+)] \\ &+I_{j\leq 0}[F_2(\alpha_1 - \mathbf{x}_{it}'\boldsymbol{\beta};\mu_j^- - \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma};\rho^-) - F_2(\alpha_1 - \mathbf{x}_{it}'\boldsymbol{\beta};\mu_{j-1}^- - \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma}; \rho^-)], \end{aligned} \tag{3.12}$$

where $F_2(\phi_1;\phi_2;\xi)$ is the c.d.f. of the standardized bivariate normal distribution with the correlation coefficient ξ between the two random variables ϕ_1 and ϕ_2.

The full unconditional probabilities to observe the outcome j for the NOP(c) model are given by

$$\begin{aligned}
&\Pr(\Delta y_{it} = j) = I_{j=0}[F(\alpha_2 - \mathbf{x}_{it}'\boldsymbol{\beta}) - F(\alpha_1 - \mathbf{x}_{it}'\boldsymbol{\beta})] \\
&+I_{j>0}[F_2(\mathbf{x}_{it}'\boldsymbol{\beta} - \alpha_2; \mu_j^+ - \mathbf{z}_{it}^{+\prime}\boldsymbol{\delta}; -\rho^+) - F_2(\mathbf{x}_{it}'\boldsymbol{\beta} - \alpha_2; \mu_{j-1}^+ - \mathbf{z}_{it}^{+\prime}\boldsymbol{\delta}; -\rho^+)] \\
&+I_{j<0}[F_2(\alpha_1 - \mathbf{x}_{it}'\boldsymbol{\beta}; \mu_j^- - \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma}; \rho^-) - F_2(\alpha_1 - \mathbf{x}_{it}'\boldsymbol{\beta}; \mu_{j-1}^- - \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma}; \rho^-)].
\end{aligned} \tag{3.13}$$

To estimate the MIOP(c) and NOP(c) models by ML, we have to solve (9), replacing the probabilities in (8) and (11) with those (12) and (13), respectively, and re-defining the vector of parameters $\boldsymbol{\theta}$ as $\boldsymbol{\theta} = (\boldsymbol{\alpha}', \boldsymbol{\beta}', \boldsymbol{\mu}^{-\prime}, \boldsymbol{\gamma}', \boldsymbol{\mu}^{+\prime}, \boldsymbol{\delta}', \rho^-, \rho^+)'$.

3.3.4 Partial effects

The partial (or marginal) effect (PE) of each continuous covariate on the probability of each discrete choice is computed as the partial derivative with respect to this covariate, holding all the others fixed at their sample median values. For the discrete-valued covariates the PE is computed as the change in the probabilities, when this covariate changes by one increment and all the others are fixed. To facilitate the derivation of the PE, the matrices of covariates and corresponding vectors of parameters can be partitioned as follows:

$$\begin{aligned}
&\mathbf{X} = (\mathbf{W}, \mathbf{P}, \mathbf{M}, \widetilde{\mathbf{X}}), \quad && \mathbf{Z}^+ = (\mathbf{W}, \mathbf{P}, \mathbf{V}, \widetilde{\mathbf{Z}}^+), \quad && \mathbf{Z}^- = (\mathbf{W}, \mathbf{M}, \mathbf{V}, \widetilde{\mathbf{Z}}^-), \\
&\boldsymbol{\beta} = (\boldsymbol{\beta}_w', \boldsymbol{\beta}_p', \boldsymbol{\beta}_m', \widetilde{\boldsymbol{\beta}}')', \quad && \boldsymbol{\delta} = (\boldsymbol{\delta}_w', \boldsymbol{\delta}_p', \boldsymbol{\delta}_v', \widetilde{\boldsymbol{\delta}}')', \quad && \boldsymbol{\gamma} = (\boldsymbol{\gamma}_w', \boldsymbol{\gamma}_m', \boldsymbol{\gamma}_v', \widetilde{\boldsymbol{\gamma}}')',
\end{aligned}$$

where $\mathbf{W}$ includes only the variables common for $\mathbf{X}$, $\mathbf{Z}^+$ and $\mathbf{Z}^-$; $\mathbf{P}$ includes only the variables common for both $\mathbf{X}$ and $\mathbf{Z}^+$, but which are not in $\mathbf{Z}^-$; $\mathbf{M}$ includes only the variables common for both $\mathbf{X}$ and $\mathbf{Z}^-$, but not in $\mathbf{Z}^+$; $\mathbf{V}$ includes only the variables common for both $\mathbf{Z}^-$ and $\mathbf{Z}^+$, but not in $\mathbf{X}$; whereas $\widetilde{\mathbf{X}}$, $\widetilde{\mathbf{Z}}^+$ and $\widetilde{\mathbf{Z}}^-$ include only those unique variables that appear only in one of the latent equations.

A matrix of covariates $\mathbf{X}^*$ and the vectors of parameters for $\mathbf{X}^*$ can be written down as

$$\begin{aligned}
&\mathbf{X}^* = (\mathbf{W}, \mathbf{P}, \mathbf{M}, \widetilde{\mathbf{X}}, \mathbf{V}, \widetilde{\mathbf{Z}}^+, \widetilde{\mathbf{Z}}^-),\ \boldsymbol{\beta}^* = (\boldsymbol{\beta}_w', \boldsymbol{\beta}_p', \boldsymbol{\beta}_m', \widetilde{\boldsymbol{\beta}}', \mathbf{0}', \mathbf{0}', \mathbf{0}')', \\
&\boldsymbol{\delta}^* = (\boldsymbol{\delta}_w', \boldsymbol{\delta}_p', \mathbf{0}', \mathbf{0}', \boldsymbol{\delta}_v', \widetilde{\boldsymbol{\delta}}', \mathbf{0}')',\ \boldsymbol{\gamma}^* = (\boldsymbol{\gamma}_w', \mathbf{0}', \boldsymbol{\gamma}_m', \mathbf{0}', \boldsymbol{\gamma}_v', \mathbf{0}', \widetilde{\boldsymbol{\gamma}}')'.
\end{aligned}$$

The partial effects of the row vector $\mathbf{x}_{it}^*$ on the overall probabilities in (12) can be now computed for the MIOP(c) model as

$$
\begin{aligned}
&\underset{\Pr(\Delta y_{it}=j)}{\mathbf{PE}} = -I_{j=0}[f(\alpha_2 - \mathbf{x}_{it}'\boldsymbol{\beta}) - f(\alpha_1 - \mathbf{x}_{it}'\boldsymbol{\beta})]\boldsymbol{\beta}^* \\
&+I_{j\geq 0}\left\{\left[F\left(\tfrac{\mathbf{x}_{it}'\boldsymbol{\beta}-\alpha_2+\rho^+(\mu_{j-1}^+-\mathbf{z}_{it}^{+\prime}\boldsymbol{\delta})}{\sqrt{1-(\rho^+)^2}}\right) f(\mu_{j-1}^+ - \mathbf{z}_{it}^{+\prime}\boldsymbol{\delta})\right.\right. \\
&\left.-F\left(\tfrac{\mathbf{x}_{it}'\boldsymbol{\beta}-\alpha_2+\rho^+(\mu_{j}^+-\mathbf{z}_{it}^{+\prime}\boldsymbol{\delta})}{\sqrt{1-(\rho^+)^2}}\right) f(\mu_{j}^+ - \mathbf{z}_{it}^{+\prime}\boldsymbol{\delta})\right]\boldsymbol{\delta}^* \\
&\left.+\left[F\left(\tfrac{\mu_j^+-\mathbf{z}_{it}^{+\prime}\boldsymbol{\delta}+\rho^+(\mathbf{x}_{it}'\boldsymbol{\beta}-\alpha_2)}{\sqrt{1-(\rho^+)^2}}\right) - F\left(\tfrac{\mu_{j-1}^+-\mathbf{z}_{it}^{+\prime}\boldsymbol{\delta}+\rho^+(\mathbf{x}_{it}'\boldsymbol{\beta}-\alpha_2)}{\sqrt{1-(\rho^+)^2}}\right)\right] f(\mathbf{x}_{it}'\boldsymbol{\beta}-\alpha_2)\boldsymbol{\beta}^*\right\} \\
&+I_{j\leq 0}\left\{\left[F\left(\tfrac{\alpha_1-\mathbf{x}_{it}'\boldsymbol{\beta}-\rho^-(\mu_{j-1}^--\mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma})}{\sqrt{1-(\rho^-)^2}}\right) f(\mu_{j-1}^- - \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma})\right.\right. \\
&\left.-F\left(\tfrac{\alpha_1-\mathbf{x}_{it}'\boldsymbol{\beta}-\rho^-(\mu_{j}^--\mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma})}{\sqrt{1-(\rho^-)^2}}\right) f(\mu_{j}^- - \mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma})\right]\boldsymbol{\gamma}^* \\
&\left.-\left[F\left(\tfrac{\mu_j^--\mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma}-\rho^-(\alpha_1-\mathbf{x}_{it}'\boldsymbol{\beta})}{\sqrt{1-(\rho^-)^2}}\right) - F\left(\tfrac{\mu_{j-1}^--\mathbf{z}_{it}^{-\prime}\boldsymbol{\gamma}-\rho^-(\alpha_1-\mathbf{x}_{it}'\boldsymbol{\beta})}{\sqrt{1-(\rho^-)^2}}\right)\right] f(\alpha_1-\mathbf{x}_{it}'\boldsymbol{\beta})\boldsymbol{\beta}^*\right\},
\end{aligned}
\tag{3.14}
$$

where f is the p.d.f. of the standard normal distribution F. The PE for the NOP(c) model are given by replacing $I_{j\geq 0}$ with $I_{j>0}$ and $I_{j\leq 0}$ with $I_{j<0}$. The PE for the NOP and MIOP models are obtained as above by setting $\rho^- = \rho^+ = 0$. The asymptotic standard errors of the PE are computed using the Delta method as.

3.3.5 Model comparison

The performance of competing models can be compared by using the model selection tests and informational criteria.

The NOP and MIOP models are nested in the NOP(c) and MIOP(c) models, respectively, as their uncorrelated special cases. The NOP model is nested in the MIOP model. The latter becomes a NOP model with the same value of the likelihood function if $\mu_{-1}^- \to \infty$ and $\mu_0^+ \to -\infty$, and hence, $\Pr(y_{it}^+ = 0|\mathbf{z}_{it}^+, r_{it} = 1) \to 0$ and $\Pr(y_{it}^- = 0|\mathbf{z}_{it}^-, r_{it} = -1) \to 0$, which can be implemented by letting μ_{-1}^- and μ_0^+ to be equal to the largest and smallest numbers available for the estimation software. Testing the NOP versus NOP(c), NOP versus MIOP, NOP versus MIOP(c), NOP(c) versus MIOP(c), and MIOP versus MIOP(c) model can be performed with the likelihood ratio (LR) test.

The OP models is not nested in either of the two-level models, and vice versa. However, the OP model is not strictly non-nested with them. All five models overlap if all their slope coefficients are restricted to being zero (i.e. if $\boldsymbol{\beta} = \mathbf{0}$, $\boldsymbol{\gamma} = \mathbf{0}$, $\boldsymbol{\delta} = \mathbf{0}$, and the vector of slope parameters in the OP latent equation is also fixed to zero), and only the thresholds are estimated. Therefore, testing the OP versus any of the two-level models, as well as the NOP(c) versus MIOP model (which overlap if both reduce to the NOP model) can be conducted with a test for non-nested overlapping models, such as the *Vuong* test (due to Vuong 1989) that utilizes the statistical significance between the difference in the log likelihoods. The testing procedure is sequential. First, we need to verify that the two models are not equivalent, i.e. separately perform t- or F-tests to check whether the parameters of interest violate the overlapping constraints. Second, if the overlapping restrictions can be rejected, we have to conduct the *Vuong* test for strictly non-nested models. The null hypothesis of this test is that both models are misspecified, but equally close to the unknown true d.g.p.. The test statistic is very simple to compute: it is equal to the average difference of the individual likelihoods divided by the estimated standard error of those individual differences. Under the null hypothesis, the *Vuong* test statistic converges in distribution to a standard normal one. If the absolute value of the test statistic is less than the critical value, say 1.96, we cannot discriminate between the two models given the data. If the test statistic exceeds 1.96, we reject the equivalence in favor of one of the models; if the test statistic smaller than -1.96, we reject the equivalence in favor of the other.

The following model-selection information criteria are computed: $AIC = -2l(\boldsymbol{\theta}) + 2k$, $BIC = -2l(\boldsymbol{\theta}) + ln(N)k$, $cAIC = -2l(\boldsymbol{\theta}) + (1 + \ln(N))k$ (consistent AIC), $AICc = AIC + 2k(k+1)/(N-k-1)$ (corrected AIC), and $HQIC = -2l(\boldsymbol{\theta}) + 2ln(ln(N))k$, where k is the total number of the estimated parameters. The adjusted *McFadden* pseudo-R^2 measure of fit (given by $1 - (l(\boldsymbol{\theta}) - k)/l_0(\boldsymbol{\theta})$, where $l_0(\boldsymbol{\theta})$ is the value of the restricted likelihood function, maximized with all the slope parameters in $\boldsymbol{\theta}$ fixed to zero) can also be used for the model selection, but its selection results are equivalent to those of the AIC, because the value of the $l_0(\boldsymbol{\theta})$ is identical in all the above models. Another measure of fit, the $Hit\ rate$, is computed as the percentage of correct predictions, where the predicted discrete outcome is that with the highest estimated probability.

3.4 Finite sample performance

In this section I report the results of massive Monte Carlo experiments to illustrate and compare the finite sample performance of the ML estimators in the single-, two- and three-equation models, namely to assess the bias and uncertainty of the estimates of parameters and partial effects and their asymptotic standard errors, the performance of the LR and *Vuong* tests and model selection criteria as discussed in the previous section, and the effect of exclusion restrictions. The simulations were performed using GAUSS software (version 10) codes with CML module (version 2) for the constrained ML estimation. Of course, all

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

the results are subject to a particular experimental design.

3.4.1 Monte Carlo design

The N observations in the repeated samples were drawn independently. This corresponds to either the cross-sectional model with uncorrelated units or to the time series model without serial dependence. Therefore the results are applicable to assess the finite-sample performance of the ML estimator with either i.i.d. cross-sectional data and $N \to \infty$ asymptotics or with dynamically complete time-series data and $T \to \infty$ asymptotics[10].

Five different d.g.p. were simulated: OP, NOP, NOP(c), MIOP, and MIOP(c). For each d.g.p. 3000 repeated samples with 250, 500 and 1000 observations were generated. Under each d.g.p. and for each sample size several competing models were estimated, always including the OP and NOP models as the benchmarks. In addition, in order to assess the effect of exclusion restrictions, three different scenarios of the overlap among the covariates in the specifications of three latent equations were simulated: "no overlap" (each covariate belongs only to one equation), "partial overlap" (each covariate belongs to two equations) and "complete overlap" (all three equations have the same set of covariates).

The specifications, values of parameters and other details of Monte Carlo design are reported in Appendix A.

3.4.2 Monte Carlo results

3.4.2.1 Estimates of parameters, probabilities and *PE*

It is worthless to compare the estimated parameters of the OP model with those of the two-level models not only because their structures and number of parameters are very different, but also because in such discrete models the parameters per se are not uniquely identified and their values depend on the arbitrary identifying assumptions. Fortunately, the probabilities of each discrete choice and the *PE* of covariates on these probabilities are absolutely *estimable* functions, i.e. they are invariant to the identifying assumptions, and basically are of main interest in empirical research. Therefore, I compare only the precision of parameters' estimates in the competing models, but not their values[11].

[10] The Monte Carlo simulations for the panel data with small N and relatively large T, where latent errors are either not autocorrelated or autocorrelated, will be added soon.

[11] The precision of parameters' estimates can be evaluated because each model was estimated assuming for the identification the same distribution of errors terms and the same value of the intercept parameter as those in the true d.g.p.. Therefore, the estimated parameters are directly comparable with their true values.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

The following measures of the accuracy of parameters' estimates for all five simulated models are computed: *Bias* - the difference between the estimated and true parameter value, averaged over all Monte Carlo runs and multiplied by 100; *RMSE* - the root mean square error of the estimated parameters relative to their true values, averaged over all replications and multiplied by 10; *CP* - the empirical coverage probability, computed as the percentage of times the estimated asymptotic 95% confidence intervals cover the true values; *M-ratio* and *A-ratio* - the ratios of the median and average of estimated asymptotic standard errors of parameters' estimates to the standard deviation of parameters' estimates in all replications.

These results are concisely summarized in Tables 8 - 10 of Appendix B, where the above measures are averaged for three groups of parameters (the slope, threshold and correlation coefficients) and contrasted across the five models (the absolute values of the individual *Bias* are used)[12]. The results suggest that (i) it requires two to three times more observations for the three-part models to achieve the same accuracy of the estimated parameters as that of the OP model; (ii) the bias and dispersion of slope coefficients' estimates are smaller than those for the thresholds, and those for the thresholds are smaller than those for the correlation coefficients; (iii) the fewer exclusion restrictions on the covariates in the three latent equations, the worse the accuracy of all parameters' estimates, though the estimated errors of the threshold and correlation coefficients are most severely affected; (iv) in small samples, the distribution of the estimates of standard errors (again, mostly for the threshold and correlation coefficients) is skewed to the right: there is a small fraction of huge estimated errors, while the rest of estimated errors are downward biased; (v) the finite-sample performance of the two-level models with exclusion restrictions and with 40 or more observations per parameter are rather good: the *M-ratio* is between 0.86 and 1.00, the *RMSE* is less than three times larger than in the OP model with the same number of observations per parameter, the *CP* are between 92% and 96% for the slope and thresholds parameters, and between 87% and 91% for the correlation coefficients.

To give a taste of how the accuracy of the estimates of *PE* of each covariate on the probability of each discrete choice differ among the models, the above measures of accuracy are computed with respect to the *PE* estimates and reported in Tables 11-13 of Appendix B for five models, estimated with 1000 observations and no overlap among the covariates[13]. In such non-linear models the *PE* depend on the values of covariates; they are estimated at the covariates' population means ($\overline{\mathbf{v_1}} = 2$, $\overline{\mathbf{v_2}} = \overline{\mathbf{v_3}} = 0$).

For brevity's sake, I do not report such detailed results for the other sample sizes and

[12] The detailed non-aggregated results for each parameter are available upon request.
[13] The only difference is that *RMSE* is now multiplied by 100.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

overlap scenarios - they are qualitatively analogous and are available upon request. Instead, in order to make more general conclusions, the *PE* were estimated for the values of covariates at each of the same 250 observations. The above accuracy measures were computed for the *PE*, averaged over 250 observations. In addition, the root mean square error of the estimated probabilities for all the outcomes and observations (*RMSEP*) was computed as $\sqrt{1/\{N(2J+1)\}\sum_{i=1}^{N}\sum_{j=0}^{2J+1}\{\widehat{\Pr}(y_i=j)-\Pr(y_i=j)\}^2}$ for each replication, averaged over all runs and multiplied by 10. *Problems* gives the percentage of runs when there was a problem with convergence or invertibility of the Hessian (this quantity should be interpreted in relative terms, since it depends on the ML estimation algorithm and can be improved by using different starting values for parameters and methods of numerical optimization; besides, there exists a trade-off between *Problems* and *A-ratio*). Table 14 of Appendix B shows these Monte Carlo results for the OP, NOP and NOP(c) d.g.p. with no overlap among the covariates. The results for the MIOP and MIOP(c) models are reported in Table 15 of Appendix B[14].

The main conclusions from these experiments can be summarized as follows. First, each of the five models under its own d.g.p., not surprisingly, estimates the *PE* better than the other models. However, under their own d.g.p. as the sample size grows, the relative performance of the OP model slowly deteriorates, while the relative performances of the NOP(c) and MIOP(c) models considerably improve. The relative performance of the NOP model with respect to the simpler OP model and that of the MIOP model with respect to simpler OP and NOP models considerably improve too, while the relative performances of the NOP and MIOP models with respect to their correlated versions slowly decrease.

Moreover, the NOP and MIOP models under the true OP d.g.p. perform much better than the OP model under the NOP and MIOP d.g.p.. As the sample size increases, the superiority in the performance of the OP model vis-â-vis the NOP and MIOP models under the OP d.g.p. even slightly decreases, whereas under the NOP and MIOP d.g.p. the superiority of the NOP and MIOP models over the OP model increases drastically. The superiority of the NOP(c) model over the OP model under both the NOP and NOP(c) d.g.p. as well as the superiority of the MIOP(c) model over the OP model under both the MIOP and MIOP(c) d.g.p. also increases sharply as the sample size grows. Under the NOP(c) and MIOP(c) d.g.p. the NOP model clearly outperforms the OP model, and this outperforming considerably improves as the sample size increases. The same applies to the MIOP model relative to the OP and NOP models under the MIOP(c) d.g.p..

Second, in terms of the *M-ratio* and *A-ratio* all of the models perform almost ideally:

[14] The values of the *Bias* in Tables 3.14 and 3.15 are multiplied by 1000.

the *A-ratio* is between 0.97 and 1.05 under all d.g.p., except for the MIOP model under the OP d.g.p., where it is between 0.90 (for 250 observations) and 0.96 (for 1000 observations). The distribution of the standard errors of the *PE* is slightly skewed to the right only for the samples with 250 observations; for larger samples the *M-ratio* and *A-ratio* are almost identical. Third, in terms of the *RMSEP*, under the OP d.g.p. the MIOP model outperforms the NOP model, and the latter is superior with respect to the OP model; under the NOP and NOP(c) d.g.p. the NOP(c) model outperforms the NOP model, and the latter performs better than the OP model; and under the MIOP and MIOP(c) d.g.p. the MIOP(c) model outperforms the MIOP model, the latter does better than the OP model, and the OP model outperforms the NOP model. In all cases, these differences deteriorate slowly as the sample size grows. Finally, the problems with the estimation were detected only for the MIOP, NOP(c) and MIOP(c) models in small samples: with 250 observations (less than 28 observations per parameter) the NOP(c) and MIOP(c) models have problems in 4.9-16.4% of runs, while with more than 45 observations per parameter they have problems in fewer than 4% of replications; and the MIOP model with fewer than 21 observations per parameter had problems in 3.5% of runs (basically, under the OP d.g.p. only), while with more than 40 observations per parameter in fewer than 2% of replications. As the sample grows, the problems with the estimation disappear.

Hypothesis testing and model selection

The results of the *Vuong* and *LR* tests are reported in Table 16 of Appendix B as the percentage of times when the test statistic is in favor of each model. All the tests are performed with the 95% nominal level.

Under any two-level d.g.p. the *Vuong* tests are in favor of the true model versus the OP model in 90-99% of replications with 250 observations, and even more overwhelmingly in 99.8-100% of replications with 500 or more observations. The two-level models are correctly favored more often as the sample size increases. However, under the OP d.g.p. the *Vuong* tests of the NOP and MIOP models versus the OP model fail to discriminate between the two models, and are never in favor of the true OP model but prefer the NOP and MIOP models in 0.8-7.5% of cases. The test statistic decreases with the sample size in favor of the OP model (since we are under the alternative hypothesis), though rather slowly. Under the MIOP and MIOP(c) d.g.p. the *Vuong* tests again mostly fail to discriminate between the NOP and OP models, but prefer the OP model, respectively, in 5.3-8.4% and 2.2-3.7% of runs, more often than the NOP model; and the test statistic decreases with the sample size in favor of the OP model.

The *LR* tests of the NOP versus NOP(c) and the MIOP versus MIOP(c) model (when the true d.g.p. is correlated) both have an empirical size between 4.1% and 5.8%, very close to the 5% nominal one. Under the alternative hypothesis, that is when the true d.g.p. is the NOP(c) or MIOP(c) model, the *Vuong* tests are in favor of the true models in 15-76% of cases; and the test statistics grow fast with the sample size in favor of the true model. The *LR* tests of the NOP versus MIOP model under the OP d.g.p. have empirical sizes ranging from 7.2% to 9% under the standard critical values, which are not valid because both models are now mis-specified; hence, the *LR* test statistics converge in distribution to the weighted sum of χ^2 distributions.

Table 17 of Appendix B reports the percentage of times when each of the information criteria and hit rate select each of the estimated models. Under the OP, NOP and MIOP d.g.p. all five information criteria for all sample sizes overwhelmingly select the true model: the *AIC* and *AICc* in 84.5-89.8%, while the *BIC*, *cAIC* and *HQIC* in 96.5-100% of cases; the *BIC* and *cAIC* have the best performance, in above 98.8% of cases, over all sample sizes. Under the NOP(c) and MIOP(c) d.g.p., the smaller the sample size the more all criteria are biased toward the less parameterized NOP and MIOP models, respectively. The *BIC* and *cAIC* select the uncorrelated versions for all sample sizes in 75.7-99.1% of cases. The *HQIC* prefers the uncorrelated versions in the samples with 250 and 500 observations in 66-89% of cases, but switches to the true correlated models with 1000 observations in 52-63% of cases. The *AIC* and *AICc* prefer the uncorrelated models only with 250 observations in 66-73% of cases, while in the larger samples they prefer the true models. Overall, while the *AIC* and *AICc* under the OP, NOP and MIOP d.g.p. select the true model slightly less frequently than the *BIC* and *cAIC*, under the NOP(c) and MIOP(c) d.g.p. they clearly outperform the *HQIC* and especially the *BIC* and *cAIC*.

The selection performance of the *Hit rate* is rather different. Under the NOP and MIOP d.g.p., it correctly selects the true model in only 47-57% of cases. Under the NOP(c) and MIOP(c) d.g.p., the *Hit rate* correctly prefers the true model only with 1000 observations, but marginally in 47-52% of cases; in smaller samples, it prefers the uncorrelated versions. Under the OP d.g.p. the *Hit rate* favors the OP model only in 35-40% of cases, while the NOP model does so in 32-36% of cases. Such low performance of the *Hit rate* is not surprising - the ML estimation is not optimized with respect to this measure of fit. Moreover, this goodness-of-fit statistic is based on the idea that is in discordance with the meaning of probabilities. The probabilities of each outcome mean that the alternative will be observed a certain fraction of times, but not that the outcome with the highest probability will be selected every time.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
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The effect of exclusion restrictions

In general, the identification of parameters of the two-level models is warranted by the non-linearity of the OP models; thus, there is no need in the exclusion restrictions on the specification of covariates in three latent equations to avoid the collinearity problems. In practice, however, the collinearity problems might still exist if most observations lie within the middle quasi-linear range of the normal c.d.f.. Then, without the explicit exclusion restrictions (for example, when $\mathbf{X}$, $\mathbf{Z}^{-}$ and $\mathbf{Z}^{+}$ are identical or have a large set of variables in common), the parameters can be estimated imprecisely, and the model can suffer from weak identification, lack of convergence and problems with invertibility of the Hessian. Hopefully, the specifications with the complete overlap of covariates in the latent equations are unlikely to be of empirical interest and supported by the data.

To assess the effect of exclusion restrictions on the performance of estimators, Table 18 of Appendix B reports the above measures of accuracy for five models with different sample sizes and under three different scenarios of the overlap among the covariates in the specifications of three latent equations: n - "no overlap", p - "partial overlap" and c - "complete overlap"[15]. The more exclusion restrictions the more accurate the estimates of the *PE,* and the fewer the problems with estimation. The simulation results suggest that the asymptotic estimator might not perform well without the exclusion restrictions, that is with the complete overlap among the covariates, in the small samples (fewer than 35 observations per parameter). In case of the NOP(c) and MIOP(c) models under the partial overlap scenario in the small samples there might be the problems with the convergence and invertibility of the Hessian.

3.5 An application to policy interest rate

> “It is highly desirable that policy practice be formalized to the maximum possible extent.”
>
> – W. Poole, then-President of the Federal Reserve Bank of St. Louis[16]
>
> “If (on Friday evening) you torture your data long enough, it will confess."
>
> – Unknown Ph.D. student

The policy rate is a key determinant of the other short-term market interest rates and of sharp interest for market participants: “What the market needs to know is the policy

[15] The values of the *Bias* in Table 3.18 are multiplied by 1000.
[16] See Poole (2006).

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician’s Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

response function by which the central bank acts in a consistent way over time" (Poole, 2003). Furthermore, "if practitioners in financial markets gain a better understanding of how policy is likely to respond to incoming information, asset prices and bond yields will tend to respond to economic data in ways that further the central bank's policy objectives" (Bernanke, 2007). Another important reason to model the policy rate is a search for better policy. In order to improve it, we have to obtain a clear empirical description of what is going to be improved. It is really hard to evaluate the monetary policy without describing it, using an econometric model.

3.5.1 Data

The proposed model is applied to explain the systematic components of policy interest rate decisions of the NBP. Since the adoption of direct inflation targeting in 1998 the NBP policy rate, the reference rate, may be undoubtedly treated as a principal instrument of Polish monetary policy[17]. The reference rate has been always set administratively by the MPC of the NBP and is not an outcome of the interaction between the market supply and demand. The MPC consists of ten members and makes policy rate decisions once per month by means of formal voting. The Council members are appointed for a non-renewable term of six years, but the Chair may serve for two consecutive terms. The first term lasted from February 1998 through January 2004[18]. The second term lasted from February 2004 through January 2010.

I employ the panel data on the individual votes of the MPC members and *real-time* macroeconomic data available at policy meetings in 1998-2009[19]. The MPC has always altered the levels of policy rates in discrete adjustments – the multiples of 25 basis points (bp) - made in the range from 25 to 250 bp. To provide reliable inference, the rate changes have been consolidated into three categories: "increase", "no change" and "decrease". Table 3.2 reports the frequency distribution of the dependent variable - the individual MPC members' votes for the changes to the rate in the period 1998/04 - 2009/12. At a monthly policy meeting each MPC member can express his or her preferred policy rate change and make a proposition to be voted on. If no proposition is made, there is no voting at all and the rate remains unchanged; otherwise, the Chair selects the largest proposed move and the members vote on it. If the first voted proposition commands a majority, then the others are not voted

[17] See Sirchenko (2008) and references therein for the background of monetary policy in Poland.

[18] However, one member was replaced before the policy meeting in January 2004, and another passed away, so his seat was filled midterm in August 2003. Because the first MPC Chair had resigned in December 2000, the Chair since then has been appointed with a three-year lag with respect to the other members.

[19] The data were taken from Sirchenko (2008) and updated till the end of 2009.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

on; otherwise, the members vote on the alternative one. As a matter of fact, the second voted proposal has always been passed. In case of two rounds of voting, the desired interest rate changes during the first round have been used in estimations. The first two meetings (in February and March 1998) of just established MPC have been dropped from the sample to account for a transition to a new policy regime of inflation targeting. The first meeting of the second MPC in February 2004 was also omitted. The policymakers have been absent at the meetings 15 times. Among the 1385 observations, used in estimations, the policymakers prefered to leave the rate unchanged 889 times (in 64 percent of cases).

The policy inclination decision is assumed to be driven by a direct response to new economic information, such as inflation developments, the prospects for the real economy, the spread between the long- and short-term market interest rates, and the recent change to the ECB policy rate. The amount decisions are expected to be driven by the tactical institutional factors such as the "policy bias" (or "balance of risks") statements, dissent among the policymakers and change to the rate at the previous policy meeting.

The indicator of policy bias $bias_t$ at the meeting t is defined as -1 if it is "easing", 0 if "neutral", and 1 if "restrictive". The measures of dissent among the policymakers are calculated as follows. Consider a committee with M members. For each i member and each policy-setting meeting t define the individual dissent indicator

$$d_{it} = \begin{cases} 1 & \text{if } \Delta y_{it} > \Delta nbpr_t, \\ 0 & \text{if } \Delta y_{it} = \Delta nbpr_t, \\ \text{-1} & \text{if } \Delta y_{it} < \Delta nbpr_t, \end{cases} \tag{3.15}$$

where Δy_{it} is the change to the reference rate preferred by member i and $\Delta nbpr_t$ is the change made by the MPC. The measure of dissent at the meeting t is then defined as the average of individual dissents across all MPC members:

$$dissent_t = \frac{1}{M}\sum_{i=1}^{M} d_{it}. \tag{3.16}$$

Table 3.21 of Appendix C reports for each MPC meeting the values of policy bias indicator $bias_t$, overall dissent at the meeting $dissent_t$ and policy rate decision of the Council. As Table 3.22 of Appendix C shows for each MPC member, the average values of individual dissents across all meetings are between -0.232 and 0.400.

A dummy variable for the expected inflation above the official inflation target is included into $\mathbf{Z}^+$only. The change to the rate at the last policy meeting is allowed to enter all three

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

equations. The detailed definitions of all variables used in the study are given in Table 3.3. The sample descriptive statistics is shown in Table 3.20 of Appendix C.

To account for the unobserved individual heterogeneity of policy preferences, I consider two alternative specifications of the MIOP and MIOP(c) models[20]. Both specifications include the following common covariates: in $\mathbf{X}$ - Δcpi, *situation*, *spread*, $\Delta ecbr$, $\Delta nbpr$; in $\mathbf{Z}^-$ - $\Delta nbpr$, *dissent*, *bias*; and in $\mathbf{Z}^+$ - $\Delta nbpr$, *dissent*, *bias*, $I(cpi^e > tar)$. In addition to the above, the fixed effects (FE) specification includes twenty dummy variables for individual MPC members, included as intercepts into all three latent equations[21]. The FE specification is an appropriate approach here, because we don't have a sample of individuals drawn randomly from a large population, but possess instead a full set of all twenty-one MPC members. Given that the cross-sectional dimension ($N = 21$) is small relative to the observed numbers of time periods (T_i are about 67 on average, ranging from 35 to 76), we don't have the "incidental parameters" problem. Neither should we expect any significant fixed T bias with such a large temporal size. Alternatively, the hawk- & dove-dummy (HD) specification is more parsimonious and includes only two dummy variables $I(h)_{it}$ and $I(d)_{it}$, defined for $t \geq 2$ as 1 if the average individual dissent (from the first up to the previous MPC meeting) is above 0.1 or below -0.1, and 0 - otherwise:

$$I(h)_{it} = \begin{cases} 1 & \text{if } \frac{1}{t-1}\sum_{j=1}^{t-1} d_{i,t-1} > 0.1, \\ 0 & \text{otherwise,} \end{cases} \quad \text{and } I(d)_{it} = \begin{cases} 1 & \text{if } \frac{1}{t-1}\sum_{j=1}^{t-1} d_{i,t-1} < -0.1, \\ 0 & \text{otherwise.} \end{cases} \tag{3.17}$$

3.5.2 Estimation results

The six competing models were estimated using the same set of explanatory variables: the conventional single-equation OP model, using all the covariates in $\mathbf{X}$, $\mathbf{Z}^-$ and $\mathbf{Z}^+$; the multinomial probit (MNP) model, using all the covariates in $\mathbf{X}$, $\mathbf{Z}^-$ and $\mathbf{Z}^+$; the two-equation ZIOP model that allows the zero observations to come from two different processes, using all the covariates in $\mathbf{X}$, $\mathbf{Z}^-$ and $\mathbf{Z}^+$ at both equations; the ZIOP(a) model, which is identical to the ZIOP model, except that all the covariates in the participation equation are taken by their absolute values; and the three-equation MIOP and MIOP(c) models with different sets of covariates in each equation. To give the ZIOP and ZIOP(a) models better chances all the

[20] Since the model is highly non-linear, failure to address the heterogeneity can lead to a bias, not just inefficiency, even if all covariates are truly exogenous, whereas no bias emerges in the linear case.

[21] The individual dummy for Gronkiewicz-Waltz, the first MPC Chair (in 1998-2000) and the only MPC member in the sample, who has never dissended, is omitted.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

MIOP covariates are included into both parts, contrary to the three-part models. Moreover, the ZIOP(a) model is allowed to have the modified values of covariates in the participation equation to take into account the binary (change versus no change) nature of the first-stage decision.

Tables 3.4 and 3.5 reports the summary statistics from seven alternative models. The two- and three-equation models demonstrate a sharp increase in the likelihood and hit rate compared to the single-equation ones. The MIOP model is overwhelmingly superior to the others according to all information criteria and the *Vuong* tests. The MIOP(c) model exhibits insignificant increase in the likelihood according to the *LR* test. The estimated correlation coefficients ρ^- and ρ^+ (and their standard errors in parentheses) are 0.77(0.36) and 0.18(0.36), respectively. The contingency tables for the OP and MIOP models are contrasted in Table 3.6. The latter demonstrates the drastic improvement in the correct predictions of cuts and hikes to the rate, while the simple OP model, as typical, tends to overpredict the most observed no-change decisions.

The details for the specifications and estimated coefficients of OP, ZIOP, MIOP and MIOP(c) models are presented in Tables 3.23, 3.24 and 3.25 of Appendix C. The coefficient on the last change to the NBP policy rate ΔRR_{t-1} has the positive sign in the policy inclination equation, but the negative sign in the amount equations of the MIOP model. The policy inclination decision indeed appears to be driven by reaction to the economic situation. The coefficients on policy bias $Bias_{t-1}$ and dissent among the policymakers $Dissent_{t-1}$ are not significant if included into $\mathbf{X}_i$, but are highly significant if included into $\mathbf{Z}_i^-$ and $\mathbf{Z}_i^+$ in both amount equations.

The *PE* on the probabilities in the OP and MIOP models are compared in Table 3.7. The OP and MIOP models have the opposite signs of the *PE* of ΔRR_{t-1} on the probabilities of all three alternatives.

Figure 3.4 shows the predicted probabilities for the range of ΔRR_{t-1} and three values of $Bias_{t-1}$, holding the rest of explanatory variables at their sample median values. The decomposition of $\Pr(\Delta y_{it} = 0)$ into three components (the loose, neutral and tight zeros) is also plotted on the right side. If the rate was reduced at the last MPC meeting by 25 bp and if the policy bias was easing, then $\Pr(\Delta y_{it} = 0)$ is totally dominated by the neutral zeros. If the policy bias was neutral, then $\Pr(\Delta y_{it} = 0)$ is composed by 26.3% of the loose zeros and 73.7% of the neutral zeros. If the policy bias was tightening, then $\Pr(\Delta y_{it} = 0)$ is composed by 75.9% of the loose zeros and 24.1% of the neutral zeros. However, if the rate was increased by 50 bp and the policy bias was easing, then $\Pr(\Delta y_{it} = 0)$ consists of 68.0% of the neutral zeros and 32.0% of the tight zeros. If the policy bias was neutral, then

$\Pr(\Delta y_{it} = 0)$ consists of 75.2% of the neutral zeros and 24.8% of the tight zeros. Finally, if the policy bias was tightening, then $\Pr(\Delta y_{it} = 0)$ is composed by 97.3% of the neutral zeros and only 2.7% of the tight zeros.

In Table 3.8 the partial effects on $\Pr(\Delta y_{it} = 0)$ are decomposed into three components (coming from the loose, neutral and tight regimes).

3.6 Conclusions

> "The model is often smarter than you are. ...(T)he act of putting your thoughts together into a coherent model often forces you into conclusions you never intended..."
>
> -Paul Krugman[22]

The ordinal responses, when a decisionmaker faces the choices to reduce, leave unchanged or increase (e.g., changes to the prices, rankings or policy interest rates) or when he has to indicate the negative, neutral or positive attitudes or opinions, are often characterized by the abundant observations in the middle neutral or zero category (indifferent attitude to survey questions, or no change to the ranking or rate). Such excessive "zeros" can be generated by different groups of population or separate decision-making processes. Besides, the "positive" and "negative" outcomes can be driven by distinct sources. In such situations, it would be a misspecification to treat all the observations as coming from the same d.g.p., and to apply a standard ordered-response model based on a single latent equation. This paper develops a more flexible cross-nested model for such types of the ordinal variables, combining three OP latent equations with different sets of covariates.

The proposed MIOP model allows the separate mechanisms to determine what we call the *inclination* decision ($\Delta y \leq 0$ versus $\Delta y = 0$ versus $\Delta y \geq 0$, interpreted as a loose, neutral or tight policy *stance*) and two *amount* decisions (the magnitude of Δy when it is nonpositive or nonnegative), conditional on the loose or tight policy stance. The inclination decision is driven by reaction to the changes in the macroeconomic environment, whereas the amount decisions allow policy stance to be offset by the tactical and institutional features of monetary policymaking. The probability of a no-change outcome is inflated, since there are the following three types of zeros: the "always" or "neutral" zeros, generated directly by the neutral policy reaction to the economic developments; and two kinds of "not-always" or "offset" zeros, the "loose" and "tight" zeros, generated by the loose or tight policy inclina-

[22] From the essay "Delusions of Growth" in Krugman (1999).

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

tions offset by the tactical reasons. The model also allows for the possible correlation among three latent decisions.

The Monte Carlo results suggest good performance of the model in the finite samples and demonstrate its superiority with respect to the conventional and nested OP models.

The MIOP model is then applied to explain policy rate decisions of the National Bank of Poland, using the panel of the individual votes of MPC members and real-time macroeconomic data available at the MPC meetings. The two-step three-regime approach attempts to address the worldwide stylized facts of interest rate setting such as discreteness, preponderance of no-change decisions and inertia. The voting preferences appeared to be well modelled by such an approach. Not only does it fit the data much better, but it also has some important advantages over the single- and two-equation models, such as the standard OP, multinomial probit and zero-inflated OP models. The empirical application demonstrates the advantages of the MIOP model in separating different decision-making paths for three types of zeros and estimating the proportion of zeros generated by each regime.

In particular, the MIOP model is able to identify the driving factors in each regime: some explanatory variables, statistically significant at the amount decisions, do not have an impact on the policy inclination one. Another important covariate, the rate change at the previous MPC meeting, has the opposing impacts on the two decisions. It means, for example, that the rate hike at the last meeting increases the probability of the tight policy stance at the next meeting, but reduces the probability of the rate hike conditional on the tight policy regime and increases the probability of the rate cut conditional on the loose stance. The conventional OP model, based on a single latent equation, is shown to confuse the marginal effects of the explanatory variables that have an impact only on one decision or opposing impacts on both decisions. Besides, the proper estimation of the marginal effects of the explanatory variables is shown to exhibit the presence of a non-monotonic relationship between these variables and outcome probabilities. It might have the important implications for the statistical inference since the OP model fails to detect such non-monotonic patterns.

Although the proposed approach indeed tends to require larger sample sizes (with 40 or more observations per parameter) than the usual OP model due to the heavier parameterization involved, the simulations suggest that the estimation of smaller data sets using the MIOP model could still provide the more accurate inference if there is a mixture of different d.g.p. in the sample.

The proposed models can be further extended by allowing for the serial correlation among the latent residuals and employing the dynamic OP specifications (Eichengreen, Watson and Grossman, 1985) of three latent equations, estimated via the Gibbs sampler.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

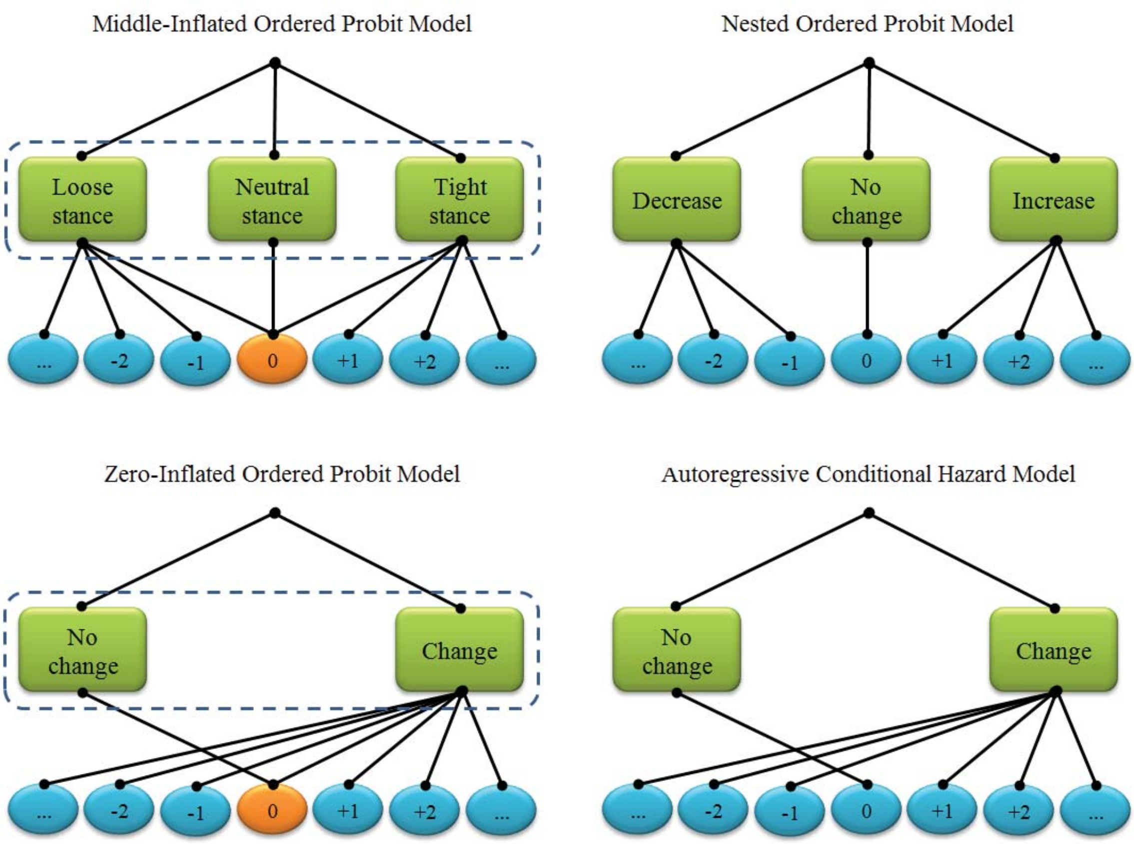
It is quite plausible that the intermediate categories (such as ± 25 bp changes to policy rates) can be also inflated and characterized by two types of observations, coming either from the loose (tight) or neutral policy stance. By adding the third amount equation with three outcome categories (no change and 25 bp cut and hike), which are conditional on the neutral policy regime, the resulting extended MIOP model will allow for inflation in the three middle categories.

In addition to the above, the presented statistical framework can be used as a basis to develop an inflated multinomial logit/probit model for unordered categorical data.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

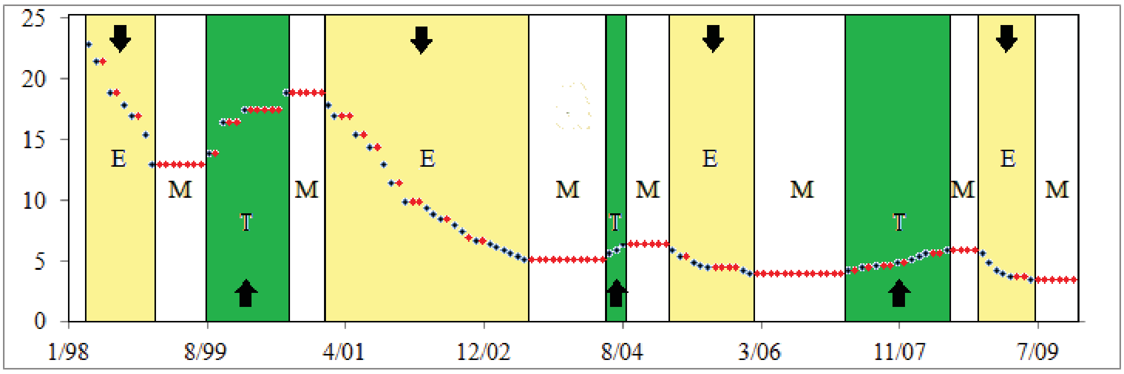
3.7 Figures

Figure 3.1: Decision trees of the MIOP, NOP, ZIOP and ACH models



Sirchenko, Andrei (2012), A Discrete-Choice Econometrician’s Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Figure 3.2: Reference rate of the National Bank of Poland



Notes: E/M/T denote the periods of policy easing/maintaining/tightening.

Figure 3.3: Histograms of CPI changes observed during decisions to reduce, increase or leave the rate unchanged between the reversals

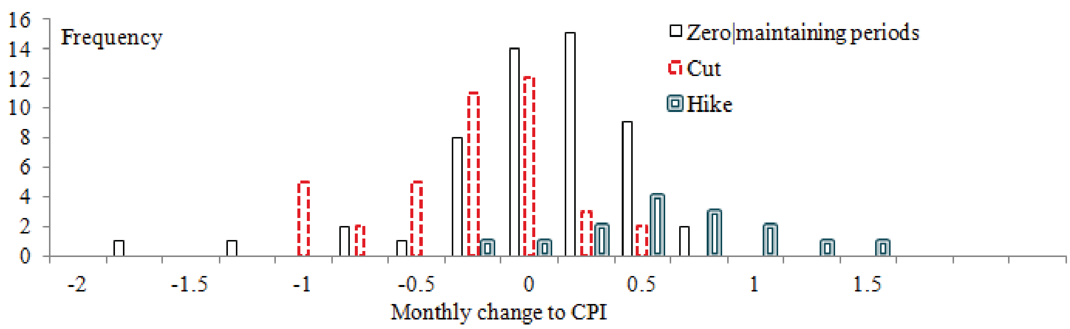


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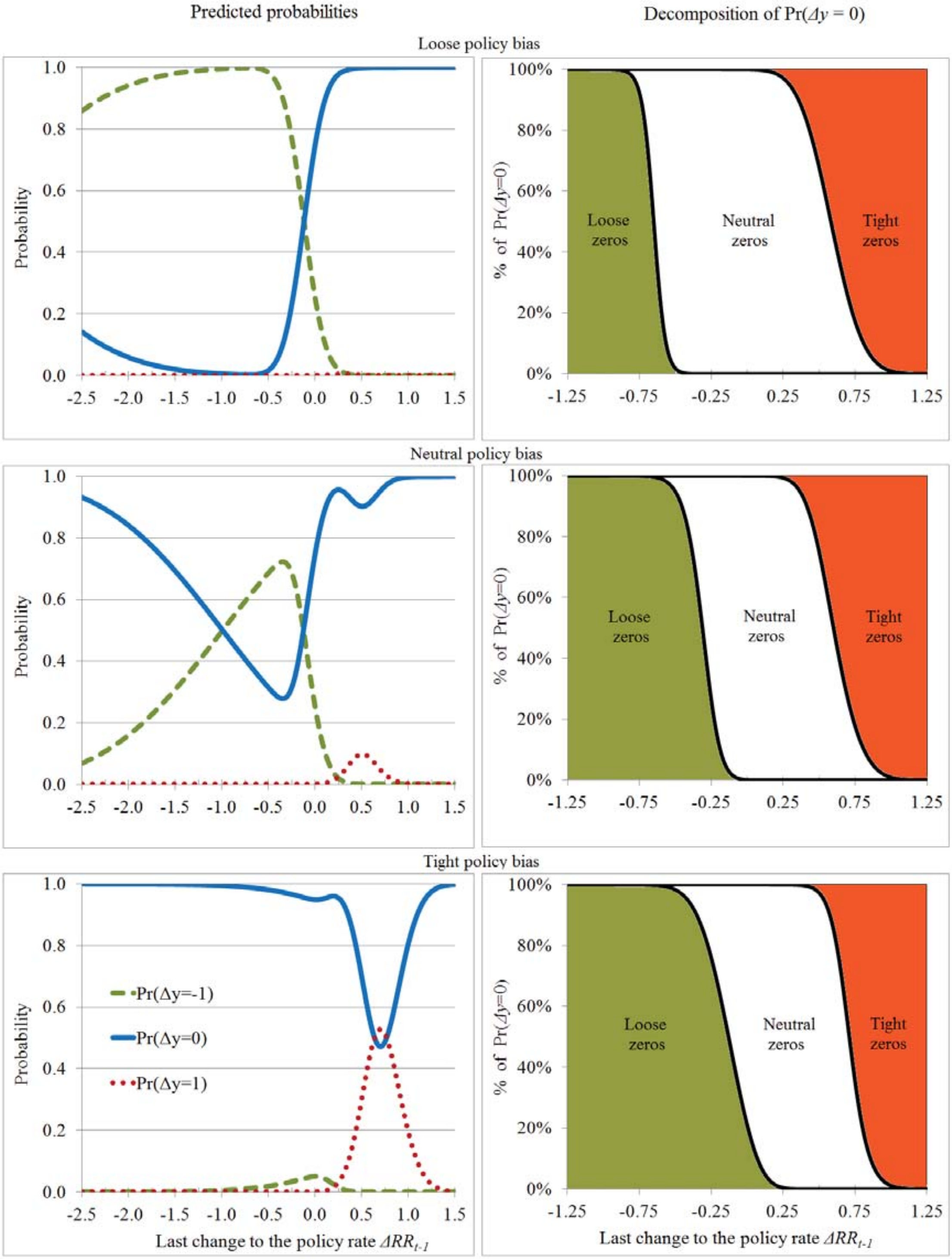
Figure 3.4: Changes to policy rate: predicted probabilities by rate change and policy bias at last meeting



3.8 Tables

Table 3.1: Average economic conditions observed at policy rate decisions of NBP

Policy period	Policy decision	*spread*	*situation*	Δcpi	*cpi - tar*
Easing	Decrease	-0.68	8.93	-0.35	-0.58
	No change	-0.71	8.29	-0.16	-0.53
Maintaining	No change	0.16	15.15	-0.05	0.11
Tightening	No change	0.25	19.80	0.17	1.90
	Increase	0.63	20.31	0.53	1.53

Notes: Sample period is from 03/1998 through 12/2009; the sub-periods of easing, maintaining and tightening the policy are shown in Figure 2; *spread* - difference between 12- and 1-month Poland interbank rate; *situation* - index of expected general economic situation in industry from Business Tendency Survey; Δcpi - recent monthly change to consumer price index; *cpi - tar* - deviation of consumer price index from NBP inflation target.

Table 3.2: Frequency distribution of the MPC votes

Δy_{it} (preferred change to the rate by member i)	Decrease	No change	Increase	All
Number of observations	309	889	187	1385
%	22%	64%	14%	100%

Notes: The sample period is from 04/1998 through 12/2009. The first meeting of the second MPC in February 2004 is omitted.

 DOI: 10.2870/60780

Table 3.3: Definitions of variables

Mnemonics	Variable description (source of data)
	Dependent variable
Δy_i	Change to NBP reference rate, preferred by i MPC member: 1 if an increase, 0 if no change, -1 if a decrease (NBP).
	Variables in **X** only
Δcpi	Last monthly change to consumer price index (CPI), annual rate in percent (GUS - Central Statistical Office of Poland).
situation	Index of expected general economic situation in industry from Business Tendency Survey, divided by 100 (GUS).
spread	Difference between 12- and 1-month Poland interbank offer rate, 5-business-day moving average, annualized percent (Thompson Reuters).
$\Delta ecbr$	Change to the ECB policy rate (since 02/1999, in 1998 - to Bundesbank policy rate, set equal to zero in 01/1999), announced at the last policy meeting, annualized percent (ECB and Bundesbank).
	Variables in **X**, $\mathbf{Z}^-$ and $\mathbf{Z}^+$
$\Delta nbpr$	Change to the NBP reference rate, announced at the last policy meeting, annualized percent (NBP).
$I(h)_i$	1 if the average $Dissent_i$ (from the first up to the last MPC meeting) is greater than 0.1, 0 - otherwise; see Eq.(17).
$I(d)_i$	1 if the average $Dissent_i$ (from the first up to the last MPC meeting) is less than -0.1, 0 - otherwise; see Eq.(17).
$I(Bal)_i$	1 if i MPC member is Balcerowicz, and 0 otherwise. The other MPC members are coded as: *Cze* - Czekaj, *Dab* - Dąbrowski, *Fil* - Filar, *Gra* - Grabowski, *Gro* - Gronkiewicz-Waltz, *Joz* - Józefiak, *Krz* - Krzyżewski, *Lac* - Łączkowski, *Nie* - Nieckarz, *Nog* - Noga, *Ows* - Owsiak, *Pie* - Pietrewicz, *Pru* - Pruski, *Ros* - Rosati, *Skr* - Skrzypek, *Sla* - Sławiński, *Was* - Wasilewska-Trenkner, *Woj* - Wojtyna, *Wojz* - Wójtowicz, *Zio* - Ziółkowska.
	Variables in $\mathbf{Z}^-$ and/or $\mathbf{Z}^+$ only
dissent	Measure of dissent at the last MPC meeting from Eq. (15) (NBP).
bias	Indicator of "policy bias" or "balance of risks" statements (available since 02/2000, set equal to zero before): -1 if "easing", 0 if "neutral", and 1 if "restrictive" (NBP).
$I(cpi^e > tar)$	1 if $cpi^e > tar$, and 0 otherwise; tar is the official inflation target; cpi^e is the expected CPI over next 12 months, annual rate in percent (Ipsos-Demoskop survey of consumers and NBP).

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Table 3.4: Changes to policy rate: comparison of alternative models with fixed effects specification

Model	REOP	OP	GOP	MNP	ZIOP	ZIOPa	MIOP
ln $l(\theta)$	-728.5	-696.1	-640.9	-639.1	-580.7	-559.3	-502.6
# of parameters	11	30	58	58	59	59	78
AIC	1479.1	1452.1	1397.7	1394.2	1279.4	1236.6	**1161.2**
BIC	1536.6	1609.1	1701.3	1697.7	1588.2	**1545.3**	1569.4
Corrected *AIC*	1547.7	1639.1	1759.7	1755.7	1647.2	**1604.3**	1647.4
HQIC	1500.6	1510.9	1511.4	1507.7	1394.9	1352.1	**1313.9**
Hit rate		0.745		0.760	0.804	0.816	0.833
Vuong vs OP					-6.98**	-8.31**	-11.41**
Vuong vs ZIOP						-1.92	-4.81**
Vuong vs ZIOPa							-3.94**

Notes: **/* denote statistical significance at 1/5 percent level, respectively.

Table 3.5: Changes to policy rate: comparison of alternative models with dummies for hawkish and dovish policymakers

Model	OP	GOP	MNP	ZIOP	ZIOPa	MIOP	MIOPc
ln $l(\theta)$	-715.1	-684.6	-682.4	-631.4	-586.6	-557.1	-556.7
# of parameters	12	22	22	23	23	22	24
AIC	1454.2	1413.2	1408.9	1308.8	1219.1	**1158.2**	1161.3
BIC	1517.0	1528.4	1524.0	1429.2	1339.5	**1273.3**	1286.9
Corrected *AIC*	1529.0	1550.5	1546.0	1452.2	1362.5	**1295.3**	1310.9
HQIC	1477.7	1456.3	1451.9	1353.9	1264.2	**1201.3**	1208.3
Hit rate	0.749		0.773	0.783	0.793	0.828	0.829
Vuong vs OP				-5.92**	-7.57**	-8.48**	-8.69**
Vuong vs ZIOP					-4.19**	-4.50**	-4.65**
Vuong vs ZIOPa						-2.06*	-2.15*
LR vs MIOP							0.87

Notes: **/* denote statistical significance at 1/5 percent level, respectively.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 3.6: Changes the policy rate: contingency tables for OP and MIOP models

	Predicted outcomes						
Actual outcomes	Cut	No change	Hike	Cut	No change	Hike	Total
	Specification with fixed effects						
	OP model			MIOP model			
Cut	**152**	157	0	**243**	66	0	309
No change	103	**758**	28	74	**767**	48	889
Hike	0	65	**122**	0	43	**144**	187
Total	255	980	150	317	876	192	1385
	Specification with dummies for hawks and doves						
	OP model			MIOP model			
Cut	**167**	142	0	**237**	72	0	300
No change	94	**746**	49	72	**771**	46	898
Hike	0	62	**125**	0	48	**139**	187
Total	261	950	174	309	891	185	1385

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Table 3.7: Changes to the policy rate: partial effects of covariates on probabilities in OP, ZIOP and MIOP models

	Pr(Δy_i = "decrease")			Pr(Δy_i = "no change")			Pr(Δy_i = "increase")		
	OP	ZIOP	MIOP	OP	ZIOP	MIOP	OP	ZIOP	MIOP
spread	-0.137***	-0.004	-0.287***	0.122***	0.014	0.269***	0.015***	-0.010	0.018**
	(0.015)	(0.012)	(0.049)	(0.016)	(0.045)	(0.051)	(0.004)	(0.033)	(0.009)
Δecbr	-0.057***	0.051	-0.061***	0.044***	-0.197**	0.042**	0.013***	0.146**	0.018**
	(0.009)	(0.042)	(0.016)	(0.008)	(0.086)	(0.017)	(0.004)	(0.065)	(0.009)
situation	-0.136*	-0.164	-0.613***	0.121*	0.635*	0.574***	0.015	-0.471*	0.039*
	(0.076)	(0.158)	(0.148)	(0.067)	(0.376)	(0.144)	(0.010)	(0.272)	(0.020)
Δcpi	-0.172***	0.179	-0.458***	0.153***	-0.695**	0.429***	0.019***	0.515**	0.029**
	(0.024)	(0.149)	(0.088)	(0.023)	(0.324)	(0.089)	(0.005)	(0.251)	(0.014)
Δnbpr	0.021***	0.102	-0.065***	-0.019***	-0.190***	0.058***	-0.002***	0.088*	0.007
	(0.005)	(0.063)	(0.016)	(0.005)	(0.068)	(0.018)	(0.001)	(0.049)	(0.005)
$I(h)_i$	-0.089***	-0.037	-0.067***	0.043***	0.168*	-0.037	0.046***	-0.131	0.103***
	(0.013)	(0.037)	(0.019)	(0.014)	(0.101)	(0.030)	(0.012)	(0.086)	(0.030)
$I(d)_i$	0.174***	-0.044	0.162***	-0.167***	0.124	-0.159***	-0.006***	-0.081	-0.003*
	(0.036)	(0.038)	(0.056)	(0.036)	(0.085)	(0.056)	(0.002)	(0.066)	(0.002)
bias	-0.101***	-0.035	-0.062***	0.005	0.015	0.049***	0.096***	0.019	0.012**
	(0.014)	(0.027)	(0.018)	(0.020)	(0.012)	(0.018)	(0.013)	(0.019)	(0.006)
dissent	-0.231***	-0.119	-0.042**	0.206***	0.039	0.036**	0.025***	0.080	0.006
	(0.042)	(0.085)	(0.017)	(0.041)	(0.033)	(0.017)	(0.007)	(0.069)	(0.004)
$I(cpi^e>tar)$	-0.017	-0.090		0.016	-0.003	-0.003*	0.002	0.093	0.003*
	(0.017)	(0.066)		(0.015)	(0.011)	(0.002)	(0.002)	(0.063)	(0.002)

Notes: ***/**/* denote statistical significance at 1/5/10 percent level, respectively.
Standard errors are in parantheses.

Table 3.8: Changes to the policy rate: partial effects of covariates on probabilities in OP, ZIOP and MIOP models

Covariates	Pr(Δy_i = "no change")		
	Loose stance	Neutral stance	Tight stance
spread	-0.101 (0.025)***	0.274 (0.084)***	0.095 (0.039)**
Δecbr	-0.021 (0.007)***	-0.033 (0.045)	0.097 (0.037)***
situation	-0.215 (0.062)***	0.586 (0.205)***	0.204 (0.088)**
Δcpi	-0.161 (0.041)***	0.437 (0.139)***	0.152 (0.063)**
Δnbpr	-0.023 (0.007)***	-0.090 (0.080)	0.171 (0.070)**
$I(h)_i$	-0.020 (0.007)***	-0.084 (0.050)*	0.067 (0.035)*
$I(d)_i$	-0.006 (0.011)	-0.139 (0.058)**	-0.014 (0.007)*
bias	0.062 (0.018)***		-0.012 (0.006)**
dissent	0.042 (0.017)**		-0.006 (0.004)
$I(cpi^e > tar)$			-0.003 (0.002)*

Notes: ***/**/* denote statistical significance at 1/5/10 percent level, respectively.
Standard errors are in parantheses.

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Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

3.10 Appendix A: Details of Monte Carlo design

Three vectors of covariates $\mathbf{v_1}$, $\mathbf{v_2}$ and $\mathbf{v_3}$ were drawn once (and held fixed in all simulations) as $\mathbf{v_1} \overset{iid}{\sim} Normal(0,1) + 2$, $\mathbf{v_2} \overset{iid}{\sim} Normal(0,1)$, and $\mathbf{v_3} = -1$ if $\mathbf{w} \leq 0.3$, 0 if $0.3 < \mathbf{w} \leq 0.7$, or 1 if $0.7 < \mathbf{w}$, where $\mathbf{w} \overset{iid}{\sim} Uniform[0,1]$[23]. The dependent variable was generated with five outcome categories: -0.5, -0.25, 0, 0.25 and 0.50. The values of the parameters were calibrated to yield on average the following frequencies of the above outcomes : 7%, 14%, 58%, 14% and 7%, respectively, which are close to the empirical ones. The vectors of disturbance terms in the latent equations were repeatedly generated as *iid* $Normal(0,1)$ in the case of OP, NOP and MIOP *dgp*, whereas in the case of NOP(c) and MIOP(c) models the errors $\boldsymbol{\nu}$ were generated as *iid* $Normal(0,1)$, but the errors $\boldsymbol{\varepsilon}^-$ and $\boldsymbol{\varepsilon}^+$ were drawn so that $(\boldsymbol{\nu}, \boldsymbol{\varepsilon}^-)$ and $(\boldsymbol{\nu}, \boldsymbol{\varepsilon}^+)$ are standardized bivariate normal *iid* with correlation coefficients ρ^- and ρ^+, respectively.

In case of the OP *dgp* the repeated samples were generated with the data matrix $(\mathbf{v_1}, \mathbf{v_2})$, vector of slope coefficients $(0.4, 0.8)'$ and vector of cutpoints $(-1.83, -1.01, 1.01, 1.83)'$. In case of the NOP *dgp* the repeated samples were generated with $\mathbf{X} = \mathbf{v_1}$, $\mathbf{Z}^- = \mathbf{v_2}$, $\mathbf{Z}^+ = \mathbf{v_3}$, $\boldsymbol{\beta} = 0.6$, $\boldsymbol{\gamma} = 0.8$, $\boldsymbol{\delta} = 0.9$, $\boldsymbol{\alpha} = (0.26,\ 2.14)'$, $\boldsymbol{\mu}^- =$ -0.54 and $\boldsymbol{\mu}^+ = 0.54$ under the "no overlap" scenario; $\mathbf{X} = (\mathbf{v_1}, \mathbf{v_2})$, $\mathbf{Z}^- = (\mathbf{v_1}, \mathbf{v_3})$, $\mathbf{Z}^+ = (\mathbf{v_2}, \mathbf{v_3})$, $\boldsymbol{\beta} = (0.6,\ 0.4)'$, $\boldsymbol{\gamma} = (0.2,\ 0.3)'$, $\boldsymbol{\delta} = (0.3,\ 0.9)'$, $\boldsymbol{\alpha} = (0.21,\ 2.19)'$, $\boldsymbol{\mu}^- =$ -0.17 and $\boldsymbol{\mu}^+ = 0.68$ under the "partial overlap" scenario; and $\mathbf{X} = \mathbf{Z}^- = \mathbf{Z}^+ = (\mathbf{v_1}, \mathbf{v_2}, \mathbf{v_3})$, $\boldsymbol{\beta} = (0.6,\ 0.4,\ 0.8)'$, $\boldsymbol{\gamma} = (0.2,\ 0.8,\ 0.3)'$, $\boldsymbol{\delta} = (0.4,\ 0.3,\ 0.9)'$, $\boldsymbol{\alpha} = (0.09,\ 2.32)'$, $\boldsymbol{\mu}^- =$ -0.72 and $\boldsymbol{\mu}^+ = 2.12$ under the "complete overlap" scenario. In case of the MIOP *dgp* the values of $\mathbf{X}$, $\mathbf{Z}^-$, $\mathbf{Z}^+$, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, and $\boldsymbol{\delta}$ were the same as under the NOP *dgp*, while the vectors of thresholds were different: $\boldsymbol{\alpha} = (0.95,\ 1.45)'$, $\boldsymbol{\mu}^- = (-1.22,\ 0.03)'$ and $\boldsymbol{\mu}^+ = (-0.03,\ 1.18)'$ with no overlap; $\boldsymbol{\alpha} = (0.9,\ 1.5)'$, $\boldsymbol{\mu}^- = (-0.67,\ 0.36)'$ and $\boldsymbol{\mu}^+ = (0.02,\ 1.28)'$ with partial overlap; and $\boldsymbol{\alpha} = (0.85,\ 1.55)'$, $\boldsymbol{\mu}^- = (-1.2,\ 0.07)'$ and $\boldsymbol{\mu}^+ = (1.28,\ 2.5)'$ with complete overlap. In case of the NOP(c) *dgp* the repeated samples were generated with $\rho^- = 0.3$, $\rho^+ = 0.6$, and all the data matrices and other parameters (except $\boldsymbol{\mu}^-$ and $\boldsymbol{\mu}^+$) the same as under the NOP *dgp*; the values of $\boldsymbol{\mu}^-$ and $\boldsymbol{\mu}^+$ were set, respectively, to -0.9 and 1.2 with no overlap, -0.5 and 1.31 with partial overlap, and -1 and 2.58 with complete overlap. In case of the MIOP(c) *dgp* the repeated samples were generated with $\rho^- = 0.3$, $\rho^+ = 0.6$, and all the data matrices and other parameters (except the thresholds) the same as under the MIOP *dgp*; the values of $\boldsymbol{\alpha}$, $\boldsymbol{\mu}^-$ and $\boldsymbol{\mu}^+$ were set, respectively, to $(0.91,\ 1.49)'$, $(-1.43,\ -0.18)'$ and $(0.42,\ 1.58)'$ with no overlap, $(0.9,\ 1.5)'$, $(-0.88,\ 0.12)'$ and $(.49,\ 1.67)'$ with

[23]Since the dependent variable represents the changes to the interest rate made once per month, the covariates $\mathbf{v_1}$, $\mathbf{v_2}$ and $\mathbf{v_3}$ mimic such variables as the output growth rate, the monthly change to the inflation rate and an indicator variable for the central bank's "policy bias" statement (-1 if it is easing, 0 if neutral, 1 if tightening), respectively.

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partial overlap, and (0.86, 1.55)$'$, (-1.35, -0.15)$'$ and (1.7, 2.72)$'$ with complete overlap.

All competing models were always estimated using the same set of covariates. Under the OP *dgp* the three models were estimated: the OP model with data matrix $\mathbf{X} = (\mathbf{v_1}, \mathbf{v_2})$, and the NOP and MOP models with $\mathbf{X} = \mathbf{Z}^{-}= \mathbf{Z}^{+} = (\mathbf{v_1}, \mathbf{v_2})$. Under the NOP and NOP(c) *dgp* the following three models were estimated: the OP model with $\mathbf{X} = (\mathbf{v_1}, \mathbf{v_2}, \mathbf{v_3})$ for all scenarios, and both the NOP and NOP(c) models with the same sets of covariates in each latent equation as in the *dgp*. Finally, under the MIOP and MIOP(c) *dgp* the four models were estimated: the OP model with $\mathbf{X} = (\mathbf{v_1}, \mathbf{v_2}, \mathbf{v_3})$ for all scenarios, and the NOP, MIOP and MIOP(c) models with the same sets of covariates in each latent equation as in the *dgp*.

The starting values for $\boldsymbol{\beta}$, $\boldsymbol{\alpha}$, $\boldsymbol{\gamma}$, $\boldsymbol{\mu}^{-}$, $\boldsymbol{\delta}$ and $\boldsymbol{\mu}^{+}$ were obtained using independent ordered probit estimations of each of the three latent equations. The starting values for each independent ordered probit model were computed using the linear OLS estimations. The starting values for ρ^{-} and ρ^{+} were obtained by maximizing the loglikelihood functions of the correlated models holding the other parameters fixed at their estimates in the corresponding uncorrelated model.

3.11 Appendix B: Summary of Monte Carlo results

This appendix reports the brief summary of the Monte Carlo simulations. The more detailed results are available upon request.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 3.9: Accuracy of estimated slope coefficients β, γ, and δ

Sample size	True *dgp* and estimated model:	OP	NOP			NOPc			MIOP			MIOPc		
	Overlap:		n	p	c	n	p	c	n	p	c	n	p	c
250	Number of	41.7	35.7	25.0	19.2	27.8	20.8	16.7	27.8	20.8	16.7	22.7	17.9	14.7
500	observations	83.3	71.4	50.0	38.5	55.6	41.7	33.3	55.6	41.7	33.3	45.5	35.7	29.4
1000	per parameter	166.7	142.9	100.0	76.9	111.1	83.3	66.7	111.1	83.3	66.7	90.9	71.4	58.8
250		0.89	5.52	3.56	7.54	3.08	3.71	8.74	4.42	3.41	6.05	2.31	3.38	11.88
500	*Bias*	0.60	2.24	1.39	2.62	1.52	1.36	11.71	2.25	1.85	2.53	1.13	1.64	10.62
1000		0.09	1.06	0.55	1.03	0.57	0.59	10.66	0.84	1.07	1.89	0.53	0.72	7.94
250		0.94	2.66	2.46	4.65	2.67	2.55	3.31	2.19	2.34	4.03	2.09	2.31	3.98
500	*RMSE*	0.63	1.54	1.39	1.70	1.51	1.47	2.62	1.43	1.51	2.32	1.42	1.54	2.90
1000		0.46	1.03	0.95	1.10	1.07	1.01	2.19	1.00	1.04	1.61	0.98	1.04	2.16
250		94.8	96.0	95.1	95.3	95.6	94.4	93.4	92.7	91.7	85.1	94.1	90.9	86.6
500	*CP*, %	95.5	95.2	95.4	95.0	95.2	94.5	91.4	93.8	92.8	85.5	94.2	91.7	87.3
1000		95.5	95.0	95.1	95.0	94.6	94.5	90.7	94.1	93.1	86.8	94.7	92.9	88.7
250		0.98	0.85	0.89	0.72	0.88	0.91	1.27	0.89	0.83	0.62	0.93	0.83	0.77
500	*M-ratio*	1.02	0.95	0.99	0.94	0.98	0.98	1.31	0.96	0.90	0.75	0.94	0.87	0.83
1000		1.00	0.98	0.99	0.97	0.97	0.99	1.25	0.97	0.93	0.80	0.97	0.92	0.89
250		0.99	1.63	1.41	2.93	1.90	2.06	1.81	0.97	0.87	0.95	0.99	0.99	1.16
500	*A-ratio*	1.02	0.97	1.00	1.04	1.01	1.00	1.65	0.97	0.92	0.77	0.97	0.95	1.12
1000		1.00	0.99	0.99	0.98	1.00	1.00	1.49	0.98	0.95	0.83	0.98	1.00	1.13

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 3.10: Accuracy of estimated threshold coefficients α, μ^{-} and μ^{+}

Sample size	True *dgp* and estimated model:	OP	NOP			NOPc			MIOP			MIOPc		
	Overlap:		n	p	c	n	p	c	n	p	c	n	p	c
250		1.85	2.69	3.52	14.72	5.24	6.91	32.37	5.02	12.36	27.29	6.97	13.69	63.86
500	*Bias*	1.09	0.99	1.13	4.91	2.44	2.40	38.69	2.55	5.16	20.80	2.66	4.94	56.68
1000		0.38	0.48	0.70	2.47	1.13	1.05	34.18	1.21	2.40	14.09	1.47	1.70	44.38
250		1.29	2.24	2.82	7.35	3.69	3.66	7.99	3.18	5.86	13.03	3.89	5.86	13.75
500	*RMSE*	0.90	1.46	1.72	3.07	2.43	2.28	7.22	2.16	3.42	9.95	2.65	3.55	11.97
1000		0.62	1.00	1.21	2.02	1.68	1.59	6.13	1.52	2.18	7.75	1.78	2.13	9.50
250		95.3	95.3	94.9	95.1	92.0	93.5	92.3	91.8	89.3	79.7	92.1	90.5	83.9
500	*CP*, %	94.7	95.1	95.5	94.7	92.7	93.6	91.3	93.2	91.3	81.1	92.8	90.5	85.2
1000		95.2	95.0	94.8	95.0	93.2	93.6	90.1	94.2	92.7	82.6	94.0	91.7	87.6
250		0.98	0.92	0.90	0.75	0.96	0.95	1.36	0.91	0.74	0.51	0.85	0.69	0.72
500	*M-Ratio*	0.98	0.97	0.99	0.96	0.98	0.99	1.30	0.97	0.85	0.57	0.87	0.74	0.70
1000		1.00	0.98	0.98	0.98	0.98	0.99	1.25	0.98	0.91	0.59	0.92	0.88	0.75
250		0.99	1.10	1.13	3.69	1.33	1.24	1.86	1.00	1.82	2.62	0.96	2.92	2604
500	*A-Ratio*	0.99	0.98	1.00	1.07	1.00	1.01	1.59	0.98	1.10	1.78	0.94	1.35	1897
1000		1.00	0.98	0.98	0.99	0.99	1.01	1.44	0.99	0.96	1.12	0.96	1.01	1575

Table 3.11: Accuracy of estimated correlation coefficients ρ^- and ρ^+

Sample size	True *dgp* and estimated model:	NOPc			MIOPc		
	Covariates' overlap:	n	p	c	n	p	c
250		8.70	14.33	41.31	9.94	22.58	54.78
500	*Bias*	3.82	5.36	43.01	3.72	10.18	45.80
1000		1.75	1.96	38.10	1.89	4.22	36.84
250		4.27	4.76	7.27	4.36	5.66	8.09
500	*RMSE*	3.02	3.40	7.44	3.12	4.24	7.34
1000		2.10	2.52	6.76	2.18	3.17	6.25
250		85.2	85.4	87.1	84.0	79.8	73.6
500	*CP*, %	88.2	87.8	82.1	87.2	81.6	73.4
1000		90.7	89.4	81.6	90.8	85.5	78.8
250		0.99	1.05	2.41	0.95	0.91	1.35
500	*M-ratio*	0.98	1.00	1.84	0.93	0.88	1.24
1000		0.98	0.97	1.68	0.95	0.91	1.35
250		0.99	1.07	334.3	0.97	1.03	454.1
500	*A-ratio*	0.97	1.01	128.2	0.95	0.95	285.5
1000		0.98	0.97	44.2	0.96	1.01	211.5

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 3.12: Partial effects of covariates on probabilities of discrete outcomes

True *dgp* :		OP			NOP			NOPc			MIOP				MIOPc			
Estimated model:		OP	NOP	MIOP	OP	NOP	NOPc	OP	NOP	NOPc	OP	NOP	MIOP	MIOPc	OP	NOP	MIOP	MIOPc
							Partial effects on Pr(y = -0.50 | v1=2, v2=0, v3=0)											
v_1	*Bias*	0.01	-0.08	-0.10	-0.70	0.04	0.08	-1.08	-0.41	0.08	-1.22	0.35	0.00	0.03	-1.32	-0.01	-0.42	0.02
	A-ratio	1.00	0.98	0.92	1.06	1.00	1.01	1.06	0.99	0.99	1.13	1.00	0.98	1.02	1.14	1.04	1.01	0.99
	RMSE	0.44	0.61	0.66	0.90	0.63	0.73	1.21	0.75	0.79	1.30	0.55	0.49	0.67	1.38	0.36	0.60	0.66
	CP, %	94.4	94.1	92.6	83.1	94.6	94.7	56.1	92.3	95.3	27.7	82.3	93.5	94.7	12.6	95.2	90.4	93.0
v_2	*Bias*	0.01	0.00	-0.04	4.25	-0.05	-0.07	4.59	0.22	-0.08	3.78	2.62	0.03	0.02	4.05	2.83	0.29	0.03
	A-ratio	1.01	0.98	0.94	0.96	1.01	1.00	0.97	0.99	1.01	0.93	1.01	1.00	1.01	0.91	0.99	0.98	0.98
	RMSE	0.43	0.55	0.58	4.27	0.79	0.83	4.60	0.84	0.89	3.81	2.69	0.79	0.83	4.08	2.90	0.86	0.87
	CP, %	95.2	94.5	94.1	0.0	95.5	95.5	0.0	92.0	95.0	0.0	1.9	94.5	94.5	0.0	1.1	91.0	93.6
v_3	*Bias*				-0.60	0.00	0.00	-0.63	0.00	0.00	-2.29	0.00	0.00	0.00	-2.45	0.00	0.00	0.00
	A-ratio				1.02	n/a	n/a	1.00	n/a	n/a	1.15	n/a	n/a	n/a	1.13	n/a	n/a	n/a
	RMSE				0.72	0.00	0.00	0.76	0.00	0.00	2.32	0.00	0.00	0.00	2.48	0.00	0.00	0.00
	CP, %				65.8	n/a	n/a	63.1	n/a	n/a	0.0	n/a	n/a	n/a	0.0	n/a	n/a	n/a
							Partial effects on Pr(y = -0.25 | v1=2, v2=0, v3=0)											
v_1	*Bias*	0.00	0.09	-0.25	2.05	-0.01	-0.05	2.98	0.41	-0.08	3.39	1.29	-0.10	-0.16	4.13	2.08	0.42	-0.11
	A-ratio	1.00	0.99	0.97	0.99	0.98	0.98	0.96	0.98	1.01	1.03	1.08	1.00	1.06	1.00	1.06	0.94	0.96
	RMSE	0.78	0.96	1.20	2.22	0.97	1.05	3.11	1.05	1.06	3.47	1.53	1.27	1.31	4.18	2.23	1.37	1.41
	CP, %	94.5	94.4	94.0	34.2	94.2	94.9	8.0	90.8	94.9	1.0	69.0	95.2	95.5	0.0	33.0	90.4	94.2
v_2	*Bias*	0.01	0.03	-0.37	-5.67	0.05	0.07	-6.02	-0.22	0.08	3.15	10.18	-0.05	-0.07	2.79	9.80	-0.53	-0.15
	A-ratio	0.98	0.97	1.02	1.01	1.01	1.00	1.04	0.99	1.01	1.02	1.01	1.01	1.02	1.01	0.99	0.99	0.98
	RMSE	0.78	0.83	1.02	5.70	0.79	0.83	6.05	0.84	0.89	3.22	10.20	1.35	1.53	2.86	9.82	1.50	1.58
	CP, %	94.7	94.1	94.6	0.0	95.5	95.5	0.0	92.0	95.0	0.6	0.0	95.7	95.4	2.2	0.0	94.7	94.9
v_3	*Bias*				-1.06	0.00	0.00	-1.12	0.00	0.00	-4.15	0.00	0.00	0.00	-4.21	0.00	0.00	0.00
	A-ratio				1.01	n/a	n/a	0.99	n/a	n/a	1.06	n/a	n/a	n/a	1.05	n/a	n/a	n/a
	RMSE				1.28	0.00	0.00	1.34	0.00	0.00	4.20	0.00	0.00	0.00	4.26	0.00	0.00	0.00
	CP, %				68.2	n/a	n/a	65.5	n/a	n/a	0.0	n/a	n/a	n/a	0.0	n/a	n/a	n/a

Table 3.13: Partial effects of covariates on probabilities of discrete outcomes

	True *dgp*:	OP			NOP			NOPc			MIOP				MIOPc			
	Estimated model:	OP	NOP	MIOP	OP	NOP	NOPc	OP	NOP	NOPc	OP	NOP	MIOP	MIOPc	OP	NOP	MIOP	MIOPc
		Partial effects on Pr(y = 0 | v1=2, v2=0, v3=0)																
v_1	*Bias*	0.01	0.01	0.01	0.03	-0.03	-0.03	0.10	0.02	0.02	0.10	-0.02	0.01	-0.01	-1.82	-1.93	-0.95	0.12
	A-ratio	1.01	1.01	0.99	1.03	1.01	1.01	1.05	1.02	1.02	1.02	1.04	0.99	1.01	1.02	1.05	0.94	0.97
	RMSE	0.72	0.72	1.62	0.93	1.06	1.06	0.88	1.05	1.05	0.62	0.61	1.60	1.80	1.88	1.99	1.87	2.15
	CP, %	95.4	95.4	95.5	96.3	95.7	95.8	96.2	95.8	95.9	95.8	96.4	94.8	95.7	4.9	4.1	86.2	95.2
v_2	*Bias*	-0.03	-0.01	0.60	0.01	0.00	0.00	0.02	0.00	0.00	-12.72	-12.80	0.02	0.05	-12.57	-12.63	0.24	0.12
	A-ratio	1.00	0.99	0.99	1.05	n/a	n/a	1.06	n/a	n/a	1.01	n/a	1.01	1.03	1.01	n/a	0.98	0.98
	RMSE	2.00	2.07	2.86	0.11	0.00	0.00	0.11	0.00	0.00	12.73	12.80	1.63	1.70	12.58	12.63	1.70	1.79
	CP, %	94.7	94.8	93.8	99.8	n/a	n/a	99.9	n/a	n/a	0.0	n/a	94.9	95.0	0.0	n/a	94.8	94.7
v_3	*Bias*				-0.16	0.00	0.00	-0.16	0.00	0.00	10.82	12.51	0.06	0.06	10.47	12.26	-2.27	0.01
	A-ratio				0.93	n/a	n/a	0.95	n/a	n/a	0.90	n/a	1.00	1.04	0.92	n/a	0.98	1.01
	RMSE				0.28	0.00	0.00	0.28	0.00	0.00	10.85	12.51	2.05	2.36	10.50	12.26	3.22	2.42
	CP, %				99.5	n/a	n/a	99.6	n/a	n/a	0.0	n/a	94.5	93.6	0.0	n/a	81.7	94.8
		Partial effects on Pr(y = 0.25 | v1=2, v2=0, v3=0)																
v_1	*Bias*	-0.01	-0.08	0.26	-1.98	0.02	0.06	-3.81	-1.13	0.08	-3.30	-1.28	0.09	0.16	-3.28	-1.15	-0.34	-0.05
	A-ratio	1.01	1.01	0.96	0.99	0.99	1.00	0.94	0.96	1.00	1.02	1.08	1.00	1.05	1.01	1.07	0.96	0.97
	RMSE	0.76	0.93	1.19	2.17	0.95	1.02	3.91	1.50	1.15	3.37	1.51	1.25	1.30	3.34	1.40	1.25	1.55
	CP, %	94.8	95.0	94.2	36.6	95.2	95.1	1.4	74.8	94.9	0.9	68.7	94.7	94.4	0.4	72.4	91.6	95.0
v_2	*Bias*	0.03	-0.19	-0.30	0.89	0.00	0.00	0.88	0.00	0.00	3.51	0.00	0.00	0.00	3.36	0.00	0.00	0.00
	A-ratio	1.01	0.99	0.94	1.00	n/a	n/a	1.02	n/a	n/a	1.03	n/a	n/a	n/a	1.03	n/a	n/a	n/a
	RMSE	1.36	2.23	2.48	1.07	0.00	0.00	1.05	0.00	0.00	3.56	0.00	0.00	0.00	3.41	0.00	0.00	0.00
	CP, %	95.0	95.1	93.6	68.4	n/a	n/a	67.4	n/a	n/a	0.0	n/a	n/a	n/a	0.0	n/a	n/a	n/a
v_3	*Bias*				7.12	-0.04	-0.07	8.14	0.26	-0.10	2.90	-6.28	-0.06	-0.13	4.97	-4.83	3.01	-0.22
	A-ratio				1.03	1.01	1.02	1.01	0.99	1.00	1.03	1.01	0.97	1.02	1.07	0.98	0.89	0.98
	RMSE				7.16	0.98	0.99	8.17	1.06	1.09	3.03	6.38	1.97	2.41	5.04	4.97	3.85	2.61
	CP, %				0.0	95.2	95.2	0.0	93.0	94.9	5.3	0.0	92.5	92.5	0.0	0.6	63.3	94.0

Table 3.14: Partial effects of covariates on probabilities of discrete outcomes

	True *dgp* :	OP			NOP			NOPc			MIOP				MIOPc			
Estimated model:		OP	NOP	MIOP	OP	NOP	NOPc	OP	NOP	NOPc	OP	NOP	MIOP	MIOPc	OP	NOP	MIOP	MIOPc
	Partial effects on Pr(y = 0.50 | v1=2, v2=0, v3=0)																	
v_1	*Bias*	-0.02	0.06	0.08	0.61	-0.03	-0.07	1.80	1.12	-0.10	1.03	-0.33	0.00	-0.02	2.29	1.01	1.28	0.02
	A-ratio	1.00	0.98	0.92	1.02	0.98	1.00	1.05	1.02	0.99	1.11	1.02	1.00	1.05	1.16	1.04	1.04	0.96
	RMSE	0.44	0.60	0.64	0.84	0.64	0.71	1.89	1.28	0.89	1.12	0.55	0.49	0.68	2.32	1.08	1.34	0.58
	CP, %	94.4	94.3	93.1	85.4	94.7	94.8	8.8	58.8	94.8	46.0	85.3	93.8	95.6	0.0	20.0	5.3	87.6
v_2	*Bias*	-0.03	0.17	0.12	0.52	0.00	0.00	0.54	0.00	0.00	2.29	0.00	0.00	0.00	2.37	0.00	0.00	0.00
	A-ratio	0.99	1.00	0.91	1.00	n/a	n/a	1.03	n/a	n/a	1.10	n/a	n/a	n/a	1.10	n/a	n/a	n/a
	RMSE	1.40	1.96	2.11	0.62	0.00	0.00	0.64	0.00	0.00	2.32	0.00	0.00	0.00	2.41	0.00	0.00	0.00
	CP, %	94.6	95.0	92.2	69.1	n/a	n/a	68.0	n/a	n/a	0.0	n/a	n/a	n/a	0.0	n/a	n/a	n/a
v_3	*Bias*				-5.30	0.04	0.07	-6.22	-0.26	0.10	-7.28	-6.23	0.01	0.07	-8.78	-7.43	-0.73	0.21
	A-ratio				0.96	1.01	1.02	0.94	0.99	1.00	0.95	1.01	1.01	1.03	0.93	0.98	0.99	1.01
	RMSE				5.32	0.98	0.99	6.24	1.06	1.09	7.33	6.33	1.50	1.52	8.82	7.53	1.79	1.68
	CP, %				0.0	95.2	95.2	0.0	93.0	94.9	0.0	0.1	95.5	95.5	0.0	0.0	90.7	95.2

Table 3.15: Performance under OP, NOP and NOP(c) dgp

Sample	True *dgp*:	OP			NOP			NOPc		
size	Estimated model:	OP	NOP	MIOP	OP	NOP	NOPc	OP	NOP	NOPc
250	Number of	41.7	25.0	20.8	35.7	35.7	27.8	35.7	35.7	27.8
500	observations per	83.3	50.0	41.7	71.4	71.4	55.6	71.4	71.4	55.6
1000	parameter	166.7	100.0	83.3	142.9	142.9	111.1	142.9	142.9	111.1
250		3.23	3.22	3.21	3.30	3.23	3.22	3.30	3.22	3.21
500	*RMSEP*	3.22	3.22	3.22	3.30	3.24	3.24	3.31	3.23	3.23
1000		3.24	3.24	3.23	3.31	3.25	3.25	3.32	3.24	3.24
250		0.25	0.45	1.48	22.31	0.30	0.36	26.03	3.10	0.55
500	*Bias*	0.22	0.31	0.99	22.14	0.11	0.19	25.75	2.69	0.30
1000		0.09	0.20	0.78	21.69	0.07	0.09	25.25	2.56	0.11
250		2.06	2.95	3.71	3.55	1.20	1.42	3.88	1.35	1.40
500	*RMSE*	1.43	2.04	2.48	3.30	0.81	0.96	3.63	1.01	0.97
1000		1.01	1.44	1.73	3.13	0.57	0.66	3.47	0.80	0.67
250		93.2	92.0	90.4	59.7	92.7	92.0	56.0	88.7	91.6
500	*CP*, %	94.2	93.4	92.2	50.1	93.9	93.3	47.1	86.0	93.0
1000		94.6	94.0	93.0	41.5	94.5	94.2	38.1	80.2	93.7
250		0.98	0.97	0.87	1.00	0.97	0.97	0.98	0.97	0.98
500	*M-ratio*	1.00	0.99	0.91	0.99	0.99	0.98	1.01	0.99	0.97
1000		1.00	0.99	0.94	1.00	1.00	0.99	1.00	0.99	0.98
250		0.99	0.97	0.91	1.01	0.98	1.00	1.00	0.98	1.01
500	*A-ratio*	1.00	0.99	0.93	1.00	0.99	1.00	1.01	1.00	1.00
1000		1.00	0.99	0.95	1.01	1.00	1.00	1.00	0.99	1.00
250		0.0	0.0	3.5	0.0	0.0	5.1	0.0	0.0	16.1
500	*Problems*, %	0.0	0.0	1.8	0.0	0.0	0.2	0.0	0.0	3.0
1000		0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.1

Table 3.16: Performance under MIOP and MIOP(c) dgp

Sample size	True *dgp*:	MIOP				MIOPc			
	Estimated model:	OP	NOP	MIOP	MIOPc	OP	NOP	MIOP	MIOPc
250	Number of observations per parameter	35.7	35.7	27.8	22.7	35.7	35.7	27.8	22.7
500		71.4	71.4	55.6	45.5	71.4	71.4	55.6	45.5
1000		142.9	142.9	111.1	90.9	142.9	142.9	111.1	90.9
250		3.368	3.398	3.269	3.266	3.379	3.406	3.274	3.268
500	*RMSEP*	3.356	3.381	3.258	3.256	3.364	3.388	3.260	3.255
1000		3.350	3.373	3.256	3.256	3.357	3.379	3.256	3.253
250		34.63	32.81	0.62	0.82	36.84	33.20	2.88	1.02
500	*Bias*	34.75	32.93	0.25	0.40	36.97	32.64	3.28	0.34
1000		34.50	32.89	0.16	0.15	36.88	32.77	3.70	0.20
250		4.86	4.44	1.96	2.34	5.20	4.59	2.22	2.36
500	*RMSE*	4.69	4.34	1.34	1.62	5.06	4.50	1.75	1.69
1000		4.59	4.27	0.96	1.11	4.97	4.44	1.42	1.17
250		36.0	45.9	91.0	90.3	28.6	45.7	87.7	89.9
500	*CP*, %	20.5	35.3	93.0	92.4	15.3	33.5	82.7	91.2
1000		13.2	27.3	94.1	93.7	10.3	24.0	74.9	92.8
250		1.03	1.03	0.92	0.93	1.05	1.04	0.96	0.93
500	*M-ratio*	1.03	1.01	0.99	1.00	1.03	1.03	0.97	0.96
1000		1.03	1.03	0.99	0.99	1.03	1.02	0.97	0.95
250		1.03	1.04	0.96	0.98	1.05	1.05	0.98	0.99
500	*A-ratio*	1.04	1.02	0.99	1.00	1.04	1.03	0.97	0.96
1000		1.03	1.03	1.00	1.03	1.04	1.03	0.98	0.97
250		0.0	0.0	0.0	4.9	0.0	0.0	0.0	16.4
500	*Problems*, %	0.0	0.0	0.0	0.4	0.0	0.0	0.0	3.2
1000		0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.2

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Table 3.17: Performance of Vuong and LR tests

True *dgp:*	OP			NOP			NOPc			MIOP			MIOPc		
Sample:	250	500	1000	250	500	1000	250	500	1000	250	500	1000	250	500	1000
Model							*Vuong* tests								
OP	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.3	5.5	8.4	2.2	2.7	3.7
NOP	2.8	1.2	0.8	90.6	99.9	100	97.8	100	100	0.7	0.8	0.7	1.4	1.3	1.2
OP				0.0	0.0	0.0	0.0	0.0	0.0						
NOPc				95.3	100	100	98.4	100	100						
OP	0.0	0.0	0.0							0.0	0.0	0.0	0.0	0.0	0.0
MIOP	7.5	3.6	3.1							94.2	99.9	100	97.5	100	100
OP										0.0	0.0	0.0	0.0	0.0	0.0
MIOPc										95.7	100	100	98.1	100	100
							LR tests								
NOP				95.9	94.2	94.9	83.2	57.3	24.8						
NOPc				4.1	5.8	5.1	16.9	42.7	75.2						
NOP	91.0	92.4	92.7							0.0	0.0	0.0	0.0	0.0	0.0
MIOP	9.0	7.6	7.3							100	100	100	100	100	100
MIOP										95.2	94.3	94.8	85.0	63.3	33.4
MIOPc										4.8	5.7	5.2	15.0	36.7	66.6

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Table 3.18: Performance of model selection criteria and hit rate

True *dgp*:		OP (1)			NOP (2)			NOPc (3)			MIOP (4)			MIOPc (5)		
Sample size:		250	500	1000	250	500	1000	250	500	1000	250	500	1000	250	500	1000
	1	84.5	87.9	87.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0
	2	9.3	7.9	8.6	87.4	84.7	86.2	66.5	40.0	12.4	0.0	0.0	0.0	0.0	0.0	0.0
AIC	3				12.6	15.3	13.8	33.5	60.0	87.6						
	4	6.3	4.2	4.4							86.5	85.2	86.1	68.3	43.6	18.8
	5										13.4	14.8	13.9	31.7	56.4	81.2
	1	100	100	100	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.2	0.0	0.0
	2	0.0	0.0	0.0	99.8	99.6	99.8	97.8	90.6	75.7	0.1	0.0	0.0	0.0	0.0	0.0
BIC	3				0.2	0.4	0.2	2.2	9.4	24.3						
	4	0.0	0.0	0.0							99.3	99.7	100	97.9	93.2	81.4
	5										0.1	0.3	0.0	2.0	6.8	18.6
	1	100	100	100	0.0	0.0	0.0	0.0	0.0	0.0	0.9	0.0	0.0	0.4	0.0	0.0
	2	0.0	0.0	0.0	99.9	99.9	99.9	99.1	94.7	82.8	0.2	0.0	0.0	0.0	0.0	0.0
cAIC	3				0.1	0.1	0.1	1.0	5.3	17.2						
	4	0.0	0.0	0.0							98.8	100	100	98.9	96.7	87.8
	5										0.1	0.0	0.0	0.7	3.3	12.2
	1	87.7	89.3	87.8	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0
	2	7.9	7.0	8.4	89.7	85.8	86.8	69.5	41.3	12.9	0.0	0.0	0.0	0.0	0.0	0.0
AICc	3				10.3	14.2	13.2	30.5	58.7	87.1						
	4	4.4	3.7	3.8							89.0	86.3	86.7	72.1	45.6	19.4
	5										10.9	13.7	13.3	27.9	54.4	80.6
	1	98.4	99.3	99.6	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0
	2	1.4	0.7	0.4	97.5	96.8	97.8	88.2	66.6	37.6	0.0	0.0	0.0	0.0	0.0	0.0
HQIC	3				2.5	3.2	2.2	11.8	33.4	62.4						
	4	0.2	0.1	0.0							96.7	96.5	97.3	88.8	73.5	48.0
	5										3.1	3.5	2.7	11.2	26.5	52.0
	1	39.7	35.1	35.9	16.3	10.4	3.9	14.9	7.2	1.9	23.1	15.8	9.2	27.0	15.1	10.2
	2	32.4	35.8	33.6	57.0	53.5	56.1	57.7	48.2	46.4	1.1	0.6	0.1	1.0	0.9	0.6
Hit rate	3				26.7	36.2	40.0	27.4	44.6	51.7						
	4	27.9	29.1	30.5							47.8	49.4	51.1	42.9	43.4	41.5
	5										27.9	34.2	39.6	29.1	40.6	47.8

Table 3.19: The effect of exclusion restrictions

Sample size	True *dgp* and estimated model:	NOP			NOPc			MIOP			MIOPc		
	Overlap:	n	p	c	n	p	c	n	p	c	n	p	c
250	Number of	35.7	25.0	19.2	27.8	20.8	16.7	27.8	20.8	16.7	22.7	17.9	14.7
500	observations per	71.4	50.0	38.5	55.6	41.7	33.3	55.6	41.7	33.3	45.5	35.7	29.4
1000	parameter	143	100	76.9	111	83.3	66.7	111	83.3	66.7	90.9	71.4	58.8
250		3.22	3.19	3.08	3.21	3.19	3.08	3.27	3.23	3.07	3.27	3.25	3.11
500	*RMSEP*	3.24	3.21	3.09	3.23	3.20	3.11	3.26	3.25	3.08	3.26	3.26	3.12
1000		3.25	3.23	3.11	3.24	3.21	3.13	3.26	3.26	3.09	3.25	3.27	3.14
250		0.28	0.30	0.43	0.55	1.31	0.59	0.60	1.34	1.24	1.02	1.76	1.52
500	*Bias*	0.12	0.23	0.29	0.30	0.41	0.35	0.24	0.82	0.77	0.34	0.86	1.22
1000		0.07	0.13	0.11	0.11	0.14	0.26	0.16	0.52	0.69	0.20	0.34	0.86
250		1.20	2.12	3.21	1.40	2.30	3.20	1.96	2.92	4.18	2.36	3.24	4.30
500	*RMSE*	0.81	1.40	2.14	0.97	1.55	2.17	1.36	1.97	2.75	1.69	2.26	2.85
1000		0.57	0.99	1.48	0.67	1.08	1.53	0.96	1.39	1.88	1.17	1.56	1.95
250		92.7	91.6	88.6	91.6	91.6	89.9	86.9	89.5	86.3	89.9	89.4	87.3
500	*CP*, %	93.9	93.6	91.4	93.0	93.0	92.5	93.0	92.0	89.4	91.2	91.0	90.4
1000		94.5	94.0	93.1	93.7	93.8	93.6	94.1	93.1	91.6	92.8	92.4	92.3
250		0.96	0.95	0.91	0.97	0.98	0.97	0.92	0.91	0.81	0.93	0.91	0.87
500	*M-ratio*	0.98	0.99	0.95	0.97	0.98	1.01	0.98	0.95	0.87	0.92	0.92	0.92
1000		1.00	0.99	0.97	0.98	0.98	1.01	0.99	0.96	0.92	0.95	0.95	0.95
250		0.98	0.96	1.00	1.01	1.01	1.11	0.92	0.94	0.88	0.99	0.99	1.06
500	*A-ratio*	0.99	1.00	0.97	1.00	1.01	1.19	0.99	0.97	0.92	0.96	0.99	1.03
1000		1.00	0.99	0.99	1.00	1.00	1.10	1.00	0.97	0.95	0.97	1.01	1.02
250		0.0	0.0	0.0	16.1	25.8	55.9	0.0	0.0	0.0	16.4	34.3	56.7
500	*Problems*, %	0.0	0.0	0.0	3.0	7.4	30.7	0.0	0.0	0.0	3.2	13.2	41.0
1000		0.0	0.0	0.0	0.1	0.5	13.4	0.0	0.0	0.0	0.2	2.8	26.7

3.12 Appendix C. Supplemental output from application

Table 3.20: Sample descriptive statistics

Variable	Mean	Std deviation	Minimum	Maximum
Δy_i	-0.088	0.592	-1.000	1.000
spread	-0.111	0.900	-3.018	1.368
$\Delta ecbr$	-0.015	0.184	-0.750	0.500
situation	0.133	0.109	-0.201	0.341
Δcpi	-0.066	0.489	-1.800	1.400
$\Delta nbpr$	-0.142	0.565	-2.500	2.500
bias	0.172	0.710	-1.000	1.000
$I(h)_i$	0.238	0.426	0.000	1.000
$I(d)_i$	0.143	0.350	0.000	1.000
dissent	0.071	0.214	-0.444	0.500
$I(cpi^e > tar)$	0.529	0.499	0.000	1.000

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 3.21: MPC decisions on policy rate and bias, and measure of dissent at MPC meetings

MPC meeting date	Policy rate change	Policy bias	Dissent	MPC meeting date	Policy rate change	Policy bias	Dissent	MPC meeting date	Policy rate change	Policy bias	Dissent
2/25/98	50	0	0.00	2/27/02	0	0	0.00	2/28/06	-25	-1	0.40
3/18/98	0	0	0.00	3/27/02	0	0	-0.30	3/29/06	0	-1	0.00
4/22/98	-100	0	0.10	4/26/02	-50	0	-0.11	4/26/06	0	-1	0.00
5/20/98	-150	0	0.10	5/29/02	-50	0	-0.20	5/31/06	0	-1	0.00
6/17/98	0	0	0.00	6/26/02	-50	0	-0.10	6/28/06	0	0	0.00
7/16/98	-250	0	0.30	7/19/02	0	0	-0.40	7/26/06	0	0	0.00
8/19/98	0	0	0.00	8/28/02	-50	0	-0.22	8/30/06	0	0	0.00
9/9/98	-100	0	0.00	9/25/02	-50	0	0.33	9/27/06	0	0	0.00
10/28/98	-100	0	0.00	10/23/02	-50	0	0.50	10/25/06	0	0	0.40
11/18/98	0	0	0.00	11/27/02	-25	0	0.10	11/29/06	0	0	0.40
12/9/98	-150	0	0.10	12/18/02	0	0	0.00	12/20/06	0	1	0.44
1/20/99	-250	0	0.25	1/29/03	-25	0	-0.20	1/31/07	0	1	0.00
2/17/99	0	0	0.00	2/26/03	-25	0	0.11	2/28/07	0	1	0.30
3/24/99	0	0	0.00	3/26/03	-25	0	0.30	3/28/07	0	1	0.50
4/21/99	0	0	0.00	4/24/03	-25	0	0.11	4/25/07	25	1	-0.40
5/27/99	0	0	0.00	5/28/03	-25	0	0.50	5/30/07	0	1	0.40
6/16/99	0	0	0.00	6/25/03	-25	0	0.50	6/27/07	25	1	-0.40
7/21/99	0	1	0.00	7/18/03	0	0	0.00	7/25/07	0	1	0.10
8/18/99	0	1	0.00	8/27/03	0	0	-0.44	8/29/07	25	1	-0.10
9/22/99	100	1	-0.11	9/30/03	0	0	0.00	9/26/07	0	1	0.00
10/20/99	0	1	0.00	10/29/03	0	0	0.00	10/31/07	0	1	0.40
11/17/99	250	1	0.00	11/26/03	0	0	0.00	11/28/07	25	1	0.00
12/15/99	0	1	0.00	12/17/03	0	0	0.00	12/19/07	0	1	0.40
1/26/00	0	1	0.00	1/21/04	0	0	0.00	1/30/08	25	1	0.20
2/23/00	100	1	0.00	2/25/04	0	0	0.00	2/27/08	25	1	0.00
3/29/00	0	1	0.00	3/31/04	0	0	0.00	3/26/08	25	1	0.30
4/26/00	0	1	0.00	4/27/04	0	1	0.00	4/30/08	0	1	0.40
5/24/00	0	1	0.00	5/26/04	0	1	0.00	5/28/08	0	1	0.40
6/21/00	0	1	0.40	6/30/04	50	1	-0.10	6/25/08	25	1	0.00
7/19/00	0	1	0.00	7/28/04	25	1	-0.20	7/30/08	0	1	0.30
8/30/00	150	1	-0.10	8/25/04	50	1	-0.20	8/27/08	0	1	0.50
9/19/00	0	1	0.00	9/29/04	0	1	0.00	9/24/08	0	1	0.50
10/25/00	0	1	0.00	10/27/04	0	1	0.00	10/29/08	0	0	0.00
11/29/00	0	1	0.00	11/24/04	0	1	0.00	11/26/08	-25	-1	0.00
12/20/00	0	0	0.00	12/15/04	0	1	0.00	12/23/08	-75	-1	0.50
1/22/01	0	0	0.00	1/26/05	0	1	0.00	1/27/09	-75	-1	0.30
2/28/01	-100	0	-0.30	2/25/05	0	-1	0.00	2/25/09	-25	-1	0.00
3/28/01	-100	0	0.50	3/30/05	-50	-1	0.10	3/25/09	-25	-1	0.50
4/26/01	0	0	0.00	4/27/05	-50	0	0.00	4/29/09	0	-1	0.00
5/30/01	0	0	-0.40	5/25/05	0	0	0.00	5/27/09	0	-1	0.00
6/27/01	-150	0	-0.30	6/29/05	-50	-1	0.00	6/24/09	-25	-1	0.50
7/20/01	0	0	0.00	7/27/05	-25	-1	0.40	7/29/09	0	-1	0.00
8/22/01	-100	0	0.10	8/31/05	-25	-1	0.40	8/26/09	0	-1	0.00
9/26/01	0	0	0.00	9/28/05	0	-1	0.00	9/30/09	0	-1	0.00
10/25/01	-150	0	0.10	10/26/05	0	-1	0.00	10/28/09	0	0	0.00
11/28/01	-150	0	0.50	11/30/05	0	-1	0.00	11/25/09	0	0	0.00
12/19/01	0	0	0.00	12/21/05	0	-1	0.00	12/23/09	0	0	0.00
1/30/02	-150	0	0.20	1/31/06	-25	-1	0.30				

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 3.22: Average measures of individual dissents of MPC members

MPC member	Average dissent	MPC member	Average dissent	MPC member	Average dissent
Filar	0.400	Łączkowski	0.145	Nieckarz	-0.086
Dąbrowski	0.353	Grabowski	0.130	Krzyżewski	-0.109
Wasilewska-Trenkner	0.343	Balcerowicz	0.111	Pietrewicz	-0.127
Noga	0.329	Sławiński	0.086	Skrzypek	-0.143
Pruski	0.229	Gronkiewicz-Waltz	0.000	Rosati	-0.197
Wojtyna	0.214	Czekaj	-0.027	Wójtowicz	-0.225
Józefiak	0.186	Owsiak	-0.057	Ziółkowska	-0.232

Notes: The individual dissents of each MPC member are computed using Eq. (3.15).

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 3.23: Estimated coefficients for OP and ZIOP models with fixed effects

	Ordered Probit Model	Zero-Inflated Ordered Probit Model	
Covariates		Participation equation	Amount equation
spread	0.61 (0.07)**	-0.06 (0.11)	1.97 (0.26)**
Δecbr	1.69 (0.24)**	1.90 (0.45)**	3.37 (0.59)**
situation	0.79 (0.42)	-0.66 (0.74)	2.75 (0.78)**
Δcpi	0.99 (0.10)**	0.84 (0.19)**	1.68 (0.24)**
Δnbpr	-0.51 (0.08)**	0.88 (0.16)**	1.02 (0.24)**
I(Fil)	1.30 (0.32)**	2.07 (0.64)**	1.41 (0.76)
I(Nie)	0.00 (0.32)	0.48 (0.56)	-0.09 (0.78)
I(Nog)	1.14 (0.32)**	2.08 (0.68)**	1.17 (0.76)
I(Ows)	0.00 (0.32)	0.48 (0.56)	-0.09 (0.78)
I(Pie)	-0.04 (0.32)	0.32 (0.55)	-0.10 (0.78)
I(Sla)	0.43 (0.32)	1.78 (0.75)*	0.17 (0.77)
I(Was)	1.14 (0.32)**	2.16 (0.65)**	1.17 (0.76)
I(Woj)	0.82 (0.32)**	2.25 (0.67)**	0.66 (0.76)
I(Cze)	0.12 (0.31)	1.04 (0.59)	-0.13 (0.77)
I(Skr)	-0.11 (0.36)	0.94 (0.78)	-0.47 (0.89)
I(Bal)	0.10 (0.31)	0.87 (0.48)	0.21 (0.75)
I(Dab)	0.98 (0.32)**	-1.01 (0.46)*	1.15 (0.92)
I(Gra)	0.05 (0.31)	0.05 (0.42)	-0.17 (0.77)
I(Joz)	0.18 (0.31)	0.04 (0.42)	0.02 (0.77)
I(Krz)	-0.46 (0.31)	0.58 (0.42)	-1.06 (0.76)
I(Lac)	0.01 (0.31)	-0.02 (0.42)	-0.41 (0.80)
I(Pru)	0.38 (0.31)	-0.18 (0.42)	0.34 (0.78)
I(Ros)	-0.47 (0.31)	0.67 (0.43)	-1.09 (0.77)
I(Wojz)	-0.53 (0.30)	0.54 (0.42)	-1.18 (0.76)
I(Zio)	-0.57 (0.30)	0.66 (0.43)	-1.26 (0.77)
bias	1.36 (0.10)**	-2.01 (0.38)**	1.53 (0.18)**
dissent	1.20 (0.20)**	-0.51 (0.37)	2.09 (0.35)**
$I(cpi^{e} > tar)$	0.05 (0.09)	0.86 (0.16)**	-0.27 (0.18)
$threshold_1$	-1.00 (0.28)**	-0.60 (0.42)	-1.35 (0.75)
$threshold_2$	2.91 (0.31)**		3.70 (0.75)**

Notes: **/* denote statistical significance at 1/5 percent level, respectively.
Standard errors are in parantheses.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
European University Institute DOI: 10.2870/60780

Table 3.24: Estimated coefficients for MIOP model with fixed effects

Covariates	Middle-Inflated Ordered Probit Model		
	Inclination equation	Policy amount equations	
		Loose regime	Tight regime
spread	2.38 (0.30)**		
Δecbr	3.94 (0.74)**		
situation	6.42 (1.40)**		
Δcpi	4.43 (0.49)**		
Δnbpr	7.16 (1.43)**	-1.08 (0.14)**	-3.69 (0.75)**
I(Fil)	1.97 (0.85)*	1.96 (0.67)**	1.88 (0.86)*
I(Nie)	0.21 (0.84)	0.45 (0.73)	-0.22 (0.87)
I(Nog)	1.74 (0.84)*	1.59 (0.64)*	1.74 (0.86)*
I(Ows)	0.21 (0.84)	0.45 (0.73)	-0.22 (0.87)
I(Pie)	0.20 (0.84)	0.45 (0.73)	-0.41 (0.87)
I(Sla)	0.94 (0.83)	0.38 (0.75)	0.57 (0.85)
I(Was)	1.57 (0.83)	1.54 (0.67)*	1.97 (0.87)*
I(Woj)	1.03 (0.83)	1.02 (0.66)	1.56 (0.86)
I(Cze)	0.11 (0.82)	0.37 (0.71)	0.29 (0.86)
I(Skr)	-0.54 (0.97)	-0.13 (1.29)	-0.12 (0.94)
I(Bal)	1.07 (0.79)	0.23 (0.46)	1.93 (0.91)*
I(Dab)	-0.75 (1.07)	2.65 (0.54)**	1.50 (1.34)
I(Gra)	0.05 (0.89)	0.73 (0.45)	-0.02 (1.07)
I(Joz)	-0.16 (0.87)	0.86 (0.44)	1.38 (1.34)
I(Krz)	-0.16 (0.84)	0.00 (0.42)	0.06 (1.01)
I(Lac)	0.06 (0.93)	0.72 (0.45)	-0.26 (1.02)
I(Pru)	-0.02 (0.99)	1.14 (0.45)*	1.34 (1.39)
I(Ros)	-0.50 (0.81)	-0.10 (0.45)	1.39 (1.39)
I(Wojz)	-0.40 (0.81)	-0.06 (0.44)	-0.45 (0.95)
I(Zio)	-0.38 (0.81)	-0.15 (0.44)	-0.46 (0.95)
bias	0.18 (0.29)	2.18 (0.28)**	1.99 (0.28)**
dissent	0.93 (0.67)	1.32 (0.36)**	1.34 (0.71)
$I(cpi^{e}>tar)$			1.56 (0.27)**
$threshold_1$	-0.43 (0.81)	1.15 (0.39)**	3.03 (0.84)**
$threshold_2$	3.44 (0.85)**		

Notes: **/* denote statistical significance at 1/5 percent level, respectively.
Standard errors are in parantheses.

Sirchenko, Andrei (2012), A Discrete-Choice Econometrician's Tale of Monetary Policy Identification and Predictability
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Table 3.25: Estimated coefficients for OP, ZIOP, MIOP and MIOP(c) model with two dummies for hawks and doves

Model	OP	ZIOP		MIOP			MIOPc		
Covariates	X	X	Z	X	Z^-	Z^+	X	Z^-	Z^+
spread	0.74**	-0.05	1.22**	2.32**			2.30**		
	(0.06)	(0.16)	(0.11)	(0.23)			(0.25)		
$\Delta ecbr$	1.57**	2.27**	2.23**	3.79**			3.82**		
	(0.24)	(0.68)	(0.34)	(0.67)			(0.66)		
situation	0.73	-2.33	1.72**	4.96**			4.46**		
	(0.41)	(1.39)	(0.57)	(1.07)			(1.34)		
Δcpi	0.92**	2.55**	1.19**	3.7**			3.65**		
	(0.10)	(0.57)	(0.14)	(0.39)			(0.42)		
$\Delta nbpr$	-0.43**	2.07**	0.69**	4.81**	-0.95**	-2.58**	4.61**	-0.96**	-2.62**
	(0.08)	(0.39)	(0.16)	(0.90)	(0.13)	(0.49)	(0.98)	(0.13)	(0.50)
$I(h)_i$	0.83**	-0.62	1.10**	1.17**	0.93**	1.14**	1.08**	0.81**	1.18**
	(0.10)	(0.44)	(0.12)	(0.22)	(0.18)	(0.25)	(0.33)	(0.25)	(0.25)
$I(d)_i$	-0.66**	0.40	-0.54**	-0.64**	-0.80**	-0.11	-0.60**	-0.82**	-0.15
	(0.11)	(0.39)	(0.13)	(0.22)	(0.22)	(0.30)	(0.23)	(0.21)	(0.30)
bias	1.18**	-1.34**	1.01**		2.03**	1.73**		1.89**	1.84**
	(0.09)	(0.41)	(0.10)		(0.22)	(0.22)		(0.31)	(0.25)
dissent	1.24**	-1.92**	1.61**		1.37**	1.13*		1.39**	1.15*
	(0.19)	(0.70)	(0.23)		(0.35)	(0.55)		(0.35)	(0.57)
$I(cpi^e > tar)$	0.09	0.93**	0.09			1.14**			1.17**
	(0.09)	(0.25)	(0.11)			(0.23)			(0.23)
$threshold_1$	-1.07**	-3.38**	-0.94**	-0.76**	0.64**	2.13**	-0.69**	0.65**	2.26**
	(0.11)	(0.75)	(0.13)	(0.19)	(0.11)	(0.25)	(0.22)	(0.11)	(0.28)
$threshold_2$	2.60**			2.61**			2.57**		
	(0.14)			(0.29)			(0.42)		
ρ^-								-0.48	
								(0.64)	
ρ^+								0.25	
								(0.29)	

Notes: **/* denote statistical significance at 1/5 percent level, respectively.
Standard errors are in parantheses.

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