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Sirchenko, A.

DOI
10.1515/snde-2018-0059

Publication date
2020

Document Version
Final published version

Published in
Studies in Nonlinear Dynamics and Econometrics

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A model for ordinal responses with heterogeneous status quo outcomes

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Abstract:
The decisions to reduce, leave unchanged, or increase a choice variable (such as policy interest rates) are often characterized by abundant status quo outcomes that can be generated by different processes. The decreases and increases may also be driven by distinct decision-making paths. Neither conventional nor zero-inflated models for ordinal responses adequately address these issues. This paper develops a flexible endogenously switching model with three latent regimes, which create separate processes for interest rate hikes and cuts and overlap at a no-change outcome, generating three different types of status quo decisions. The model is not only favored by statistical tests but also produces economically more meaningful inference with respect to the existing models, which deliver biased estimates in the simulations.

Keywords: MPC votes, ordinal responses, policy interest rate, regime switching, zero-inflated model

DOI: 10.1515/snde-2018-0059

Article Note: The first draft of this paper was circulated in the proceedings of the 2nd Doctoral Workshop in Economic Theory and Econometrics (MOOD-2012) at Einaudi Institute for Economics and Finance in Rome in June 2012.

1 Introduction

"To do nothing is sometimes a good remedy." – Hippocrates

Ordinal responses, when decision-makers face a choice to reduce, leave unchanged or increase a price (consumption, rating, or policy interest rate) are often characterized by abundant no-change outcomes that may emerge from fundamentally different behavioral mechanisms. For example, an absolute majority of policy interest rate decisions by many central banks are status quo decisions (zeros). The policy rates can remain unchanged in three different situations: in periods of policy tightening; in periods of maintaining between rate reversals; and in periods of policy easing (see Figure 1).

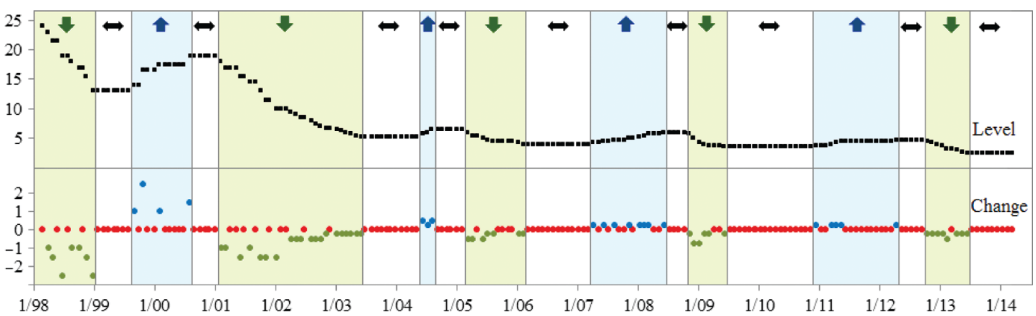

Figure 1: The policy rate remains unchanged in different circumstances: during the periods of policy easing, maintaining and tightening.
↓/↔/↑ denote the periods of policy easing/maintaining/tightening. The period of easing or tightening is the period during which the rate only moves in one direction (down or up, respectively) from the first to the last sequential unidirectional rate change (decrease or increase, respectively). The period of policy maintaining is the status quo period between the rate reversals. The data correspond to the reference rate of the National Bank of Poland. See Figure B1 in Online Appendix B for the similar cases of the US Federal Reserve, the Bank of England and the European Central Bank.

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Many of the zeros, observed between rate hikes during policy tightening, can emerge in rather different economic circumstances compared with many of those that are observed between rate cuts in policy easing periods. Many of the zeros, situated between rate reversals in maintaining periods, may also differ from the status quo decisions during periods of easing or tightening.

The predominance and heterogeneity of zero observations pose a problem for conventional discrete-choice methods such as the ordered probit (OP) model (McKelvey and Zavoina, 1975). This paper develops a flexible dynamic cross-nested ordered probit (CronOP) model that accommodates the unobserved heterogeneity of data-generating process (*dgp*) by assuming three implicit decisions, and illustrates the model in the context of discrete adjustments to policy interest rates.

The top left panel of Figure 2 shows the decision tree of the proposed model, in which an ordinal dependent variable can exist in three latent regimes. The regime, interpreted as the monetary policy stance (loose, neutral or tight), is determined by a *regime* decision, which serves the role of sample differentiation (or policy stance), and is endogenously driven by a direct policy reaction to current economic conditions and past policy choices. If the policy stance is neutral, no further actions are taken and the rate is maintained. If the stance is loose/tight, the policymakers can cut/hike the rate by a certain discrete amount or leave it unchanged. These unidirectional *amount* decisions, which are conditional on the regime, determine the magnitude of the rate adjustment, intensifying or weakening the policy inclinations. The model simultaneously estimates the three dynamic (with the lags of the observed policy choices among regressors) OP equations, which represent the latent regime and amount decisions, and allows for a possible correlation among them. Using this interpretation, we can classify zeros into three types and describe how they arise: the "always" or "neutral" zeros, which are directly generated by a neutral reaction to economic conditions, and the two types of "not-always" zeros – the "loose" and "tight" zeros – which are generated by loose or tight policy inclinations and are offset by tactical and institutional reasons.

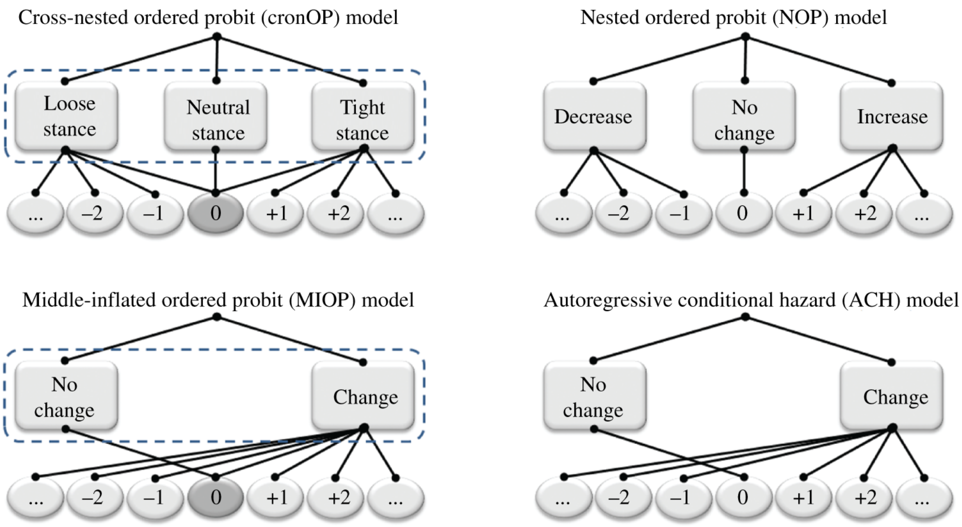

Figure 2: Decision trees: the CronOP model is an extention of the NOP, MIOP and ACH models.

For example, despite a loose policy stance, policymakers can maintain the rate for the following reasons. First, the rate was already lowered at the last meeting (central bankers, who face uncertainty about the economy and incur the costs in the case of the subsequent rate reversal, are generally reluctant to move the rate on a frequent basis, prefer to wait and see, and react to accumulated economic information). Second, the dissenting policymakers at the last meeting preferred a higher rate, creating an upward pressure on the rate at the current meeting (monetary policy is commonly conducted by a committee that is often composed of heterogeneous members). Third, the recent "balance-of-risks" statement of the central bank, indicating the most likely policy direction in the immediate future, was symmetrical (policymakers are concerned about the competence and credibility of central bank communication).

The preponderance of status quo or neutral outcomes is a common phenomenon in many fields, and the heterogeneity of zeros is well recognized. Numerous studies make a distinction among the different types of zeros – for example, no medical appointments due to chance, doctor avoidance, lack of insurance, or medical costs; no children due to infertility or choice; no illness due to strong resistance or lack of infection; a "genuine nonuser" versus a " potential user" (for a review of this literature, see Winkelmann, 2008; Greene and Hensher, 2010). In the decision-making experiments and micro-level studies of consumer choices, election votes and other repeated choices, the prevalence of no-change decisions is often attributed to the status quo bias – the tendency to do nothing or maintain a previous decision, although it is not always objectively superior to other available options (Hartman, Doane and Woo, 1991; Kahneman, Knetsch and Thaler, 1991). It is a cognitive bias, explained by both the rational causes (informational or cognitive limitations, transition or analysis costs) and irrational ones (mental illusions and various psychological inclinations) – see Samuelson and Zeckhauser (1988) for an excellent exposition. Due to the special features of monetary policymaking, such as publicity and transparency, a high level of expertise, reputation and responsibility among policymakers, and research and administrative support, we may disregard the irrational routes of the observed status quo bias.

This paper introduces a discrete-choice policy rule to the vast literature on monetary policy regime switching, which is exclusively focused on the models for a continuous dependent variable. Methodologically, the proposed model is an extension of the conventional, nested and zero-inflated ordered probit models. Section 2 describes the relation and contribution of the proposed method to the literature, sets up the CronOP model in the panel context, and discusses its estimation via maximum likelihood (ML). The Monte Carlo experiments outlined in Section 3 suggest the reasonable performance of the new models in small samples and demonstrate their superiority with respect to the conventional and nested OP models, which produce asymptotically biased estimates if the underlying *dgp* is heterogeneous with different types of status quo outcomes. The new and existing models are applied in Section 4 to explain the policy interest rate decisions (votes) of each member of the Monetary Policy Council (MPC) of the National Bank of Poland (NBP) using the vintages of real-time macroeconomic data as they were truly known 1 day before each MPC meeting. The MPC of the NBP is an example of the individualistic committee (using the taxonomy of Blinder 2004), in which each MPC member can express his policy preference and make a proposition to be voted on. A separate contribution of the paper is a collection of the MPC voting records and the real-time vintages of the consumer price index (which has been repeatedly revised during the sample period) through the requests to the NBP and Central Statistical Office of Poland. Section 5 concludes the paper. The codes, replication files and three appendices with supporting materials are available online.

The real-world data overwhelmingly favor the new approach, which not only produces substantial improvements in statistical fit relative to the existing models, but also is capable of extracting important additional information and provides an economically more reasonable inference. In particular, the statistical rejection of the single-equation OP model provides a compelling empirical evidence of the presence of heterogeneity in the *dgp*. The average estimated probability of a neutral policy stance is 0.41, whereas the observed frequency of status quo decisions is 0.65. Less than two-thirds of zeros seem to be generated by a neutral policy reaction to economic conditions; the remaining zeros originate under the loose or tight policy stance. More than forty percent of all outcomes in the loose and tight regimes are zeros; the amount decisions tend to smooth the interest rate by weakening the up- and downward policy inclinations. These findings suggest a considerable degree of deliberate interest-rate smoothing in the decision-making process of the NBP.

The CronOP model allows all variables to affect the regime and amount decisions in different ways. For instance, the coefficient on the previous change to the rate has a positive sign in the regime equation, whereas it has the negative signs in the amount equations. This enables the previous policy choice to have the same sign of the marginal effect on the probabilities of both a cut and a hike; by contrast, the single-equation structure of the OP model always implies the opposite direction of these effects. According to the CronOP model, a rate hike at the last meeting (relative to a status quo decision) expectedly lowers the probabilities of both a cut and a hike and raises the probability of no change; by contrast, according to the OP model, it reduces the probabilities of a hike and a status quo but counterintuitively increases the probability of a cut. If a certain variable has an impact on both latent decisions, the OP model cannot reveal the distinct effects on the probabilities of different types of zeros (with respect to both a sign and a magnitude), incorrectly estimates that variable's total impact by focusing on the observed zeros, and produces the misleading estimates of the choice probabilities and marginal effects.

2 Model

2.1 Relation and contribution to the literature

From a macroeconomic point of view, the proposed CronOP model is related to a vast literature on monetary policy regime switching, inspired by the seminal work of Hamilton (1989). Oscillating switches in policy regimes are typically modelled by a stochastic Markov-chain process, which is exogenous to the rest of the model. The monetary policy rule in this literature is typically represented by a model for continuous outcomes. In the real world, the major central banks move policy rates by discrete increments, and the policy regime changes are endogenous to the economic conditions, which are actively monitored by the central banks. To the best of my knowledge, the CronOP model is the first implementation of discrete-choice monetary policy rule with (observationally driven) regime switching. The existing applications of discrete-choice approach to monetary policy rules (Hamilton and Jorda, 2002; Hu and Phillips, 2004; Dolado, Maria-Dolores and Naveira, 2005; Piazzesi, 2005; Basu and de Jong, 2007; Kauppi, 2012; Van den Hauwe and Dijk, 2013) do not allow for a regime-switching behavior.

The CronOP model can be described as a cross-nested generalization of a two-level nested ordered probit (NOP) model with three nests (see the top right panel of Figure 2). In the case of unordered categorical data, when choices can be grouped into the nests of similar options, the nested logit model is a popular method. Various types of multinomial logit models with overlapping nests are proposed (Vovsha, 1997; Wen and Koppelman, 2001). The (cross)-nested models, specifically designed for the ordered alternatives, are scarce.[1] The difference between the decision trees of the NOP and CronOP models is that all three nests of the latter overlap at a status-quo response. In the former, the decisions at both levels are observable – it is always known to which nest the observed outcome belongs, whereas in the latter, the zeros are observationally equivalent – it is never known from which of the three regimes the status quo outcomes originate.

The CronOP model can also be considered as a three-part zero-inflated model. The two-part (or hurdle) model introduced by Cragg (1971) combines a binary choice model for the probability of crossing the hurdle (the regime decision) with a truncated-at-zero model for the outcomes above the hurdle (the amount decision). An example of the two-part model for time series data (such as discrete-valued changes to the federal funds rate target) is the autoregressive conditional hazard (ACH) model of Hamilton and Jorda (2002) (see the right bottom panel of Figure 2). The zero-inflated models – the natural extensions of the two-part models – are developed to address the unobserved heterogeneity of (typically) abundant zero outcomes. The examples are the zero-inflated ordered probit (ZIOP) model of Harris and Zhao (2007) for non-negative ordinal responses, where abundant zeros are situated at one end of the ordered scale, and the middle-inflated ordered probit (MIOP) model of Bagozzi and Mukherjee (2012) and Brooks, Harris, and Spencer (2012) for ordinal outcomes that range from negative to positive responses, and where abundant zeros are situated in the middle of the choice spectrum (see the left bottom panel of Figure 2). The difference between the ACH and MIOP models is that the two parts are separately estimated in the former and the zero observations are excluded from the second part; thus, the discrimination among the different types of zeros is not accommodated. In the latter, the two nests overlap assuming the two types of zeros; thus, the probability of a zero is "inflated".

The three-part CronOP model is a natural extension of the two-part ACH, ZIOP and MIOP models. A trichotomous participation decision ("an increase or no change", "no change", or "a decrease or no change") seems to be more realistic than a binary decision ("a change" or "no change") if applied to ordinal data that assume negative, zero and positive values. The policymakers, who are willing to adjust the rate, have already decided in which direction they wish to move it. As a practical matter, the decision to lower or increase the rate can be influenced by the direction-specific determinants and differently by the same ones. The empirical rejection of the MIOP in favor of the CronOP model suggests that the effects of the explanatory variables on the amount decisions are asymmetric; combining these two distinct decisions ("an increase" or "a decrease") into one branch of the decision tree, as implemented in the two-part models, may seriously distort an inference.

2.2 The cross-nested ordered probit model

I describe the econometric framework of the CronOP model in a panel-data context using a double subscript, where the index i denotes one of N cross-sectional units and the index t denotes one of T time periods. An application to cross-sectional or time-series data is straightforward by setting T or N to one. For ease of exposition and without loss of generality, the observed dependent variable Δy_{it} is assumed to take on a finite number of integer values j coded as $\{-J, \dots, 0, \dots, J\}$, where $J \geq 1$ and a heterogeneous (inflated) response is coded as zero. The inflated outcome does not have to be in the *very* middle of ordered categories. However, if it is located at the *end* of the ordered scale, the CronOP model reduces to the ZIOP model of Harris and Zhao (2007).

I interpret the model in the context of interest rate decisions that are taken repeatedly at the policy-making meetings by each member of a monetary policy committee. The model assumes three regimes. The regime decision – the upper level of the decision tree – is determined by the continuous latent variable r_{it}^* representing the degree of the policymaker i's policy stance. It is set at the meeting t in response to the observed data according to a *regime equation*

$$r_{it}^* = \mathbf{x}_{it}'\boldsymbol{\beta} + \nu_{it}, \tag{1}$$

where $\mathbf{x}_{it}$ is the t^{th} row of the observed $T_i \times K_\beta$ data matrix $\mathbf{X}_i$, which in addition to predetermined explanatory variables may also include the lags of observed policy choice Δy_{it} and individual dummies; 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 that is independently and identically distributed (*iid*) across i and t.

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

$$r_{it} = -1 \text{ if } r^*_{it} \leq \alpha_1,\ 0 \text{ if } \alpha_1 < r^*_{it} \leq \alpha_2, \text{ and } 1 \text{ if } \alpha_2 < r^*_{it},$$

where $-\infty < \alpha_1 \leq \alpha_2 < \infty$ are the unknown threshold parameters.

Under the assumption that ν_{it} is distributed according to the cumulative distribution function (*cdf*) Φ, the probabilities of each possible outcome of r_{it} are given by

$$\begin{aligned}
\Pr(r_{it} = -1|\mathbf{x}_{it}) &= \Pr(r^*_{it} \leq \alpha_1|\mathbf{x}_{it}) = && \Phi(\alpha_1 - \mathbf{x}'_{it}\boldsymbol{\beta}),\\
\Pr(r_{it} = 0|\mathbf{x}_{it}) &= \Pr(\alpha_1 < r^*_{it} \leq \alpha_2|\mathbf{x}_{it}) = && \begin{cases}\Phi(\alpha_2 - \mathbf{x}'_{it}\boldsymbol{\beta})\\ -\Phi(\alpha_1 - \mathbf{x}'_{it}\boldsymbol{\beta}),\end{cases}\\
\Pr(r_{it} = 1|\mathbf{x}_{it}) &= \Pr(\alpha_2 < r^*_{it}|\mathbf{x}_{it}) = && 1 - \Phi(\alpha_2 - \mathbf{x}'_{it}\boldsymbol{\beta}).
\end{aligned} \tag{2}$$

At the lower level of the decision tree, three latent regimes exist. Conditional on being in the regime $r_{it} = 0$, no further actions are taken and the rate remains unchanged:

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

Thus, the conditional probability of the outcome j in the neutral policy stance is

$$\Pr(\Delta y_{it} = j|r_{it} = 0) = \begin{cases} 0 & \text{for } j \neq 0,\\ 1 & \text{for } j = 0.\end{cases} \tag{3}$$

Conditional on being in the regime $r_{it} = -1$ or $r_{it} = 1$, the continuous latent variable Δy^*_{it} representing the desired change to the rate, is determined by the direction-specific *amount equations*

$$\begin{aligned}
\Delta y^*_{it}|(\mathbf{z}^-_{it}, r_{it} = -1) &= \mathbf{z}^{-\prime}_{it}\boldsymbol{\gamma}^- + \varepsilon^-_{it},\\
\Delta y^*_{it}|(\mathbf{z}^+_{it}, r_{it} = 1) &= \mathbf{z}^{+\prime}_{it}\boldsymbol{\gamma}^+ + \varepsilon^+_{it},
\end{aligned} \tag{4}$$

where $\boldsymbol{\gamma}^-$ and $\boldsymbol{\gamma}^+$ are the $K^- \times 1$ and $K^+ \times 1$ vectors of unknown coefficients; $\mathbf{z}^-_{it}$ and $\mathbf{z}^+_{it}$ are the t^{th} rows of the observed $T_i \times K^-$ and $T_i \times K^+$ data matrices $\mathbf{Z}^-_i$ and $\mathbf{Z}^+_i$, which may include the lags of Δy_{it} and individual dummies; and ε^-_{it} and ε^+_{it} are the *iid* error terms with the *cdf* Φ^- and Φ^+, respectively.

The discrete change to the rate Δy_{it} is determined by

$$\begin{aligned}
\Delta y_{it}|(\mathbf{z}^-_{it}, r_{it} = -1) &= j \text{ if } \mu^-_{j-1} < \Delta y^*_{it}|(\mathbf{z}^-_{it}, r_{it} = -1) \leq \mu^-_j \text{ for } j \leq 0,\\
\Delta y_{it}|(\mathbf{z}^+_{it}, r_{it} = 1) &= j \text{ if } \mu^+_j < \Delta y^*_{it}|(\mathbf{z}^+_{it}, r_{it} = 1) \leq \mu^+_{j+1} \text{ for } j \geq 0,
\end{aligned}$$

where $-\infty \equiv \mu^-_{-J-1} \leq \mu^-_{-J} \leq \ldots \leq \mu^-_0 \equiv \infty$ and $-\infty \equiv \mu^+_0 \leq \mu^+_1 \leq \ldots \leq \mu^+_{J+1} \equiv \infty$ are the $2J$ unknown thresholds.

The conditional probability of the outcome j can be computed as

$$\begin{aligned}
\Pr(\Delta y_{it} = j|\mathbf{z}^-_{it}, r_{it} = -1) &= \begin{cases}\Phi^-(\mu^-_j - \mathbf{z}^{-\prime}_{it}\boldsymbol{\gamma}^-)\\ -\Phi^-(\mu^-_{j-1} - \mathbf{z}^{-\prime}_{it}\boldsymbol{\gamma}^-) & \text{for } j \leq 0,\\ 0 & \text{for } j > 0,\end{cases}\\
\Pr(\Delta y_{it} = j|\mathbf{z}^+_{it}, r_{it} = 1) &= \begin{cases}0 & \text{for } j < 0,\\ \Phi^+(\mu^+_{j+1} - \mathbf{z}^{+\prime}_{it}\boldsymbol{\gamma}^+)\\ -\Phi^+(\mu^+_j - \mathbf{z}^{+\prime}_{it}\boldsymbol{\gamma}^+) & \text{for } j \geq 0.\end{cases}
\end{aligned} \tag{5}$$

Assuming that the error terms ν_{it}, ε^-_{it} and ε^+_{it} are mutually independent, the full probabilities of the outcome j are given by combining probabilities in (2), (3) and (5):

$$
\begin{aligned}
&\Pr(\Delta y_{it} = j|\mathbf{x}_{it}, \mathbf{z}^-_{it}, \mathbf{z}^+_{it}) \\
&= \begin{cases} I_{j\le 0}\Pr(r_{it} = -1|\mathbf{x}_{it})\Pr(\Delta y_{it} = j|\mathbf{z}^-_{it}, r_{it} = -1) \\ +I_{j=0}\Pr(r_{it} = 0|\mathbf{x}_{it})\Pr(\Delta y_{it} = j|\mathbf{x}_{it}, r_{it} = 0) \\ +I_{j\ge 0}\Pr(r_{it} = 1|\mathbf{x}_{it})\Pr(\Delta y_{it} = j|\mathbf{z}^+_{it}, r_{it} = 1) \end{cases} \\
&= \begin{cases} I_{j\le 0}\Phi(\alpha_1 - \mathbf{x}'_{it}\boldsymbol{\beta})[\Phi^-(\mu^-_j - \mathbf{z}^{-\prime}_{it}\boldsymbol{\gamma}^-) - \Phi^-(\mu^-_{j-1} - \mathbf{z}^{-\prime}_{it}\boldsymbol{\gamma}^-)] \\ +I_{j=0}[\Phi(\alpha_2 - \mathbf{x}'_{it}\boldsymbol{\beta}) - \Phi(\alpha_1 - \mathbf{x}'_{it}\boldsymbol{\beta})] \\ +I_{j\ge 0}[1 - \Phi(\alpha_2 - \mathbf{x}'_{it}\boldsymbol{\beta})][\Phi^+(\mu^+_{j+1} - \mathbf{z}^{+\prime}_{it}\boldsymbol{\gamma}^+) - \Phi^+(\mu^+_j - \mathbf{z}^{+\prime}_{it}\boldsymbol{\gamma}^+)], \end{cases}
\end{aligned}
\tag{6}
$$

where $I_{j\ge 0}$ is an indicator function such that $I_{j\ge 0} = 1$ if $j \ge 0$, and $I_{j\ge 0} = 0$ if $j < 0$ (analogously for $I_{j=0}$ and $I_{j\le 0}$).

Each latent equation (which is a function of stationary exogenous variables, lags of the choice variable and a stationary shock) can be consistently estimated by asymptotically normal ML estimator under fairly general conditions (Basu and de Jong, 2007). To jointly estimate the three OP equations, as is common in the identification of discrete choice models, Φ, Φ^- and Φ^+ are assumed to be standard normal, and the intercept components of $\boldsymbol{\beta}$, $\boldsymbol{\gamma}^-$ and $\boldsymbol{\gamma}^+$ (which are identified up to scale and location, that is only jointly with the corresponding threshold parameters $\boldsymbol{\alpha}$, $\boldsymbol{\mu}^-$, and $\boldsymbol{\mu}^+$ and variances of $\boldsymbol{\nu}$, $\boldsymbol{\varepsilon}^-$ and $\boldsymbol{\varepsilon}^+$) are fixed to zero. As long as $\mathbf{X}$, $\mathbf{Z}^-$ or $\mathbf{Z}^+$ contains a single regressor that varies over i or t, the probabilities in (6) are absolutely estimable. They are invariant to the identifying assumptions, and can be estimated using a pooled ML estimator of the vector of the parameters $\boldsymbol{\theta} = (\boldsymbol{\alpha}', \boldsymbol{\beta}', \boldsymbol{\mu}^{-\prime}, \boldsymbol{\gamma}^{-\prime}, \boldsymbol{\mu}^{+\prime}, \boldsymbol{\gamma}^{+\prime})'$ that solves

$$
\max_{\boldsymbol{\theta}} \sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{j=-J}^{J} q_{itj}\ln[\Pr(\Delta y_{it} = j|\mathbf{x}_{it}, \mathbf{z}^-_{it}, \mathbf{z}^+_{it}, \boldsymbol{\theta})], \tag{7}
$$

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

All parameters in $\boldsymbol{\theta}$ are separately identified (up to scale and location) via the functional form due to the nonlinearity of OP equations (Wilde 2000). In practice, however, the standard normal *cdf* is often an approximately linear function over an extensive range of its argument. Thus, the simultaneous estimation of the three equations may be subject to a weak identification problem, if $\mathbf{X}$, $\mathbf{Z}^-$ and $\mathbf{Z}^+$ have all variables in common. In this case, exclusion restrictions may be necessary to avoid weak identification. To account for the individual heterogeneity, $\mathbf{x}_{it}$, $\mathbf{z}^-_{it}$ and $\mathbf{z}^+_{it}$ may include the individual fixed effect dummies. The fixed effects are more appropriate in the policy-rate-setting context than the random effects because instead of a random sample of individuals we have a complete set of all MPC members.

The starting values for $\boldsymbol{\theta}$ can be obtained using the independent OP estimations of each latent equation. The asymptotic standard errors of $\hat{\boldsymbol{\theta}}$ can be computed from the Hessian matrix. The conducted Monte Carlo simulations (see Section 3) demonstrate that the proposed estimator (written using GAUSS programming language) does a good job in estimating parameters and their standard errors.

2.3 Allowing for correlation among regime and amount decisions

The CronOP model can be extended by relaxing the assumption that the mechanisms generating the regime and amount decisions are independent, i.e. that the error terms $\boldsymbol{\nu}$, $\boldsymbol{\varepsilon}^-$ and $\boldsymbol{\varepsilon}^+$ are uncorrelated. To obtain the CronCOP model – a correlated version of the CronOP model – I assume that $(\boldsymbol{\nu}, \boldsymbol{\varepsilon}^-)$ and $(\boldsymbol{\nu}, \boldsymbol{\varepsilon}^+)$ follow the standardized bivariate normal distributions with the correlation coefficients ρ^- and ρ^+, respectively. This correlation may emerge, for instance, from common but unobserved covariates.

The probabilities of the outcome j for the CronCOP model are given by

$$
\Pr(\Delta y_{it} = j|\mathbf{z}^-_{it}, \mathbf{z}^+_{it}, \mathbf{x}_{it}) = \begin{cases} I_{j\le 0}[\Phi_2(\alpha_1 - \mathbf{x}'_{it}\boldsymbol{\beta}; \mu^-_j - \mathbf{z}^{-\prime}_{it}\boldsymbol{\gamma}^-; \rho^-) \\ \quad - \Phi_2(\alpha_1 - \mathbf{x}'_{it}\boldsymbol{\beta}; \mu^-_{j-1} - \mathbf{z}^{-\prime}_{it}\boldsymbol{\gamma}^-; \rho^-)] \\ \quad + I_{j=0}[\Phi(\alpha_2 - \mathbf{x}'_{it}\boldsymbol{\beta}) - \Phi(\alpha_1 - \mathbf{x}'_{it}\boldsymbol{\beta})] \\ \quad + I_{j\ge 0}[\Phi_2(\mathbf{x}'_{it}\boldsymbol{\beta} - \alpha_2; \mu^+_{j+1} - \mathbf{z}^{+\prime}_{it}\boldsymbol{\gamma}^+; -\rho^+) \\ \quad - \Phi_2(\mathbf{x}'_{it}\boldsymbol{\beta} - \alpha_2; \mu^+_j - \mathbf{z}^{+\prime}_{it}\boldsymbol{\gamma}^+; -\rho^+)], \end{cases} \tag{8}
$$

where Φ is the *cdf* of the standard normal distribution, and $\Phi_2(\phi_1;\phi_2;\xi)$ is the *cdf* of the standardized bivariate normal distribution of the two random variables ϕ_1 and ϕ_2 with the correlation coefficient ξ. To estimate the CronCOP model by ML, we have to solve (7) by replacing the probabilities in (6) with the probabilities in (8), and redefining the parameter vector as $\boldsymbol{\theta} = (\boldsymbol{\alpha}', \boldsymbol{\beta}', \boldsymbol{\mu}^{-\prime}, \boldsymbol{\gamma}^{-\prime}, \boldsymbol{\mu}^{+\prime}, \boldsymbol{\gamma}^{+\prime}, \rho^-, \rho^+)'$. The starting values for ρ^- and ρ^+ can be obtained using the grid search from −1 to 1 and maximizing the logarithm of the likelihood function holding the other parameters fixed at their CronOP estimates.

2.4 Marginal effects

The marginal effect (ME) of a continuous covariate on the probability of each discrete choice is computed as the partial derivative with respect to this covariate, holding all other covariates fixed. For a discrete-valued covariate, the ME is computed as the change in the probabilities when this covariate changes by one increment and all other covariates are fixed. To facilitate the ME derivation, the matrices of the covariates (where the subscript i is omitted for the sake of brevity) and the corresponding vectors of the parameters can be partitioned as

$$\begin{aligned} &\mathbf{X} = (\mathbf{A}, \mathbf{P}, \mathbf{M}, \widetilde{\mathbf{X}}), && \mathbf{X}^+ = (\mathbf{A}, \mathbf{P}, \widetilde{\mathbf{Z}^{\pm}}, \widetilde{\mathbf{Z}^{+}}), && \mathbf{X}^- = (\mathbf{A}, \mathbf{M}, \widetilde{\mathbf{Z}^{\pm}}, \widetilde{\mathbf{Z}^{-}}), \\ &\boldsymbol{\beta} = (\boldsymbol{\beta}_A', \boldsymbol{\beta}_P', \boldsymbol{\beta}_M', \tilde{\boldsymbol{\beta}}')', && \boldsymbol{\beta}^+ = (\boldsymbol{\gamma}_A^{+\prime}, \boldsymbol{\gamma}_P^{+\prime}, \widetilde{\boldsymbol{\gamma}_{\pm}^{+}}', \widetilde{\boldsymbol{\gamma}^{+}}')', && \boldsymbol{\beta}^- = (\boldsymbol{\gamma}_A^{-\prime}, \boldsymbol{\gamma}_M^{-\prime}, \widetilde{\boldsymbol{\gamma}_{\pm}^{-}}', \widetilde{\boldsymbol{\gamma}^{-}}')', \end{aligned}$$

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

The matrix of all explanatory variables $\mathbf{X}^*$ and the vectors of the parameters for $\mathbf{X}^*$ can be written as

$$\begin{aligned} &\mathbf{X}^* = (\mathbf{A}, \mathbf{P}, \mathbf{M}, \widetilde{\mathbf{X}}, \widetilde{\mathbf{Z}}^{\pm}, \widetilde{\mathbf{Z}}^{-}, \widetilde{\mathbf{Z}}^{+}), && \boldsymbol{\beta}^* = (\boldsymbol{\beta}_A', \boldsymbol{\beta}_P', \boldsymbol{\beta}_M', \tilde{\boldsymbol{\beta}}', \mathbf{0}', \mathbf{0}', \mathbf{0}')', \\ &\boldsymbol{\gamma}^{-*} = (\boldsymbol{\gamma}_A^{-\prime}, \mathbf{0}', \boldsymbol{\gamma}_M^{-\prime}, \mathbf{0}', \boldsymbol{\gamma}_{\pm}^{-\prime}, \widetilde{\boldsymbol{\gamma}^{-}}', \mathbf{0}')', && \boldsymbol{\gamma}^{+*} = (\boldsymbol{\gamma}_A^{+\prime}, \boldsymbol{\gamma}_P^{+\prime}, \mathbf{0}', \mathbf{0}', \boldsymbol{\gamma}_{\pm}^{+\prime}, \mathbf{0}', \widetilde{\boldsymbol{\gamma}^{+}}')'. \end{aligned}$$

The MEs of the row vector $\mathbf{x}_{it}^*$ on the probabilities in (8) can be computed for the CronCOP model as

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

where f is the probability density function of the standard normal distribution. The MEs for the CronOP model are obtained by setting $\boldsymbol{\rho}^- = \boldsymbol{\rho}^+ = 0$. The asymptotic standard errors of the MEs are computed using the Delta method as the square roots of the diagonal elements of

$$\widehat{Avar}\Big(\underset{\Pr(\Delta y_{it}=j)}{\widehat{\mathbf{ME}}(\boldsymbol{\theta})}\Big) = \nabla_\theta \underset{\Pr(\Delta y_{it}=j)}{\widehat{\mathbf{ME}}(\boldsymbol{\theta})}) \widehat{Avar}(\hat{\boldsymbol{\theta}}) \nabla_\theta \underset{\Pr(\Delta y_{it}=j)}{\widehat{\mathbf{ME}}(\boldsymbol{\theta})})'.$$

3 Finite sample performance

I conducted the extensive Monte Carlo experiments to illustrate and compare the finite sample performance of the ML estimators in the competing models, namely, to assess the bias and uncertainty of the estimates (and their asymptotic standard errors), the performance of the likelihood ratio (LR) and Vuong (1989) tests, the model selection criteria and hit rate (the percentage of correct predictions), and the effects of the exclusion restrictions.

To save the space, I provide a brief summary of Monte Carlo design and main findings. Table 1 shows the performance of the ML estimators in the competing models under the alternative *dgp*s. The details of Monte Carlo design and the comprehensive results of these simulations are reported and discussed in Online Appendix A.

The simulations demonstrate that the ME estimates in the OP and NOP models are biased when the underlying *dgp* is characterized by three types of zeros, and that the CronOP and CronCOP estimates systematically provide superior coverage probability (CP) as well as smaller bias. The cross-nested models under the true OP and NOP *dgp* perform much better than the OP and NOP models under the cross-nested *dgp*; as the sample size increases, the relative performance of the CronOP and CronCOP models under the OP *dgp* improves, although the Cron(C)OP models do not nest the OP one, whereas the OP and NOP estimates under the cross-nested dgp remain biased. Under the MIOP *dgp*, as the sample size grows, the CronOP estimator's bias does not decrease (and with 1000 observations is 30 times as large as the bias of the MIOP estimator), and its CP moves away from the nominal level down to 52%. Under the CronOP *dgp*, the MIOP estimates are severely biased: as the sample size grows, the bias almost does not change (and with 1000 observations is 27 times as large as the bias of the CronOP estimator), and the CP moves away from the nominal level down to 46%. The MIOP and CronOP models do not nest each other. Consequently, both MIOP and CronOP estimators are severely biased and inconsistent under each other's true *dgp*.

Table 1: Selected Monte Carlo results: The behavior of ML estimators under alternative *dgp*s.

Sample size	True *dgp*:	OP			CronOP				MIOP		CronOP	
	Estimated model:	**OP**	**NOP**	**CronOP**	**OP**	**NOP**	**CronOP**	**CronCOP**	**MIOP**	**CronOP**	**MIOP**	**CronOP**
250	Bias	0.25	0.45	1.48	34.6	32.8	0.62	0.82	2.98	19.0	15.2	2.04
500		0.22	0.31	0.99	34.8	32.9	0.25	0.40	1.58	18.9	14.9	1.06
1000		0.09	0.20	0.78	34.5	32.9	0.16	0.15	0.69	20.5	14.8	0.56
250	RMSE	2.06	2.95	3.71	4.86	4.44	1.96	2.34	2.08	3.24	2.43	2.34
500		1.43	2.04	2.48	4.69	4.34	1.34	1.62	1.40	2.74	2.08	1.60
1000		1.01	1.44	1.73	4.59	4.27	0.96	1.11	0.96	2.60	1.83	1.10
250	CP, %	93.2	92.0	90.4	36.0	45.9	91.0	90.3	91.4	67.6	74.5	93.7
500		94.2	93.4	92.2	20.5	35.3	93.0	92.4	93.9	62.9	59.8	94.2
1000		94.6	94.0	93.0	13.2	27.3	94.1	93.7	94.6	52.4	46.0	94.7

See Online Appendix A for the details of Monte Carlo design. Bias is the difference between the estimated and true values of the MEs, averaged over all replications and multiplied by 100. RMSE is the root mean square error of the estimated MEs relative to their true values, averaged over all replications and multiplied by 100. Coverage probability (CP) is computed as the percentage of times the estimated asymptotic 95 percent confidence intervals cover the true values of the MEs.

I found that it requires two-three times as many observations for the three-part models to achieve the same accuracy of the estimated parameters as for the OP model (if all models are correctly specified). As long as the number of observations per parameter exceeds 25, the asymptotic distribution is a reasonable approximation of the finite sample distribution of the Cron(C)OP parameters; in the smaller samples, the distributions of the standard error estimates (mostly for the threshold and correlation coefficients) are skewed to the right (there is a small fraction of huge estimated errors, while the rest of the estimated errors is downward biased).

In addition, to assess the effects of exclusion restrictions, three different cases of the overlap among the explanatory variables in the three latent equations (1) and (4) were simulated: "no overlap" (each regressor belongs only to one equation), "partial overlap" (each regressor belongs to two equations) and "complete overlap" (all three equations have the same set of regressors). The simulations suggest that the exclusion restrictions are not necessary for the consistent estimation of the cross-nested models. I found that, not surprisingly, the larger is the number of exclusion restrictions, the more accurate are the estimates: in the case of the substantial overlap among the covariates in the three latent equations, the asymptotic estimator can experience problems with the convergence and the invertibility of the Hessian matrix if the sample size is small (fewer than 25 observations per parameter).

4 Empirical application

"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)

I apply the OP, MIOP, CronOP and CronCOP models to explain the systematic components of the NBP policy rate decisions, employing a novel panel of the individual policy preferences of the MPC members and the vintages of the real-time economic data available to the public 1 day prior to each policy-setting MPC meeting during the 2/1998 – 4/2014 period.

4.1 Data and model specification

After the adoption of direct inflation targeting in 1998, the NBP policy rate – the reference rate[2] – may be undoubtedly treated as a principal instrument of Polish monetary policy. The reference rate is administratively set by the MPC, which consists of ten members who make policy rate decisions by formal voting once per month (since 2010, 11 times per year). The MPC moves policy rates by discrete adjustments – multiples of 25 basis points (*bp*), i.e. a quarter of a percent. At a policy meeting, each MPC member can express his preferred adjustment to the rate and make a proposition to be voted on. The individual policy preferences (reported in Table B1 in Online Appendix B) are consolidated into three categories: "an increase", "no change" and "a decrease". Such classification reflects the higher volatility of policy interest rate and inflation before 2002, making a 250-bp change made before 2002 comparable with a 50-bp change made after 2002. The sample contains the desired policy actions expressed by 31 policymakers at 190 MPC meetings. Among the 1719 observations employed in the estimations, the policymakers preferred to leave the rate unchanged 1125 times (65%), to increase the rate 253 times (15%) and to reduce it 341 times (20%).

Table B2 in Online Appendix B provides the definitions and sources of all variables. The sample descriptive statistics are summarized in Table B3 in Online Appendix B. All employed macroeconomic variables are stationary at the 0.01 significance level according to the augmented Dickey-Fuller unit root test, as shown in Table B4 in Online Appendix B.

Given the NBP strategy of direct inflation targeting, the policy regime decision in the CronOP model is assumed to be driven by a direct reaction to the changes in the economic conditions controlled by: (i) Δcpi_t – the recent monthly change to the current rate of inflation; (ii) Δcpi_t^{tar}, which is equivalent to Δcpi_t if the inflation is above the target, and zero otherwise (to allow for an asymmetric reaction to inflation changes depending on whether the inflation rate is above or below the target); (iii) $\Delta ecbr_t$ – the change to the European Central Bank (ECB) policy rate made at the last policy meeting (as a proxy for the recent economic trends in the European Union); (iv-v) $\Delta cpi_t^{tar} I_t^{2010}$ and $\Delta ecbr_t I_t^{2010}$, where I_t^{2010} is an indicator variable, which is one since February 2010, and zero otherwise (to allow for a different policy reaction in the post-crisis period during the third MPC term); (vi) $spread_t$ – the spread between the long- and short-term market interest rates (as a low-dimension market-based aggregator of publicly available information on inflationary expectations that are not reflected in the current inflation rate); (vii) $\Delta rate_{i,t-1}$ – the original (unconsolidated) change to the policy rate proposed by the MPC member i at the previous meeting (sequential decisions are not independent – the recent policy choice affects subsequent actions); and (viii) $bias_{t-1}$ – an indicator of the "policy bias" or "balance of risks" statements of the MPC at the previous meeting (to address the policymakers' concerns about the competence and credibility of central bank communication). The expected sign of the coefficients on these variables is positive – the larger is the value of a covariate, the larger is the probability of a tight policy stance and the smaller is the probability of a loose stance.

The amount decisions, which fine-tune and smooth the rate, are conditional on the tight or loose policy stance and controlled by (i) $\Delta rate_{i,t-1}$ (the larger is the hike/cut at the previous meeting, the lower is the probability of the second hike/cut in a row); (ii) $bias_{t-1}$ (the tightening/easing bias is expected to increase/decrease the probability of a higher rate); (iii) $spread_t$ (the rate hike is much more likely if the 12-month interbank rate is above the 1-week rate, rather than vice versa); (iv) the indicator variable I_t^{2002}, which is one since April 2002, and zero otherwise (to account for higher levels and stronger moves in the inflation and the policy rate prior to April 2002); and I_t^{2010} (to allow for a different policy reaction during the third MPC term). The expected sign of the coefficients is positive for $spread_t$ and $bias_{t-1}$, negative for $\Delta rate_{i,t-1}$, and should be opposite in the tight and loose regimes for I_t^{2002} and I_t^{2010}: a positive sign in the tight stance but a negative sign in the loose stance enable rate moves to be triggered by smaller changes to the explanatory variables after April 2002 and February 2010, respectively.

There are no interindividual differences in the values of the macroeconomic explanatory variables. To better account for the individual heterogeneity of policy preferences (not fully controlled by $\Delta rate_{i,t-1}$), I augment this specification by including the individual fixed effect (FE) dummies. For parsimony reasons, I only allow for variation in the intercepts – thirty individual dummy variables are included in each latent equation.[3] Slope heterogeneity is not a concern because our interest is in the estimation of the average effects of the explanatory variables, not of the individual policy reactions. Under the assumption that the slope coefficients randomly differ across the individuals, the pooled ML estimator yields consistent estimates of these aggregate effects while simultaneously providing a greater statistical power and a more reliable inference. We should not expect any significant fixed T asymptotic bias of our estimator – with our temporal size (T_i is 55 on average) we are in the realm of a time-series analysis.[4]

The fixed effects are more appropriate than the random effects because we do not have a sample of individuals who were randomly obtained from a large population but instead possess a full set of the MPC members. However, the FE specification with its 110 parameters is likely subject to a weak identification problem: there are fewer than 16 observations per parameter in the sample, and the sets of the covariates in the three latent equations overlap substantially. To prevent an overparameterization and obtain more reliable estimates, I also estimated a more parsimonious specification. I constructed the individual-specific variable $dissent_{i,t}$, which indicates a direction of member i's dissent at a meeting t: it is equal to 1/0/-1, if the member prefers the higher/same/lower rate than the MPC. The lags of $dissent_{i,t}$ reflect the dynamics of the deviation of member i's desired rate from the rate set by the MPC at the previous meetings. I included three lags in the regime equation, two lags in the amount equation under the loose regime, and three lags under the tight regime (with the expected positive sign of all coefficients – if a member preferred a higher/lower policy rate at the previous meeting, he is likely to be more hawkish/dovish at the subsequent meeting).[5]

4.2 Estimation results

The parsimonious specification with three lags of $dissent_{i,t}$ (see Table 2) adequately captures the heterogeneity of policy preferences: it has a slightly lower log likelihood than the FE specification (−629.2 vs. −626.2), but far fewer parameters (30 vs. 110), and is strongly preferred by the information criteria (the AIC is 1318 vs. 1472, the BIC is 1482 vs. 2072).

Table 2: Modeling changes to policy rate: the CronOP parameters in the baseline specification.

Variables	Regime equation	Amount equations	
		Loose regime	Tight regime
Δcpi_t	−0.22 (0.24)		
Δcpi_t^{tar}	7.99 (1.11)***		
$\Delta\ cpi_t^{tar} {*} I_t^{2010}$	−7.75 (1.16)***		
$\Delta ecbr_t$	11.02 (1.73)***		
$\Delta ecbr^t {*} I_t^{2010}$	−9.58 (1.78)***		
$\Delta rate_{i,t-1}$	2.44 (0.44)***	−1.08 (0.16)***	−3.1 (0.55)***
$spread_t$	1.93 (0.17)***	0.70 (0.14)***	0.67 (0.18)***
$dissent_{i,t-1}$	0.66 (0.17)***	1.64 (0.32)***	1.62 (0.28)***
$dissent_{i,t-2}$	0.23 (0.17)	0.74 (0.15)***	0.47 (0.23)**
$dissent_{i,t-3}$	0.51 (0.14)***		0.78 (0.28)***
$bias_t$	0.51 (0.14)***	6.99 (0.56)***	2.02 (0.21)***
I_t^{2002}		−1.37 (0.28)***	0.80 (0.21)***
I_t^{2010}		6.93 (0.73)***	1.42 (0.54)***
$threshold_1$	−1.27 (0.12)***	−0.79 (0.25)***	2.51 (0.32)***
$threshold_2$	2.50 (0.19)***		

1719 observations. For the definitions of the variables refer to Table B2 in Online Appendix B. ***/**/* denote the statistical significance at the 1/5/10 percent level. The robust asymptotic standard errors are shown in parentheses.

The FE specification is heavily overparameterized: the coefficients on 40 individual dummies are not significantly different from zero at the 0.05 level, as reported in Table B6 in Online Appendix B. Therefore, the specification with the lags of $dissent_{i,t}$ in Table 2 (henceforth the *baseline* specification) was employed in the further analysis. It saves 80 degrees of freedom, has an advantage of a greater statistical power, and can produce more efficient estimates of interest. Importantly, the estimated policy reactions to economic conditions are robust to different ways of accounting for individual heterogeneity: the coefficients on all common variables in the regime equation and on all but three variables in the amount equations are remarkably similar in both specifications. All coefficients in the baseline specification have an expected sign and are significant at the 0.01 level, with the exception of the coefficient on $dissent_{i,t-2}$ (the p-value is 0.17) and Δcpi_t (the p-value is 0.35) in the regime equation. Our expectation that the policy reaction to changes in inflation depends on whether inflation level is above or below the target is confirmed: the reaction is not significant if inflation is below the target.

Observing a large fraction of zeros does not always indicate that existing models are unsuitable. We can test which alternative model is favored by the real-world data: (i) the conventional OP model including all covariates from the CronOP model (see Table B7 in Online Appendix B); (ii) the MIOP model in which its dichotomous regime equation includes all covariates in the CronOP dichotomous amount equations and its trichotomous amount equation includes all covariates in the CronOP trichotomous regime equation (see Table B7 in Online Appendix B); (iii) the CronOP model with the baseline specification (see Table 2); and (iv) the CronCOP model with the baseline specification (see Table B8 in Online Appendix B). The NOP model is not listed because, in the case of the three outcome categories, it reduces to the usual OP model.

Table 3 compares the five competing models. The two- and three-equation models demonstrate a significant increase in the likelihood compared to the single-equation OP model. The CronOP and CronCOP models are overwhelmingly superior to the OP and MIOP models according to both information criteria and are favored by the Vuong tests (the p-value is 10^{-20}). There is no significant difference between the likelihoods of the CronOP and CronCOP models according to the LR test (the p-value is 0.999). The CronOP model is preferred by both information criteria.

Table 3: Comparison of competing models: the CronOP model is favored by real-world data.

Model	OP	MIOP	CronOP	CronCOP
Log likelihood	−813.3	−758.2	−629.2	−629.2
AIC	1656.5	1560.4	**1318.3**	1322.3
BIC	1738.3	1680.3	**1481.8**	1496.7
Hit rate	0.77	0.80	0.83	0.83
Vuong test vs. OP		−3.97***	−11.02***	−11.02***
Vuong test vs. MIOP			−9.38***	−9.37***
LR test vs. CronOP				0.002

1719 observations. ***/**/* denote the statistical significance at the 1/5/10 percent level.

I also estimated it with the same set of variables in both amount equations (by including $dissent_{i,t-3}$ under the loose regime) to test whether the rate hikes and cuts are generated by different processes. In our case with only three outcome categories of the dependent variable, the CronOP nests the MIOP model under "symmetrical" restrictions on the parameters in the amount equations. The LR test strongly rejects the symmetrical restrictions and prefers the CronOP model (the p-value is 10^{-37}).

The CronOP model also demonstrates a substantial improvement in the percentage of correct predictions (for rate cuts and hikes) and noise-to-signal ratios (for cuts and zeros), as shown in Table 4. The noise-to-signal ratios for hikes and the hit rates for zeros are similar across the three models, although slightly better in the CronOP model. Interestingly, the OP and MOP models predict more zeros (1224 and 1228) than the CronOP model (1171), but they *correctly* predict only 977 and 1004 zeros, respectively, whereas the CronOP model *correctly* predicts 1005 zeros.

Table 4: Comparison of competing models: the CronOP model has the best hit rates and noise-to-signal ratios.

Actual outcome	Hit rate			Adjusted noise-to-signal ratio		
	OP	MIOP	CronOP	OP	MIOP	CronOP
Decrease	0.60	0.71	**0.78**	0.12	0.07	**0.06**
No change	0.87	**0.89**	**0.89**	0.48	0.42	**0.31**
Increase	0.56	0.51	**0.64**	**0.06**	0.07	**0.06**

Notes: 1719 observations. The hit rate is the percentage of correct predictions. 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 was predicted and occurred; let B denote the event that the decision was predicted but did not occur; let C denote the event that the decision was not predicted but occurred; and let D denote the event that the decision was not predicted and did not occur. 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)].

To give the MIOP model additional chances, I also estimated it (a) including all CronOP covariates in both parts (the log likelihood is −725.1; see Table B9 in Online Appendix B) and (b) taking additionally all covariates in the regime equation by their absolute values to account for the binary ("a change" or "no change") nature of the regime decision (the log likelihood is −713.6; see Table B10 in Online Appendix B). In both cases, the CronOP remains overwhelmingly superior to the MIOP model according to the information criteria[6] and Vuong tests (the *p*-value is 10^{-9}).

The model comparison relies heavily on statistical criteria. Are we simply fine-tuning the OP and MIOP models or are the resulting improvements economically meaningful? The three models produce a conflicting inference and have incompatible and opposite estimates of the MEs of some explanatory variables on choice probabilities. The most striking differences across the models are in the effects of the previous change to the rate $\Delta rate_{i,t-1}$ (see Table 5).

Table 5: Comparison of competing models: the CronOP model provides the economically more meaningful estimates of the MEs of $\Delta rate_{i,t-1}$ on choice probabilities.

	OP	MIOP	CronOP
$\Pr(\Delta y_{i,t}$ = "increase")	−0.003 (0.001)***	−0.001 (0.001)	0.000 (0.000)
$\Pr(\Delta y_{i,t}$ = "no change")	−0.021 (0.003)***	−0.009 (0.010)	0.084 (0.024)***
$\Pr(\Delta y_{i,t}$ = "decrease")	0.025 (0.004)***	0.009 (0.010)	−0.084 (0.024)***

Notes: 1719 observations. ***/**/* denote the statistical significance at the 1/5/10 percent level. The robust asymptotic standard errors are shown in parentheses. The marginal effects are computed as a change in the probabilities when $\Delta rate_{i,t-1}$ changes from −25 bp to 0 bp, the inflation rate is above the target, and the other variables are fixed at their sample median values.

We expect a positive coefficient on $\Delta rate_{i,t-1}$ in the OP model. In the case of a rate hike, the probability of a hike/cut at the next meeting should be larger/smaller than in the case of a cut. The coefficient has a negative sign in the OP model, which nonsensically implies that the larger is the hike at the last meeting, the more likely is a cut at the next meeting. The CronOP model assumes that the rate change is the combined result of the two distinct decisions, on which a given variable may have different and even opposite effects. We expect a high level of persistency in the latent policy regime due to the slow cyclical fluctuations of macroeconomic indicators, which exogenously drive the policy stance. Central banks are typically conservative and dislike frequent reversals in the direction of interest rate movements. Therefore, we expect a positive coefficient on $\Delta rate_{i,t-1}$ in the regime equation. Policymakers are cautious and tend to wait and see after they have moved the rate; an adjustment is typically followed by a status quo decision. The CronOP amount decisions are unidirectional, either non-positive or non-negative, if the policy stance is loose or tight, respectively. Thus, we expect a negative coefficient on $\Delta rate_{i,t-1}$ in the amount equations. Indeed, the coefficient has a positive sign in the regime equation but the negative signs in the amount equations. It implies that the larger is the hike at the last meeting, the larger is the probability of a tight regime at the next meeting and, conditional on the tight/loose stance, the smaller is the probability of a hike/cut and the larger is the probability of no change.

The differences in the MEs of $\Delta rate_{i,t-1}$ on the choice probabilities obtained across the three models are intriguing: the CronOP model has the opposite signs of the MEs compared with the OP and MIOP models.[7] According to the CronOP model, if $\Delta rate_{i,t-1}$ changes from −25 *bp* to 0 *bp*, holding all other variables fixed, the probability of a rate cut decreases by 0.084, the probability of a hike increases insignificantly, and the probability of no change increases by 0.084. By contrast, the OP and MIOP models produce a conflicting and misleading inference: the probability of a cut increases by 0.025 and 0.009, the probability of a hike decreases by 0.003 and 0.001, and the probability of no change decreases by 0.021 and 0.009, respectively.

The impact of $\Delta rate_{i,t-1}$ on choice probabilities from the three models is also graphically compared in Figure 3. The predicted probabilities exhibit sharp contradictions. For example, if the policy bias is easing and $\Delta rate_{i,t-1}$ increases, the probability of no change increases in the CronOP model but decreases in the OP and MIOP models. Similarly, the three models make a conflicting inference regarding the probability of a rate reduction. The OP and MIOP models fail to provide an accurate assessment of the relationship between the explanatory variables and outcome probabilities and produce an absurd inference. In contrast, the capability of the CronOP model to disentangle the opposite directions of the effect of $\Delta rate_{i,t-1}$ on the regime and amount decisions produces an economically more reasonable inference.

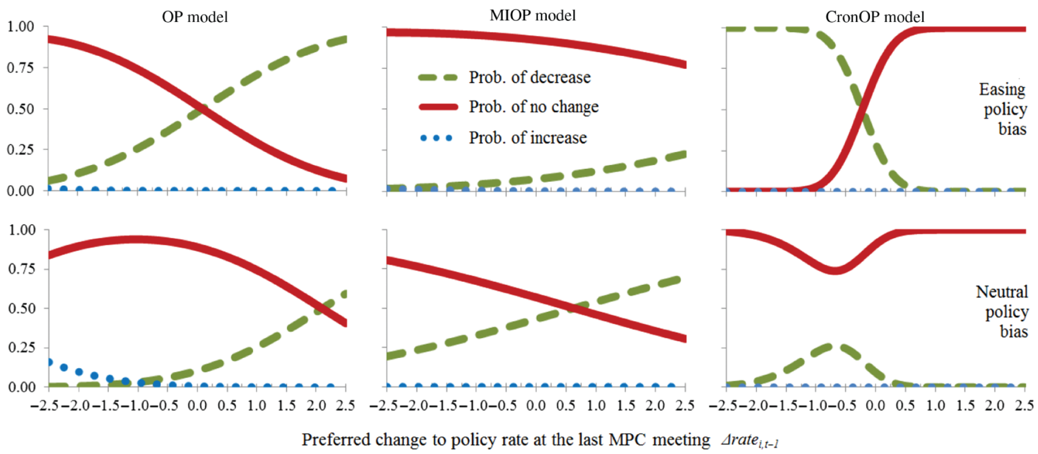

Figure 3: Comparison of competing models: the CronOP model provides the economically more reasonable estimates of choice probabilities.
Notes: 1719 observations. The probabilities are shown for the range of the preferred change to the rate $\Delta rate_{i,t-1}$ and two values of $\Delta bias_{t-1}$ (easing and neutral) at the last MPC meeting if the inflation rate is above the target and the other variables are fixed at their sample median values.

Figure 4 shows the estimated probabilities of latent policy regimes, which are averaged for each meeting across all MPC members. The probability profiles differ considerably in the periods of policy easing, maintaining and tightening, as demonstrated in Figure 5. Averaged over all meetings, the probabilities of the loose, neutral and tight policy stances are 0.33, 0.41 and 0.26, respectively, whereas the observed frequencies of the cuts, status quo decisions and hikes are 0.20, 0.65 and 0.15, respectively. Not all zeros are generated by a neutral policy stance.

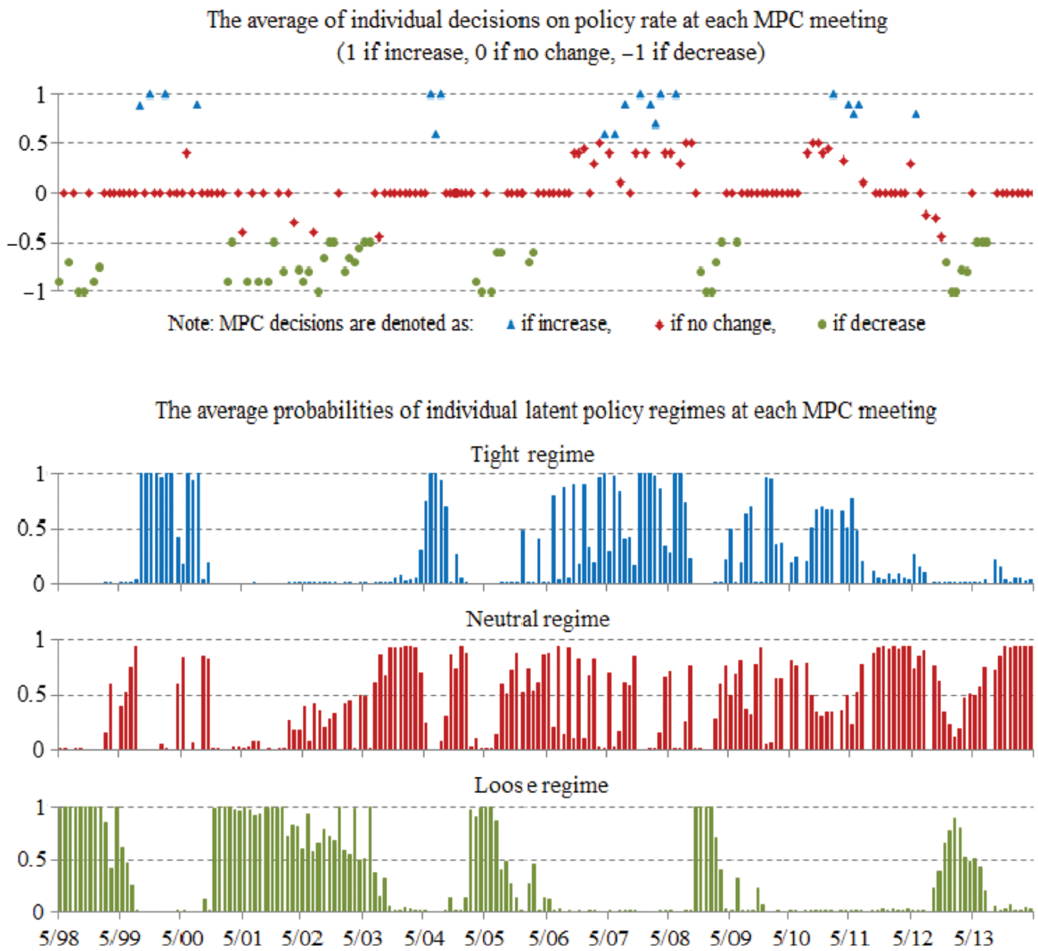

Figure 4: Actual policy decisions and estimated probabilities of latent policy regimes.

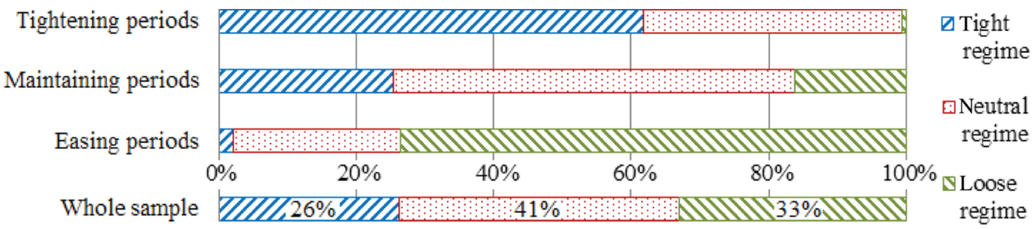

Figure 5: Probabilities of latent regimes in different policy periods remarkably differ.
Notes: 1719 observations. The estimates are obtained from the baseline CronOP model. For the definitions of the policy periods, refer to Figure 1.

These findings are refined in Figure 6, which reports the decomposition of unconditional probability of no change into three parts, $\Pr(\Delta y_{i,t} = 0|r_{i,t} = -1)$, $\Pr(\Delta y_{i,t} = 0|r_{i,t} = 0)$ and $\Pr(\Delta y_{i,t} = 0|r_{i,t} = 1)$, conditional on the loose, neutral and tight zeros, respectively. This decomposition substantially varies and, as we hypothesized, the identified three types of zeros are unproportionally distributed across different policy periods. During policy easing and tightening, the fractions of neutral zeros are 0.47 and 0.63, respectively. The fraction of neutral zeros is only 0.70 even among the zeros that are clustered between the rate reversals during policy maintaining. For the entire sample, the portions of the loose, neutral and tight zeros are 0.20, 0.62 and 0.18, respectively. The average predicted probability of a no-change decision during the observed no-change outcomes is decomposed similar as 0.19/0.64/0.17 (see Table B12 in Online Appendix B). Less than two-thirds of the status quo decisions appear to be generated by the neutral policy regime. The policymaking process in the NBP appears to be inertial by choice: 40% and 44% of all outcomes in the loose and tight regimes, respectively, are the status quo decisions.

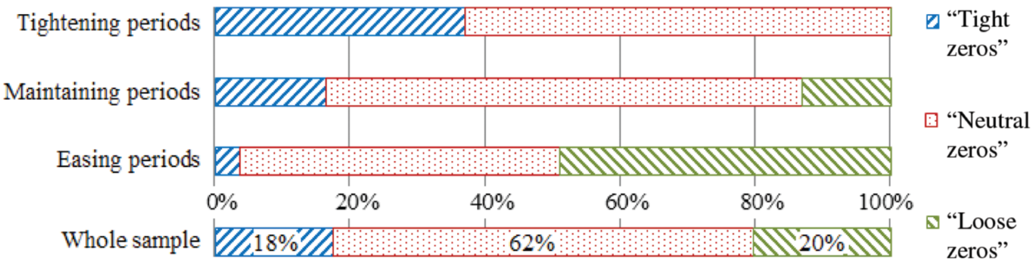

Figure 6: The decomposition of $\Pr(\Delta y_{i,t} = 0)$ into the probabilities conditional on the loose, neutral or tight regimes remarkably differs in different policy periods.
Notes: 1719 observations. The estimates are obtained from the baseline CronOP model. For the definitions of the policy periods, refer to Figure 1.

The MEs on the unconditional probability of no change can also be decomposed into three components. For example, the 0.084 (with the 0.024 robust standard error) ME of $\Delta rate_{i,t-1}$ on $\Pr(\Delta y_{i,t} = 0)$ is the combined result of the −0.098 (0.025), 0.178 (0.040) and 0.003 (0.002) effects conditional on the loose, neutral and tight policy regimes, respectively (see Table B13 in Online Appendix B).

To graphically illustrate how the decomposition of $\Pr(\Delta y_{i,t} = 0)$ depends on data, it can be plotted as a function of two explanatory variables, holding all others fixed. For example, Figure 7 shows that if the individual policy choice at the last MPC meeting was to leave the rate unchanged, the inflation is above the target, the last ECB policy decision was a 25-*bp* cut, and the other variables are fixed at their sample median values, then $\Pr(\Delta y_{i,t} = 0)$ is composed, on average, of 88% of loose and 12% of neutral zeros. However, if the ECB left the policy rate unchanged, then it is composed of 6% of loose and 94% of neutral zeros. If the ECB decision was a 25-*bp* hike, then $\Pr(\Delta y_{i,t} = 0)$ is composed of 49% of neutral and 51% of tight zeros.

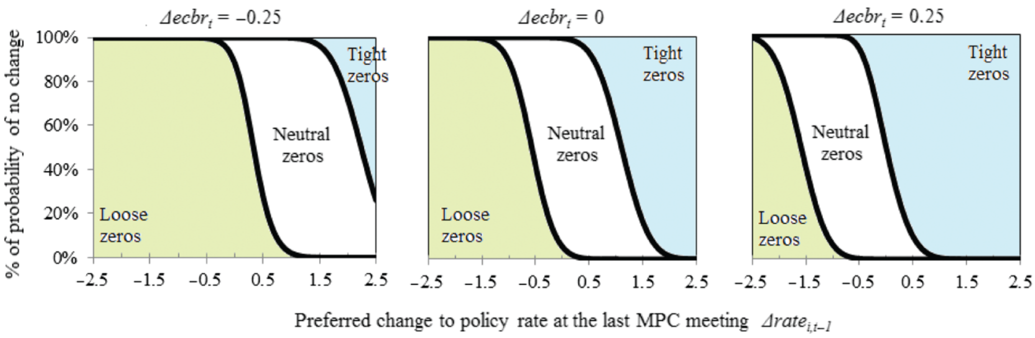

Figure 7: The decomposition of Pr ($\Delta y_{i,t} = 0$) into three components conditional on the loose, neutral and tight policy regimes as a function of policy rate choice at the last MPC meeting $\Delta rate_{i,t-1}$ and recent ECB policy decision $\Delta ecbr_t$. Notes: 1719 observations. The probabilities are computed for the range of $\Delta rate_{i,t-1}$ and three values of $\Delta ecbr_t$ if the inflation rate is above the target and all other variables are held at their sample median values. The estimates are obtained from the baseline CronOP model. For the definitions of the policy periods, refer to Figure 1.

The sensitivity of the obtained empirical results is examined along several dimensions (see Online Appendix C for details). All key empirical findings – the parameter estimates from the CronOP model (see Table C1 in Online Appendix C), the comparison of the ME estimates from the OP, MIOP and CronOP models (see Table C2 in Online Appendix C) and the model performance comparison (see Table C3 in Online Appendix C) – are highly robust with respect to various modifications of the baseline specification such as: the alternative definitions of the individual policy rate preferences and the previous policy choices, the different measures of explanatory variables, the inclusion of other potentially influential explanatory variables, and use of different subsamples.

5 Concluding remarks

Ordinal dependent variables with negative, zero and positive values are often characterized by abundant observations in the middle status quo or neutral category. Observing a large fraction of zeros does not necessarily imply that conventional discrete-choice models are not suitable. However, if zeros are generated by different groups of population or by separate decision-making processes, and positive and negative outcomes are driven by the distinct forces, treating all observations as originating from the same data-generating process and applying a standard single-equation model would be a misspecification. The standard models are hindered by overpredicting the most popular choice; in addition, a failure of the data homogeneity assumption and the way, in which the status quo observations are treated, usually result in the biased and inefficient estimates of the choice probabilities and the marginal effects of the explanatory variables on these probabilities.

To address these issues, this paper develops a flexible three-part ordered-choice model with overlapping latent regimes. In the empirical application to policy interest rate, the new model not only dominates the conventional models and demonstrates that the presence of heterogeneity in the data generating process is convincing, but also provides a qualitatively different and economically more reasonable inference.

The proposed cross-nested ordered probit model is well suited to explain monetary policy decisions by many central banks, and can be applied to a variety of ordinal datasets (changes to consumption, prices, or rankings) and survey responses (when respondents are asked to indicate a negative, neutral or positive attitude).

Funding

Global Development Network, Grant Number: #R10-0221. Economics Education and Research Consortium, Grant Number: Zvi Griliches Excellence Award.

Notes

1 Small (1987) proposed “the ordered generalized extreme value model” with overlapping and containing only two adjacent alternatives nests.
2 The rate on the 28-day (from 1998 to 2003), 14-day (from 2003 to 2005) and 7-day (since 2005 to present) NBP money market bills.
3 A dummy for Gronkiewicz-Waltz, who was the first MPC Chair (1998–2000) and the only MPC member in the sample who never dissented, and I_t^{2010} are omitted to avoid the dummy variable trap.
4 Using Monte Carlo simulations, Greene (2004) investigated bias in the discrete-choice panel models, including the OP model. As T increases from 2 to 20, the 160% bias reduces to 6%.
5 The third lag of $dissent_{i,t}$ is not included in the amount equation under the loose regime because its coefficient is not statistically significantly different from zero at the 0.22 level (see Table B5 in Online Appendix B) and the LR test fails to reject its redundancy (the p-value is 0.31).
6 The AIC and BIC are 1318 and 1482 for the CronOP model but only 1508 and 1666 for the MIOP model in the case (a) and 1485 and 1643 in the case (b), respectively.
7 The MEs of all explanatory variables are reported in Table B11 in Online Appendix B.

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Supplementary Material: The online version of this article offers supplementary material (DOI: https://doi.org/10.1515/snde-2018-0059).