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Policy Rate Decisions and Unbiased Parameter Estimation in Conventionally Estimated Monetary Policy Rules

Jiří Podpiera*

Abstract

The use of estimated policy rules has been on the rise over the past few decades as central banks have increasingly relied on them as policy benchmarks. While simple, conventionally estimated rules have proven insightful, their value is generally seen to depend, among other things, on the ability of the benchmark to accurately reflect the policy environment and on the relevance of the econometric assumptions behind the estimation method. This paper addresses a potential source of econometric bias that might naturally arise and adversely affect the accuracy of conventionally estimated policy rules as benchmarks. In particular, the discrete nature of the policy rate setting process at central banks leaves open the possibility that observed policy rate changes may include significant rounding errors. If so, parameter estimates using conventional econometric methods could be seriously biased; technically, this is an example of a censoring bias. To address this concern, the paper offers a new method for estimating monetary policy rules and demonstrates the ability of the resulting bias-adjusted policy rules to outperform conventionally estimated ones in characterizing the policy environments in the cases of the Czech Republic and the United States.

JEL Codes: E4, E5
Keywords: Bias in parameters, Monetary policy, Policy rule.

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Nontechnical Summary

The use of estimated policy rules has been on the rise over the past few decades as central banks have increasingly relied on them as policy benchmarks. While simple, conventionally estimated rules (ordinary least squares and two-sided tobit type II) have proven insightful, their value is generally seen to depend, among other things, on the ability of the benchmark to accurately reflect the policy environment and on the relevance of the econometric assumptions behind the estimation method.

In part, questions about the usefulness of estimated Taylor-type rules as benchmarks have been reflected in the recent academic literature. On the one hand, estimated Taylor rules suggest a tight fit with the actual policy decisions of central banks. On the other hand, the poor predictability of future market rates by financial market participants may suggest that the estimated rules may fit too well in-sample, i.e., they may be overfit.

To address the possibility that the discrete nature of policy rate changes may be adversely compromising the quality of conventionally estimated Taylor-type rules (especially those estimated by ordinary least squares) as policy benchmarks, the paper develops an estimation technique that takes into account the possibility of censoring, i.e., the effect of rounding policy rate settings by central banks, on the parameter estimators of Taylor-type rules. If this type of censoring is significant, the methods proposed in this paper would offer an improved way to estimate such benchmark rules for policy purposes.

To illustrate the benefit of this approach, two applications are considered. First, we examine the policy experience in the Czech Republic from 2003–2005. For this small, open economy with an explicit inflation target, we find that the parameters in a Taylor-type rule estimated by ordinary least squares are inconsistent. The systematic difference in the parameter estimates is large enough to have considerable policy implications. In particular, in a simulation with the forecasting framework of the Czech National Bank, I found, for the policy rule calibrated according to the results from the least squares estimates, excessive inflation, output gap and policy rate levels at the monetary policy horizon, compared to the benchmark (the actual model). Second, we examine the policy experience in the United States from 1974–1995. For this large, somewhat closed economy with an implicit target, we find that the new method delivers significant parameters with intuitive sign, compared to the conventional estimators.

1. Introduction

Conventional estimators applied to typical monetary policy rules neglect the discrete and censored nature of policy rate changes and thus yield biased parameter estimates. Macroeconomists tend to focus on a set of variables including the output gap, the inflation forecast and its target, and neutral real interest rates. However, as noted by Rudebusch (2002, 2006) and Soderlind et al. (2005), such policy rules fit the historical data well, but fail to predict the future and therefore the conventionally estimated policy rule parameters may be biased.

Even though the issue of biased parameter estimates in policy rules has often been neglected in the literature, the recent widespread use of estimated policy rules for macroeconomic models and policy advice makes unbiased estimation of parameters in policy rules increasingly relevant. A policy recommendation from staff to policymakers ought to be based on correctly estimated policy sensitivities to the fundamentals, since biased simulations would distort the relevant policy tradeoffs that policymakers face and could lead to suboptimal decisions. In turn, such decisions could raise doubts about the abilities of the central bank and adversely affect its credibility. Therefore, in this paper I propose an unbiased estimator for policy rule estimation and provide two applications.

For seminal papers in the empirical literature devoted to studying policy rules we go back to Rosett (1959), who suggested applying an ordered probit to address the discrete nature of discount rate moves by the Federal Reserve (Fed). A sequence of papers applying alternative discrete dependent variable models followed, including Feinman (1993) and Hakkio and Pearce (1992). Most recently, Choi (1999) derived a two-sided type II tobit that accounts not only for the discrete nature of the discount rate but also for its partial censoring. It is apparent that zero policy rate changes have the potential to be censored, which is Choi's conjecture; however, he also assumes that non-zero policy rate changes are uncensored. The latter assumption may not, however, be entirely correct. The monetary authority adjusts its policy rate usually by a quarter of a percentage point to avoid sudden policy rate reversals, i.e., it aims at avoiding instability in financial markets (as advocated by Cukierman, 1989; Goodfriend, 1991; and Rudebusch, 1995) and limits the number of large policy rate changes that could lead to a loss in credibility (see Goodhart, 1997).

Thus, the outcome of a monetary policy decision meeting would most often be a quarter of a percentage point increase (decrease) in the policy rate even if the selected fundamentals (usually specified in the Taylor rule with smoothing) would justify an adjustment in rates by half a percentage point or more. This implies that *non-zero* policy rate changes are also potentially censored due to the presence of some kind of selection (or censoring) rule determining how much policy rates should be changed by.

Since all policy rate decisions are potentially censored, estimation of the typical Taylor rules by conventional methods can be a poor approximation. Thus, depending on the nature of the approximation errors, special estimation methods may be necessary to produce unbiased and consistent estimates. In order to account for possible censoring of all policy rate changes, I devise a two-stage estimation procedure that combines an ordered probit and a censored regression. Since the ordered probit delivers unbiased parameter estimates, I suggest using these for deriving a censoring indicator (including non-censored observations) that I subsequently use in the censored regression. This procedure accounts for generally unknown censoring rules and thus delivers unbiased coefficients without loss in the efficiency of the estimates. In addition, since the resulting marginal effects are constant, they are directly comparable to the calibrated linear policy rules. Therefore, it is advantageous to use the method for initial calibration, verification, and updating of linear policy rules in policy practice.

The empirical analysis addresses two aspects. First, I empirically explore the issue of biasedness of the policy rule parameters estimated by least squares using the example of the Czech National Bank's (CNB) policy rule. I show that while the Taylor-type rule fits the past data almost perfectly, the future policy rate variation remains unpredicted by the market. I speculate that this issue is possibly connected to the specific aspect of the policy rate decision process

Second, I use two country examples to demonstrate the benefit of the new estimation method. Firstly, I estimate the policy rule of the CNB. I chose the CNB because it is an inflation targeting central bank that uses an unconditional inflation forecast and also because I had access to the real-time data that determined the endogenous trajectory of the policy rate, based on which the Bank Board decides on policy rates. Secondly, I apply the method to the U.S. data set used by Choi (1999) and discuss the improvements in the new estimator compared to the two-sided type II tobit and least squares.

In the case of the CNB's rule, the new estimator revealed that the bias-adjusted policy rule (accounting for censoring) was consistent with the one used by staff for making recommendations to the Bank Board. In this way, the bias-adjusted rule appears to capture the policy environment better than conventionally estimated rules. In the case of the United States, the estimates derived using the new method also helped to reconcile some of the counterintuitive inferences from conventionally estimated rules.

The rest of the paper is organized as follows: in Section 2 I explore the bias of the conventional Taylor-type rules. In Section 3 I describe a model of the policy rate decisions and in Section 4 I present the new policy rule estimation procedure. Section 5 reports estimation results for the Czech National Bank's policy rule and Section 6 presents the results for the Federal Reserve's policy rule. Section 7 concludes.

2. The Bias in Conventional Policy Rule Estimates

Under the assumption of rational expectations of financial market participants, the future policy rate changes of the monetary authority should be more predictable in the distant future, the more the policy maker applies policy rate smoothing. Rudebusch (2002) provides evidence of a low degree of variability in future policy rates forecastable by financial market expectations in the U.S. (as do many other authors, for instance Fuhrer and Moore, 1995, and Mankiw and Miron, 1986) and presents his evidence as proof of, in fact, a non-inertial policy rule (claiming that shocks are correlated and the monetary authority is free of inertia). This argument, however, stands in contrast to a significant portion of the current literature, for instance Goodhart (1999), McCallum and Nelson (1999), and Clarida et al. (2000), who find high policy rate inertia in empirical investigations using various policy rule specifications.

In this paper we present evidence from the term structure implications for monetary policy inertia in the Czech Republic and document that failure of rational financial market participants to predict policy rate changes in the distant future might not be clear proof of non-inertial behavior by the monetary institution. We especially put forward the observation of low forecastable variation in future policy rates by the monetary authority (staff) itself, by using the endogenous policy rate trajectory produced by the Czech National Bank's staff for predicting future policy rate changes. Consequently, we face the following contradictory observations. On the one hand, neither the market nor the central bank (staff) itself can predict the future policy rates (see subsection 2.1). On the other hand, the bank applies a very high degree of smoothing, which is embedded in the endogenous policy rate trajectory. In addition, it turns out to be even higher in empirical estimates (see subsection 2.2) and such a policy rule seems to perfectly explain the policy actions in the past.

2.1 Marginal Regressions

We start by evaluating the variance of future policy rate changes forecastable by market participants. We take the term structure of forward rate agreements and test the predictability of the policy rate changes in a variety of forecast horizons. The following relation was tested using quarterly data covering unconditional inflation targeting in the Czech Republic from October 2003 to January 2006:

$$i_{t+j}-i_t = \alpha_j+\beta_j\, (i_{t,t+j}^{FRA} - i_t)+\varepsilon_t\ . \tag{2.1}$$

The letter j stands for quarters and runs from one to four. The three-month interest rate (the interbank three-month rate – 3M PRIBOR) from *forward rate agreements* (FRA) set at time t for the period starting in j quarters is denoted as $i_{t,t+j}^{FRA}$. The interbank spot rate is denoted by i_t, while α_j represents the average term premium for the respective period $t+j$ and β_j is the coefficient representing the relation between the realized and *j-th* horizon expected change in the rate. The error term ε_t is assumed to be i.i.d.

In order to perform a complementary test for the central hypothesis that if the central bank smoothes its policy rates, a large share of the variability in policy rates at more distant horizons should also be forecastable, we collected data for the endogenous trajectories of the policy rate at each quarterly staff inflation-forecast round in the Czech National Bank and evaluated the forecastable variance in the policy rate changes implemented. The endogenous trajectory is based on a policy rule with a smoothing coefficient of 0.75. The smoothing in the policy rule seems to be rather close to the maximum smoothing of 0.8 that is justified by reasonable calibration of theoretical models.[1] Therefore, provided that the whole model is a correct description of reality, a small portion of the future policy rate variability explained by the endogenous policy rate trajectory would be contradictory evidence leading to rejection of the central hypothesis that high policy rate smoothing implies high future rate predictability. Hence, we estimate the following equation for the central bank:

$$i_{t+j}-i_t = \alpha_j+\beta_j\, (i^{*}_{t,t+j} - i_t)+\varepsilon_{t.}, \tag{2.2}$$

[1] Rudebusch (2002) provides an interval 0–0.8 for optimal smoothing, which is also consistent with the findings by Woodford (1999) and Levin et al. (1999), for instance.

where $i^*_{t,t+j}$ represents the future policy rate from the endogenous policy rate trajectory[2] (mapping the three-month interbank rate[3]) set at time t for j quarters ahead.

And finally, we also tested whether the central bank has sufficient credibility among market participants, i.e., whether the market successfully anticipates the endogenous policy rate trajectory of the central bank. For this purpose, we estimate another similar equation:

$$i^*_{t,t+j} - i_t = \alpha_j + \beta_j \, (i_{t,t+j}^{FRA} - i_t) + \varepsilon_t \,. \tag{2.3}$$

2.2 Data and Estimation Results

Making use of data from the internal documents of the Bank Board of the Czech National Bank about unconditional macroeconomic projections (containing the endogenous policy rate trajectory for j quarters ahead), which are made public with a delay of six years, and data from the Bloomberg database about forward rate agreements at corresponding frequency to match the quarterly projections, we estimated the relations (2.1) through (2.3).

The first result that follows from regression (2.1), as displayed in Table 1, is that the interest rate at distant horizons is rather unpredictable by the market. In particular, we found a relatively large portion of explained variability in the future realized policy rate path only at horizons up to two quarters ahead. An exclusively high portion of explained variability was found in the first quarter and a somewhat lower one in the second; however, as we move towards more distant quarters the share of explained variability drops literally to zero. Also, the slope coefficient declines from unity rather rapidly, as it is insignificant by the third quarter.

Table 1: Forecasting Actual Policy Rate

Quarters j	$i_{t+j} - i_t = \alpha_j + \beta_j \, (i_{t,t+j}^{FRA} - i_t)$				$i_{t+j} - i_t = \alpha_j + \beta_j \, (i^*_{t,t+j} - i_t)$			
ahead	α_j	β_j	R^2-*adj.*	*Obs*	α_j	β_j	R^2-*adj.*	*Obs*
1Q	0.016(0.02)	0.894***(0.074)	0.95	9	-0.001(0.058)	0.732***(0.216)	0.57	9
2Q	-0.092(0.088)	0.978***(0.264)	0.61	9	-0.018(0.10)	0.696**(0.227)	0.51	9
3Q	-0.21(0.17)	0.526(0.34)	0.17	8	-0.114(0.166)	0.363(0.27)	0.10	8
4Q	-0.231(0.289)	0.271(0.41)	0.001	7	-0.123(0.234)	0.093(0.327)	0.001	7

***Note**:* The stars denote significance as follows: ***1%, ** 5% and * 10%. Standard errors are given in parentheses.

The second result follows from the estimation of regression (2.2), also presented in Table 1. The results suggest that the endogenous policy rate trajectory is not an appreciably better predictor of future rates than financial market futures. The proportion of explained variability in total variability in the policy rate plummets to zero after a few quarters for both predictors. The slope coefficient diverges from unity relatively quickly as well.

[2] For time t it is derived as $i^*_t = 0.75 i_{t-1} + (1-0.75)(r_t^{eq} + p_t^e + 1.2(p_t^e - p_t^{tar}) + 0.4 gap_t)$, and similarly for time $t+1$, etc. by moving the explanatory variables into the future.

[3] Since there is a very close relationship between the policy rate, i.e., the two-week repo rate, and the three-month PRIBOR.

Table 2: Forecasting Endogenous Trajectory

Quarters j ahead	$i^*_{t+j} - i_t = \alpha_j + \beta_j (i_{t,t+j}^{FRA} - i_t)$			
	α_j	β_j	R^2-adj.	Obs
1Q	0.016(0.06)	0.787***(0.222)	0.59	9
2Q	-0.10(0.089)	1.016***(0.23)	0.66	9
3Q	-0.174(0.127)	1.06***(0.237)	0.67	9
4Q	-0.212(0.154)	1.113***(0.22)	0.73	9

Note: The stars denote significance as follows: ***1%, ** 5% and *10%.
Standard errors are given in parentheses.

The results for the last equation (2.3), which are displayed in Table 2, show that the predictability of the trajectory by the market is very high at all horizons. The portion of explained variability reaches 65–75 percent. In addition, the slope is close to unity and statistically significant.

This could suggest that the Bank Board has been relatively successful in communicating with the markets regarding the trajectory of policy rates. This interpretation could be seen as speaking highly for the credibility of the Czech National Bank.

In sum, the results appear to imply that policy authorities do communicate their policy outlook with the public despite the difficulty in predicting future policy rates accurately beyond a few quarters. The weak predictability does not, however, suggest that policymakers do not smooth policy rates. But it does suggest that predictability and smoothing are not as closely linked as some in the literature have suggested (Rudebusch, 2002).

2.3 The Fit of the Inertial Taylor Rule

As disseminated in the Forecasting and Policy Analysis System (CNB 2003), the Czech policy rate appears to be consistent with the following forward-looking Taylor rule:

$$i_t = \beta_0 i_{t-1} + (1-\beta_0)(r_t^{eq} + p_t^e + \beta_1(p_t^e - p_t^{tar}) + \beta_2 gap_t) + e_t, \qquad (2.4)$$

where β_0, β_1, and β_2 are calibrated parameters, i_t denotes the quarterly average of the actual policy rate (the two-week repo rate) and i_{t-1} denotes its one-period (quarter) lag. r_t^{eq} stands for the real equilibrium interest rate, p_t^e stands for forecasted inflation one year ahead and p_t^{tar} denotes the corresponding inflation target. The output gap is denoted by gap_t. The variables r_t^{eq}, $(p_t^e - p_t^{tar})$, and gap_t have been taken from the unconditional quarterly forecast rounds carried out by the Czech National Bank's staff. As such, these variables, together with the calibrated parameters β in the model, define the model's quarterly average of the policy rate (i.e., the endogenous trajectory).[4]

Nevertheless, the policy rate decision meetings take place at monthly frequency and so the quarterly averages of the policy rates do not perfectly match the model's policy rate. Thus, when

[4] Since a result of every unconditional quarterly forecast round carried out by the Czech National Bank's staff is a consistent set of variables values, I used such real-time determinants for explaining the actual policy rate. Even though the forecasted inflation is a result of a simulation within the model's framework, there is no endogeneity problem to be addressed in the estimation. This is due to the fact that the explanatory variables are not endogenously related across the quarterly forecast rounds (only the current-quarter forecast in each particular quarterly forecast round is used).

estimated on real data (quarterly averages of the policy rate) there is a discrepancy that is represented in (2.4) by e_t, i.e., the error term.[5]

The estimate by ordinary least squares of equation (2.4) resulted as follows:

$$\underset{(0.05)}{i_t = 0.83^{***}\, i_{t-1}} + \underset{(0.05)}{0.17^{***}(r_t^{eq} + p_t^e)} + \underset{(0.08)}{0.24^{**}(p_t^e - p_t^{tar})} + \underset{(0.07)}{0.09\, gap_t} \qquad (2.5)$$

(R^2-adjusted = 0.99; Obs = 12, 2Q2003-1Q2006, s.e. in parentheses, stars denote significance: *10%, **5%, and ***1%).

It follows that the policy rule (2.5) accounts for most of the variation of the policy rate in the sample, since the R^2-adjusted equals 0.99.[6] However, if one assumes that the financial market predicts future policy rates based on least-squares projections (similar to that of 2.5), then the small forecasting ability of future policy rates by forward rates is a puzzle. The issue is possibly connected to a specific aspect of the policy rate decision process. In the following text I offer an alternative modeling framework.

3. The Policy Rate Model

The decision about the setting of the key policy rate is a result of a complex process. At every monetary policy decision meeting, the policymakers assess the current and forecasted macroeconomic conditions (such as the output gap, inflation, and the equilibrium interest rate), which define a set of core indicators (which usually enter a typical estimated rule), and considering all other relevant information (hard data as well as soft arguments), they decide whether to adjust the current policy rate or to keep it unchanged.

The observed changes in the policy rate are characterized by lumpiness (induced by the limited number of policy meetings in a year and the discrete changes in the policy rate) and as such they fall into the category of discrete and potentially censored data. However, the discreteness and potential censoring is man-made, i.e., it is generated by the policymakers, and thus there exists a censoring rule together with its determinants.

Let us define $\Delta i_t^* = i_t^* - i_{t-1}$, which represents the uncensored change in the policy rate that would correspond to the typical Taylor rule. Hence, the changes in the observed policy rate settings Δi_t might only partially coincide with the unobserved Δi_t^* due to the impact of the censoring rule on Δi_t. It follows that

$$\Delta i_t = \Delta i_t^* + \xi(Z_t'\delta) + \eta_t = X_t'\beta + \xi(Z_t'\delta) + \eta_t \qquad (3.1)$$

where η_t represents a random discretion – an i.i.d. random error – and its size falls into the range of ±12.5 basis points (b.p.) – the effect of rounding up or down to entire multiples of 25 b.p. This

[5] If we denote the model's policy rate (the endogenous trajectory) as i^*_t then the actual policy rate is given as $i_t = i^*_t + e_t$. The structure of the error term is discussed in the subsequent sections; the accent is placed on the difference between the rounding error and the effect of the selection (censoring) rule.

[6] High values of R^2 are common to similar types of regressions for the U.S. for instance (see Clarida et al., 2000) and the distant future predictability of policy rates by the market is also similarly weak (see Rudebusch, 2002).

represents the obvious source of lumpiness in the policy rate. The second part of the error term is the effect of the censoring rule, denoted by $\xi(Z_t'\delta)$.The effect of the censoring rule $\xi(.)$ is driven by a set of variables Z_t, which may also contain some or all of the variables in X_t. The composite error term $(\xi(Z_t'\delta) + \eta_t) \sim N(0, \sigma^2)$.

Thus, not accounting for the censoring rule biases the estimates of β in the least squares regression if $X_t'\xi(Z_t'\delta) \neq 0$, which is likely to be the case since the censoring rule could be correlated with the explanatory variables in X_t.[7]

If we denote by β the coefficients pertaining to the explanatory variables in X_t, which can be thought of as variables in the typical Taylor-type rules, we can model the partially observed policy rate (Δi_t*)

$$\Delta i_t^* = X_t'\beta \tag{3.2}$$

by using the following formalization of the observation-by-observation censored model. Observations are said to be censored from the right, uncensored, and censored from the left as follows:

$$\begin{aligned} \xi(Z_t'\delta) + \eta_t &\leq T_l \\ T_l < \xi(Z_t'\delta) + \eta_t &\leq T_u \\ \xi(Z_t'\delta) + \eta_t &> T_u\,, \end{aligned} \tag{3.3}$$

where the thresholds T_u and T_l are equal to +12.5 and -12.5 b.p., respectively. If $\xi(Z_t'\delta) = 0$, then it holds for all t that $\Delta i_t^* + \eta_t = \Delta i_t$ and the estimation can proceed with a linear estimator since $E(\Delta i_t^*) = E(\Delta i_t)$. Since in practice we know neither the uncensored continuous policy rate Δi_t^* nor the censoring rule and its determinants, we ought to devise an appropriate estimation method that would deliver unbiased parameter estimates in the widely used Taylor rules. In the next section I present such an estimation method.

4. The Estimation Procedure: 2S-CNREG

I suggest using the following two-stage estimation procedure for estimating the type of model as described in (3.1) through (3.3). If one possesses information about the censoring of the observations, as described in (3.3), one can go directly to the second stage. However, since the censoring information about the observations is often not known, I suggest a minor amendment to the definition of the censoring of the observations (3.3), which is given in (4.3) and which follows from the application of the first stage – an ordered probit.[8] Let Δi_t be an observed discrete ordered policy rate response taking values $\{m_1, m_2, \ldots, m_n\}$, where m_j denotes a particular magnitude of the observed change in the policy rate; there are n such distinct sizes of policy rate changes. The change in the implicit policy rate Δi_t^*, defined as $\Delta i_t^* = i_t^* - i_{t-1}$, is determined by the following identity:

$$\Delta i_t^* = X_t'\alpha\,, \tag{4.1}$$

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[7] The estimate of β is equal to $\hat{\beta} = (X_t'X_t)^{-1}X_t'\Delta i_t - (X_t'X_t)^{-1} X_t'\xi(Z_t'\delta)$, while not accounting for $\xi(Z_t'\delta)$ leads to $\hat{\beta}^* = (X_t'X_t)^{-1}X_t'\Delta i_t$. It follows that $\hat{\beta}^* \neq \hat{\beta}$ if $X_t'\xi(Z_t'\delta) \neq 0$ (see Greene, 2003).

[8] Similarly to the frictions model by Rosett (1959).

where α denotes the vector of coefficients corresponding to the explanatory variables in X_t. The estimation of α is based on the variability of the difference between the implicit policy rate (4.1) and the observed policy rate as in (3.1), namely $(\xi(Z_t'\delta) + \eta_t) \sim N(0, \sigma^2)$. We can express the relation between the latent (implicit policy rate) variable Δi_t^* and the observed variable Δi_t as follows:

$$\begin{aligned} \Delta i_t &= m_1 && \text{if} && \Delta i_t^* \leq Tm_1 \\ &= m_2 && \text{if} && Tm_1 < \Delta i_t^* \leq Tm_2 \\ &\ldots \\ &= m_n && \text{if} && \Delta i_t^* > Tm_n, \end{aligned} \tag{4.2}$$

which means that at each of the m_j thresholds, denoted as $Tm_1 < Tm_2 < \ldots < Tm_n$, the magnitude of the policy rate change m_j in the observed policy rate discretely switches to a different one in an ordered manner. There are n such thresholds in the sample.

The maximum likelihood for ordered probit is:

$$L = \Pi_{t=1,\ldots,n}\{[1-\Phi(X_t'\,\alpha - Tm_1)]^{I(\Delta it=m1)}\,[\Phi(X_t'\,\alpha - Tm_1) - \Phi(X_t'\,\alpha\, - Tm_2)]^{\,I(\Delta it=m2)}\ldots$$

$$[\,\Phi(X_t'\,\alpha - Tm_n)]^{\,I(\Delta it=mn)}\}.$$

If the data contain multiple sizes of changes (n is large), ordered probit will deliver consistent but inefficient parameter estimates. Besides, the inconstancy (non-linearity) of the marginal effects of the exogenous variables in ordered probit complicates their direct use for policy rule calibration. Therefore, I suggest using the consistently estimated parameters α from ordered probit (see White, 1982) for evaluating the censoring indicator and subsequently perform a censored regression.

Since the estimated sizes of the thresholds in ordered probit $Tm_1, Tm_2 \ldots, Tm_n$ will depend on the direction and frequency of censoring, and since the policy rate is usually adjusted by entire multiples of 25 b.p., the true thresholds take the values of entire odd multiples of 12.5ρ b.p.

The term ρ represents a normalization of the generally rescaled thresholds in ordered probit, which has the unique function of converting the size of the thresholds to ones directly comparable with the policy rate values: $\rho = \sigma_{Xt'\alpha}/\sigma_{\Delta it}$ and $\sigma_{Xt'\alpha}$ denotes the standard deviation of $X_t'\alpha$, while $\sigma_{\Delta it}$ stands for the standard deviation of Δi_t.[9]

Thus, multiples of 12.5ρ b.p. are used for the evaluation of the censoring indicator, since the underlying idea is to compare what the policymakers would have done – conditional on $X_t'\alpha$, given that they adjust the policy rate by multiples of a quarter of a percentage point – with what they actually did.

In particular, in order to classify the observed policy rate changes into censored from the left, censored from the right, and uncensored, I need to evaluate for each single observation the

[9] Such rescaling is sufficient only under the assumption of equal means of the fitted values ($X_t'\alpha$) and the observed policy rate changes (Δi_t). However, since ordered probit might rescale the coefficients, the mean of the fitted values might differ from the mean of the observed variable. In such a case, the fitted values need to be adjusted by the difference in the means in order to ensure comparability of the fitted and observed values (and imposed thresholds). Alternatively, the imposed threshold values need to be adjusted (for the difference in the means) to correspond to the fitted values.

conditional probability[10]: (1) that the size of the implied policy rate change corresponds to the observed change up to ±12.5 b.p., i.e., $P(\Delta i_t \approx \Delta i_t^* | X_t'\alpha) = P(-0.125 < \Delta i_t - (1/\rho)X_t'\alpha \leq 0.125)$, (2) that the size of the implied rate change is higher than the observed one by more than the rounding up error, i.e., more than 12.5 b.p., i.e., $P(\Delta i_t + 0.125 \leq \Delta i_t^* | X_t'\alpha) = P(\Delta i_t - (1/\rho)X_t'\alpha \leq -0.125)$, and finally (3) that the size of the implied rate change is lower than the observed one by more than 12.5 b.p., i.e., $P(\Delta i_t - 0.125 > \Delta i_t^* | X_t'\alpha) = P(\Delta i_t - (1/\rho)X_t'\alpha > 0.125)$.[11]

Observations are then said to be censored from the left, censored from right, and uncensored as follows:

$$\begin{aligned} P(\Delta i_t - 0.125 > \Delta i_t^* \mid X_t'\alpha) &= \max_{\psi \in \{\Delta i_t \approx \Delta i_t^*, \Delta i_t + 0.125 \leq \Delta i_t^*, \Delta i_t - 0.125 > \Delta i_t^*\}} \{P(\psi \mid X_t'\alpha)\} \\ P(\Delta i_t + 0.125 \leq \Delta i_t^* \mid X_t'\alpha) &= \max_{\psi \in \{\Delta i_t \approx \Delta i_t^*, \Delta i_t + 0.125 \leq \Delta i_t^*, \Delta i_t - 0.125 > \Delta i_t^*\}} \{P(\psi \mid X_t'\alpha)\} \\ P(\Delta i_t \approx \Delta i_t^* \mid X_t'\alpha) &= \max_{\psi \in \{\Delta i_t \approx \Delta i_t^*, \Delta i_t + 0.125 \leq \Delta i_t^*, \Delta i_t - 0.125 > \Delta i_t^*\}} \{P(\psi \mid X_t'\alpha)\} \end{aligned} \quad (4.3)$$

and since $\sum_{\psi \in \{\Delta i_t \approx \Delta i_t^*, \Delta i_t + 0.125 \leq \Delta i_t^*, \Delta i_t - 0.125 > \Delta i_t^*\}} P(\psi \mid X_t'\alpha) = 1$, the observations are uniquely classified.[12]

In other words, the first relation in (4.3) with the highest probability states that when observing a change in the announced policy rate Δi_t, the policy rate implied by variables X_t and parameter estimated α suggests a significantly (more than 12.5 b.p.) greater decrease in the policy rate (Δi_t^*) than observed (Δi_t) and thus we speak about a censored observation from the left.

Similarly, the second relation in (4.3) with the highest probability states that a greater increase in the policy rate would have occurred had the decision been based only on the variables contained in X_t and parameter estimated α – thus we observe censoring from the right. And finally, according to the last relation in (4.3), if the probability that the difference between the implicit rate change and the observed rate change is equal to the rounding error of ±12.5 b.p., which is the

[10] I suggest using the median rule for classifying observations into censored and uncensored ones and perform an observation-by-observation censored regression. Such an approach to the classification of observations into outliers is not uncommon in robust estimation, where the probability of being an outlier is also used for identification of outliers (see, for instance, Rousseeuw and Leroy, 1987). In our case, however, it is not a just general outlier classification; there is a strong rationale for considering the observations to be potentially censored.

[11] $P(\Delta i_t - (1/\rho)X_t'\alpha \leq -0.125 \mid X_t'\alpha) = 1 - \Phi(\Delta i_t - (1/\rho)X_t'\alpha + 0.125)$; $P(\Delta i_t - (1/\rho)X_t'\alpha > 0.125 | X_t'\alpha) = \Phi(\Delta i_t - (1/\rho)X_t'\alpha - 0.125)$; and $P(-0.125 < \Delta i_t - (1/\rho)X_t'\alpha \leq 0.125 | X_t'\alpha) = \Phi(\Delta i_t - (1/\rho)X_t'\alpha + 0.125) - \Phi((\Delta i_t - (1/\rho)X_t'\alpha - 0.125)$. The presented evaluation of the probabilities uses the difference between the observed and implied policy rate change, which is measured against the thresholds. Nevertheless, it is equivalent to the notation where thresholds take various sizes, not just ±0.125, but entire odd multiples of 0.125. This follows from the fact that, for instance, the probability $P(\Delta i_t - (1/\rho)X_t'\alpha \leq -0.125 \mid X_t'\alpha)$ can be rewritten as $P(-X_t'\alpha \leq -\rho\ (0.125+\Delta i_t) | X_t'\alpha)$, which states that the fitted values are compared to the threshold $\rho\ (0.125+\Delta i_t)$, which is dependent on the size of the observed policy rate change (an entire multiple of 0.25 p.p.). In the empirical application I use a set of (so-called "discretion") thresholds instead of computing the difference between the actual and implied policy rate change. Nevertheless, both ways lead to identical results.

[12] Since cdf is a continuous transformation of $X_t'\alpha$, and because for all values $\Delta i_t^* | X_t'\alpha$ one of the following three uniquely holds: $\Delta i_t - 0.125 > \Delta i_t^* | X_t'\alpha$; $\Delta i_t + 0.125 \leq \Delta i_t^* | X_t'\alpha$; or $\Delta i_t - 0.125 \leq \Delta i_t^* | X_t'\alpha < \Delta i_t + 0.125$, all observations are uniquely classified.

maximum probability out of the three evaluated probabilities, such observation is declared to be uncensored.

In the second stage we complement the censored regression model by using the indicator of censoring derived on the basis of the first stage estimation (as described above). Besides preserving the efficiency of the estimates, in the presence of uncensored observations, the parameters will be constant and compatible with those calibrated in the linear policy rules.[13] The second stage of the model can be represented as follows:

$$\Delta i_t^* = X_t'\beta \tag{4.4}$$

The estimation of the censored regression follows the standard maximum likelihood method. The estimation of β is based on the variability of the difference between the implicit policy rate and the observed policy rate. The likelihood function for the observation-by-observation censored regression model can be written as follows:

$$L = \Pi_{t=1,\dots,n}\{[1-\Phi(X_t'\beta-\Delta i_t)]^{I(CI=-1)}\,[\sigma^{-1}\,\phi\,[(\Delta i_t - X_t'\beta)/\sigma]]^{I(CI=0)}\,[\Phi(X_t'\beta-\Delta i_t)]^{I(CI=1)}\},$$

where observations censored from the left, censored from the right, and uncensored are assigned the values -1, 1, and 0, respectively, in the censoring indicator (CI). Since some of the observations in the dependent variable have been adjusted so that they are closer to the median observations, the distribution of the errors has been changed and thus might exhibit heavier tails compared to normal. In order to account for this I suggest using a bootstrap (Bradley, 1979) to derive the standard errors using the sampling distribution.

5. Estimating the CNB's Policy Rule

The verification of the proposed method is demonstrated using data for the policy rule of the Czech National Bank, which is one of the pioneers of explicit inflation targeting in Central and Eastern Europe. The advantage of using the Czech example lies mainly in the availability of unique data for the true (and real-time data)[14] determinants and calibrated coefficients of the change in the policy rate Δi_t^*:

$$\Delta i_t^* = X_t'\beta\,,$$

based on which the CNB Bank Board has been advised to adjust the policy rate

$$\Delta i_t = X_t'\beta + \xi(Z_t'\,\delta) + \eta_t\,. \tag{5.1}$$

[13] The main difference between parameters α and β is that the former is varying in variables, whereas the latter is constant. The conversion of the former into the latter is not straightforward, as the literature is not consensual on the issue. See Greene (2003).

[14] In this way we can avoid the argument of Lansing (2002) that the estimated high policy rate inertia on revised data is misleading since estimations with real-time data on the output gap show much smaller policy rate inertia.

The term $\xi(Z_t'\ \delta)$ represents the censoring effect of the Bank Board due to variables in Z_t, which can contain some or all of the variables in X_t.

5.1 Specification and Data

Although the inflation targeting regime was implemented at the beginning of 1998, the Czech National Bank switched to an unconditional inflation forecast in early 2003. Since then, besides producing and publishing inflation forecasts and announcing inflation targets as previously, a policy rule has become an integral part of the policy framework. As disseminated in the Forecasting and Policy Analysis System (CNB, 2003), the model's policy rate $\Delta i_t{*}$ obeys the following forward-looking Taylor rule:

$$\Delta i_t{*} = (\beta_0\text{-}1)i_{t-1} + (1\text{-}\ \beta_0)(r_t^{eq} + p_t^e + \beta_1(p_t^e\text{-}p_t^{tar}) + \beta_2 gap_t), \tag{5.2}$$

which is also the main input into the Board's decision about the policy rate setting Δi_t:

$$\Delta i_t = (1\text{-}\ \beta_0)(r_t^{eq} + p_t^e\text{-}\ i_{t-1}) + (1\text{-}\ \beta_0)\beta_1(p_t^e\text{-}p_t^{tar}) + (1\text{-}\ \beta_0)\beta_2 gap_t + \xi(Z_t'\ \delta) + \eta_t, \tag{5.3}$$

where $\xi(Z_t'\ \delta)$ and η_t represent the censoring and rounding effects, respectively. Further, β_0, β_1, and β_2 are calibrated parameters, and i_{t-1} denotes the one-period (month) lagged policy rate. The real equilibrium interest rate is denoted by r_t^{eq}, while p_t^e stands for forecasted inflation one year ahead, and p_t^{tar} denotes the corresponding inflation target. The output gap is denoted as gap_t.

Besides the monthly two-week repo rate (policy rate), the data comprises the quarterly deviation of forecasted inflation from its target, the output gap, and the equilibrium nominal policy rate, which we collected from the CNB's internal baseline forecast database for each quarterly inflation forecast. For the sake of using monthly observations of policy rate changes, we interpolated the quarterly explanatory variables into monthly frequency by quadratic match-average. Our sample spans from January 2003 to December 2005. This is motivated by the fact that since early 2003, when a policy rule recalibration took place, the calibration of the policy rule has not been changed. Descriptive statistics of the data used in the analysis are shown in Table 3.

Table 3: Sample Descriptive Statistics (in %)

	Mean	Std. Dev.	Max.	Min.
Two-week repo rate	2.14	0.27	1.75	2.5
Policy neutral rate	3.62	0.46	2.66	4.35
Inflation forecast deviation from target (p.p.)	-.86	0.47	-1.63	-0.12
Output gap	-1.17	0.73	-2.44	-0.39

The sample period is characterized by a negative output gap, a below-target inflation forecast, and policy rates below their neutral level. As for the statistics on policy rate changes, the rate was changed nine times out of the 36 monthly meetings of the Board. The Board decided three times to increase the rate and six times to decrease it. All the changes in the two-week repo rate were of the magnitude of 25 b.p. At 27 meetings the rates remained unchanged.

5.2 Estimation Results

I present three regressions. First, I estimated equation (5.3) using ordinary least squares, i.e., ignoring possible policy rate censoring issues. Then, I estimated the two-sided-type II tobit,[15] allowing only zero policy rate changes to be potentially censored. And finally, I applied the two-stage 2S-CNREG procedure, which consists of ordered probit in the first stage and observation-by-observation censored regression in the second stage (as described in section 4).

The results of the parameter estimates are summarized in Table 4, along with the statistics pertaining to them. In all the estimated equations, the Durbin *h* statistics confirm no autocorrelation of the first degree at the 5% significance level. Two standard deviations are reported in the 2S-CNREG procedure, one pertaining to the normality assumption imposed on the residuals and the other to the sampling distribution (using a bootstrap with 50 sample replications). The bootstrapped standard errors are slightly higher, thus somewhat lowering the statistical significance of the estimated parameters.

In order to test the consistency of the estimates from the different methods, I make use of the Hausman specification test (Hausman, 1978). One can construct the Hausman *m*-statistic and test the following hypothesis. Under H0: both the OLS (two-sided type II tobit) and 2S-CNREG estimates are consistent and asymptotically efficient, while under H1: only the estimates from the 2S-CNREG procedure are consistent.

Testing the differences between the OLS and 2S-CNREG estimates by means of the Hausman test[16] (see Table 4) for a systematic difference in the estimates, where the result from 2S-CNREG is always consistent and OLS is possibly consistent and more efficient, I confirmed that the OLS estimates are systematically biased at the 10% significance level.

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[15] The modified two-step Heckman procedure for the two-sided type II tobit (Choi, 1999). The first step is the sign determining ordered probit; the likelihood function follows: $L = \Pi_{t=1,\dots,n}\{[1-\Phi(X_t'\beta_o - To_1)]^{I(\Delta it=-1)}[\Phi(X_t'\beta_o - To_1) - \Phi(X_t'\beta_o - To_2)]^{I(\Delta it=0)} \dots [\Phi(X_t'\beta_o - To_n)]^{I(\Delta it=1)}\}$, where To_i denotes the tolerance ancillary parameters. The second step proceeds with ordinary least squares with an inverse Mill's ratio (λ_t): $\Delta i_t = X_t'\beta + \gamma\hat{\lambda}_t + \varepsilon_t + \eta_{H,t}$, where ε_t denotes the model error and ε_t stands for the Heckman approximation error, $\eta_{H,t} = \lambda_t - \hat{\lambda}_t$. The estimate of λ_t is denoted by $\hat{\lambda}_t$ and $\hat{\lambda}_t = I_{(\Delta it=-1)}[-\phi(X_t'b_o - To_1/\Phi(X_t'b_o - To_1)] + I_{(\Delta it=1)}[\phi(X_t'b_o - To_2/\Phi(X_t'b_o - To_2)]$. The vector of parameters b_1 is the estimate of β_o. I applied White's (1980) approach to derive consistent standard errors using the second step residuals e_i as $(K_t'K_t)^{-1}K_t'Var(\varepsilon_t)K_t(K_t'K_t)^{-1}$, where $K_t'Var(\varepsilon_t)K_t = \Sigma_{i=1,2,\dots,n}\, e_i k_i k_i'$. By k_i I denote the element of $K_t = (X_t : \hat{\lambda}_t)$.

[16] The *m*-statistic, for OLS vs. 2S-CNREG, reads: $m = q'(V_{OLS}-V_{2S\text{-}CNREG})^{-1}q$, where V_{OLS} and $V_{2S\text{-}CNREG}$ represent consistent estimates of the asymptotic covariance matrices of β_{OLS} and $\beta_{2S\text{-}CNREG}$, and $q = \beta_{OLS} - \beta_{2S\text{-}CNREG}$. The *m*-statistic is then χ^2_k distributed with *k* degrees of freedom, where *k* is the rank of the matrix $(V_{OLS}-V_{2S\text{-}CNREG})$. A generalized inverse is used, as recommended by Hausman (1978).

Table 4: Estimation Results of the CNB´s Policy Rule

	Heckman's proc.	2S-CNREG	OLS	MODEL
First step				
i^{eq}-i^{t-1} [1-β_o]	5.6***(1.9)	5.6***(1.9)		
p^e-p^{tar} [(1-β_o)β_1]	-2.2*(1.3)	-2.2*(1.3)		
ygap [(1-β_o)β_2]	1.5**(0.7)	1.5**(0.7)		
LL	-14.32	-14.32		
T_{m1}	6.2***(2.8)	6.2***(2.8)		
T_{m2}	11.5***(4.1)	11.5***(4.1)		
T_{m0*}		-5.3		
T_{m1*}		5.3		
T_{m2*}		10.6		
T_{m3*}		26.3		
Second step				
i^{eq}-i^{t-1} [1-β_o]	0.08***(0.03; 0.04)	0.09***(0.02; 0.05)	0.06***(0.02)	0.09
p^e-p^{tar} [(1-β_o)β_1]	0.12***(0.04; 0.06)	0.09***(0.035; 0.05)	0.07**(0.03)	0.11
ygap [(1-β_o)β_2]	0.05(0.03; 0.06)	0.05* (0.03; 0.04)	0.04(0.03)	0.04
LL		23.29		
σ		0.11***(0.01; 0.02)		
IMR	0.07*(0.03; 0.03)			
(ps)-R^2	0.78	(truncated at) 1	0.3	
Hausman test	$\chi2_{(3)}$[-4.76]~N/A	consistent	$\chi2_{(3)}$[6.93] = 0.07	calibrated
DW	1.64	1.86	2.28	
Durbin's *h*	1.09	0.42	-0.85	

Note: Standard errors in parenthesis; In Heckman´s procedure the second s.e. is computed using White´s (1980) approach. In the second step of the 2S-CNREG, the second standard deviation in parenthesis is derived using a bootstrap with 50 replictions. The discretion thresholds

T_{m0*}, T_{m1*}, T_{m2*}, and T_{m3*} are computed using $\sigma_{(Xt'\alpha)} = 4.66$ and $\sigma_{(\Delta it)} = 0.11$.

The results for the two-sided type II tobit estimated by Heckman's procedure (see Table 4) are partially insignificant due to the small sample of non-zero rate changes. The small sample is a general problem for this method since the second stage is performed on a subsample of non-zero policy rate changes that is often substantially smaller. Thus, the estimates are not more efficient than those from 2S-CNREG and thus the asymptotical assumptions imposed in the Hausman test are not satisfied (see the inference in a larger sample in section 6).

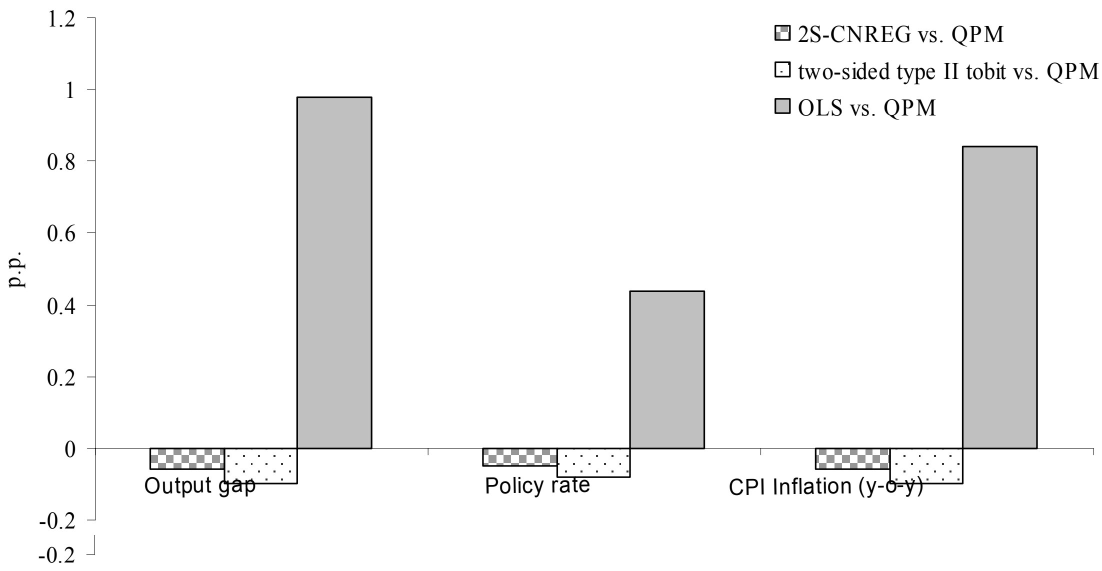
As for economic importance, as we can see from comparing the 2S-CNREG, the two-sided type II tobit estimated by Heckman's procedure, OLS, and the CNB's policy rule calibration (see MODEL in Table 4), the parameter estimates from all the methods are statistically very close to the calibrated rule[17] (at the 95% significance level). Nevertheless, the actual difference in the point estimates is potentially important from the point of view of policy implementation. The

[17] The numbers displayed in the MODEL column in Table 4 represent *the monthly frequency equivalents of the original quarterly frequency calibration of the policy rule. The conversion is based on the following relation: β_0 – quarterly = (β_0 –monthly)^3.*

implications of even relatively small differences in the policy rule calibration can best be demonstrated using a simulation with the CNB's staff forecasting framework (the QPM – see CNB, 2003). I consider three alternative calibrations of the policy rule (based on the rules estimated by OLS, 2S-CNREG, and two-sided type II tobit) to the actual calibration (MODEL).

I use the model's Baseline database of variables Q2-2007 and evaluate the differences in the results in the three key variables, i.e., the output gap, inflation, and the policy rate. I compare the cumulative effect in the four-quarter period 2008 Q2–2009 Q1. The results are shown in Figure 1.

Figure 1: Cumulative Effect (2008/Q2 – 2009/Q1), Based on Baseline Database 2007/Q2



As we can see from Figure 1, major differences in the simulated policy outcome result from the use of OLS estimates. In fact, the key policy rate would be roughly half a percentage point higher and the output gap and inflation approximately one percentage point higher at the policy horizon than the outcome using the actual policy rule calibration. By contrast, the differences stemming from the use of 2S-CNREG or two-sided type II tobit are very small – nearly negligible.

Thus using OLS estimates for policy rule calibration as compared to the other two methods would yield policy that is increasingly inertial (a small response in the current period), leaving the output gap and inflation to reach higher peaks and at the same time implying a stronger overall policy rate response in the future in order to bring inflation back to the target.

6. Estimating the Fed's Policy Rule

The other example of policy rule estimation is intended to provide more evidence of the performance of the new estimation technique, especially in a larger data sample. I follow the Benchmark specifications of the discount rate estimations as formulated by Choi (1999)[18], since

[18] I use the exact specification and data as used by Choi (1999) since I would like to see just the differences in the estimation methods. I acknowledge that the specification does not take into account the structural breaks in the time series (a change in the chairmanship of the Fed, policy strategy, etc.). Therefore, the differences

his model appears to be, to my knowledge, the most advanced model to date. Hence the Benchmark regression I (which corresponds to 'Model I: equation (1a)' in Choi, 1999) specification is

$$\Delta i_t = \beta_1 + \beta_2 \Delta i_{t-1} + \beta_3 i_{t-1} + \beta_4 y_{t-1} + \beta_5 \Delta y_t + \beta_6 \pi_{t-1} + \beta_7 \Delta \pi_t + u_{t,} \qquad (6.1)$$

and the extended specification for some additional potential objectives, denoted as Benchmark regression II (which corresponds to 'Model I: equation (1b)' in Choi, 1999), is written as follows

$$\Delta i_t = \beta_1 + \beta_2 \Delta i_{t-1} + \beta_3 i_{t-1} + \beta_4 y_{t-1} + \beta_5 \Delta y_t + \beta_6 \pi_{t-1} + \beta_7 \Delta \pi_t + \beta_8 m_t + \beta_9 s_t + v_t \qquad (6.2)$$

where $\Delta i_t = i_t - i_{t-1}$ and $\Delta i_t^* \approx \Delta i_t$. In both specifications (6.1) and (6.2) an identification problem might arise stemming from the censoring rule effect (contained in residuals u_t and v_t) as described in section 3 such that $\Delta i_t^* \neq \Delta i_t$ and hence the policy rule parameter estimates in OLS and potentially also in the two-sided type II tobit are biased.

The lagged official discount rate as the last day rate is denoted as i_{t-1} and the (lagged) difference in the official discount rate as Δi_t (Δi_{t-1}).[19] The lagged percentage deviation of the industrial production index (1987=100) from its trend is denoted as y_{t-1}, where the trend is derived as a geometric interpolation of the benchmark rates (see Choi, 1999). Similarly, Δy_t is the first difference of the gap in industrial production. Furthermore, π_{t-1} is the lagged deviation of y-o-y inflation from the assumed implicit inflation target of 2% and $\Delta \pi_t$ is its first difference. And finally, m_t stands for y-o-y M1 monetary aggregate growth as a deviation from its Hodrick-Prescott trend and s_t stands for the difference of the lagged official discount rate from the Federal funds rate target set prior to the discount rate announcement (for further details, see Choi, 1999).

The descriptive statistics of the data sample, spanning from September 1974 to March 1995, used in the analysis are presented in Table 5.

Table 5: Sample Descriptive Statistics (in %)

	Mean	Std. Dev.	Max.	Min.
Discount rate (last day rate)	7.16	2.76	14	3
Inflation deviation from implicit target (p.p.)	3.73	3.38	12.65	-1.26
Industrial production gap	-0.24	3.77	6.62	-10.67
Misalignment (discount rate vs. market rate) (p.p.)	-0.28	1.16	1.25	-5.55
M1 gap (HP trend)	0.13	1.58	5.37	-4.13

As we can see from Table 5, the investigated period was characterized by quite substantial variation in the policy rate (attaining its maximum at 14% and minimum at 3%) as well as in the difference of inflation from the implicit inflation rate target (peaking at 12.6% and reaching its minimum at -1.26%). On average, inflation seems to be above the implicit target (the mean of the difference is 3.73%). Similarly, quite a large degree of variation can be seen in the gaps of the
difference is 3.73%). Similarly, quite a large degree of variation can be seen in the gaps of

(advantages) of the 2S-CNREG are to be viewed only with respect to correction of the deficiencies in the estimates by the two-sided type II tobit as stipulated in Choi (1999).

[19] Nevertheless, it would probably be more appropriate to use the U.S. Federal funds rate target as the dependent variable instead. However, since I am presenting the benefits of the new estimator I preserve the original specifications and variable definitions as in Choi (1999).

industrial production and monetary aggregate M1. Nevertheless, the gaps seem to be well stabilized over the sample period, as follows from the nearly zero mean in both variables. And finally, the misalignment of the discount rate with the market rate is also rather small on average.

Employing the data set, I first present a replication of the results for the Benchmark regressions by Choi (1999) and then apply the 2S-CNREG method to the same data set and specification and interpret the differences. In addition, I present simple ordinary least squares as the most conventionally used policy rule estimation method. Table 6 contains the results.

In the case of the 2S-CNREG method, the second step uses a transformed dependent variable and thus the errors might follow a different sample distribution. Therefore, I provide an alternative standard deviation that results from a bootstrap of 50 replications of the re-sampling and as such better corresponds to the new sample distribution. The standard errors are, however, very robust to the number of replications and exhibit similarity to the estimate using the assumption of normality. As such, the significances in the results are not changed by using the sample distribution instead of the normal one.

Table 6: Estimation Results for the FED´s Policy Rate

	Benchmark regression I a)			Benchmark regression II b)		
	Heckman's proc.	**2S-CNREG**	**OLS**	**Heckman's proc.**	**2S-CNREG**	**OLS**
First step						
Δi_{t-1}	0.270	0.523*		-0.37	-0.09	
	(0.301)	(0.286)		(0.35)	(0.32)	
i_{t-1}	-0.077*	-0.09**		-0.28***	-0.29***	
	(0.044)	(0.041)		(0.06)	(0.06)	
y_{t-1}	0.137***	0.109***		0.11***	0.09***	
	(0.03)	(0.028)		(0.04)	(0.03)	
π_{t-1}	0.097***	0.102***		0.18***	0.17***	
	(0.067)	(0.035)		(0.04)	(0.04)	
Δy_t	0.789***	0.69***		0.73***	0.62***	
	(0.137)	(0.119)		(0.15)	(0.13)	
$\Delta\pi_t$	0.306	0.434*		0.53	0.67***	
	(0.252)	(0.239)		(0.29)	(0.26)	
m_t				0.14*	0.15*	
				(0.08)	(0.07)	
s_t				-0.75***	-0.73***	
				(0.13)	(0.12)	
T_l	-1.799***	-3.8/-2.9/-1.9/-1.8		-2.69***	-5.3/-4.1/-2.8/-2.7	
	(0.296)			(0.39)		
T_u	1.39***	1.3/1.4/2/2.1/2.9		1.17***	1.1/1.2/1.9/2.1/3.3	
	(0.279)			(0.32)		
T_{l*}		-2.8/-1.9/-0.9/-0.3			-4.7/-3.1/-1.6/-0.5	
T_{u*}		0.3/0.9/1.6/2.2/2.8			0.5/1.6/2.6/3.6/4.7	
Log-L	-129.55	-189.27		-105.69	-160.76	
Second step						
intercept	0.129	0.047	0.048	0.11	0.02	0.14***
	(0.11, 0.11)	(0.046; 0.056)	(0.052)	(0.11;0.1)	(0.04; 0.04)	(0.05)
Δi_{t-1}	0.424**	0.347***	0.141**	0.17	0.16***	0.01
	(0.12, 0.11)	(0.068; 0.084)	(0.063)	(0.12;0.11)	(0.05; 0.062)	(0.06)
i_{t-1}	-0.03	-0.045***	-0.017**	-0.07***	-0.06***	-0.05***
	(0.02, 0.02)	(0.008; 0.013)	(0.008)	(0.02;0.02)	(0.01; 0.011)	(0.01)
y_{t-1}	-0.001	0.033***	0.016***	-0.01*	0.004	0.003
	(0.01, 0.01)	(0.005; 0.0049)	(0.006)	(0.01;0.01)	(0.005; 0.048)	(0.01)
π_{t-1}	0.033*	0.039***	0.021***	0.04***	0.03***	0.03***
	(0.01, 0.01)	(0.007; 0.011)	(0.007)	(0.01;0.01)	(0.01; 0.01)	(0.01)
Δy_t	0.153***	0.208***	0.141***	0.1***	0.08***	0.1***
	(0.04, 0.04)	(0.021; 0.008)	(0.025)	(0.04;0.04)	(0.02; 0.02)	(0.02)
$\Delta\pi_t$	0.211*	0.197***	0.096*	0.26***	0.14***	0.13***
	(0.1, 0.12)	(0.046; 0.036)	(0.06)	(0.09;0.1)	(0.04; 0.02)	(0.05)
m_t				0.06***	0.04***	0.02
				(0.03;0.03)	(0.01; 0.01)	(0.01)
s_t				-0.21***	-0.17***	-0.14***
				(0.03;0.03)	(0.02; 0.042)	(0.02)
IMR/σ	0.296***	0.183***		0.25***	0.15***	
	(0.03, 0.03)	(0.013; 0.022)		(0.04;0.04)	(0.01; 0.024)	
Hausman test c)	$\chi2(6)[11.57] = 0.07$	consistent	$\chi2(6)[31.42] = 0.00$	$\chi2(7)[42.45] = 0.00$	consistent	$\chi2(7)[183.3] = 0.00$
Durbin's *h*	-	0.25	4.96	-	1.02	3.26
R^2/Nob/DW	0.87/57/-	0.78/247/1.98	0.26/247/1.79	0.89/57/-	0.78/247/1.92	0.43/247/1.59

Note: Standard errors are reported in parentheses. Stars denote significance level as follows: *10%, **5%, ***1%. Two standard errors are reported for Heckman's procedure. The first pertains to the OLS estimate and the second is the adjusted standard error through White's (1980) procedure. In 2S-CNREG, the second standard deviation in parenthesis is computed using a bootstrap with 50 replications. a) Benchmark regression I corresponds to Model I: equation (1a) in Choi (1999). b) Benchmark regression II corresponds to Model I: equation (1b) in Choi (1999). However the results differ from those in Choi (1999): Table I, since none of the monetray aggregates provided yielded replication. I thus opted for the closest estimates that resulted when using the gap in M1. c) In the Hausman test for Benchmark regression II, the insignificant variable yt-1 was dropped to meet the asymptotic assumptions for the Hausman test.

As we can see from the table, the column entitled Heckman's procedure (two-sided type II tobit) denotes the replicated regression of Choi (1999). Restating his findings in the second step of the estimation procedure applied to Benchmark regression I, all coefficients except for y_{t-1} have the correct sign ($\beta_3 < 0$ and $\beta_4, \beta_5, \beta_6,$ and $\beta_7 > 0$) and all variables except for Δi_{t-1} and y_{t-1} are statistically significant. Turning our attention to 2S-CNREG, the results in the second column reveal that by permitting all observations to be potentially censored, all coefficients, including β_4 (y_{t-1}), preserve their correct sign (according to the presumptions made by Choi, 1999) and all variables appear statistically significant at the 1 percent significance level. In addition, there are number of coefficients that are statistically different in magnitude from Choi's estimates (testing whether Choi's parameter point estimate falls into the interval estimate of the ordered probit and censored regression): y_{t-1}, i_{t-1}, and Δy_t, suggesting bias in the parameters of the two-sided type II tobit, due to ignoring the censoring of the non-zero observations. Also, based on the Hausman test, I could reject the consistency of the estimates of the two-sided type II tobit at the 10% significance level (p-value = 0.07).

Benchmark regression II includes two additional explanatory variables, i.e., the money gap m_t and the measure of the misalignment of the discount rate and the market rate, s_t. Heckman's procedure delivers coefficients that all have the correct sign except for y_{t-1} and all variables appear significant except for Δi_{t-1}. In the case of the estimates derived by 2S-CNREG, all coefficients have the correct sign and all coefficients are statistically significant, except for y_{t-1}. In addition, the point estimates are statistically different from the two-sided type II tobit in the following three variables: $\Delta\pi_t$, m_t, and s_t, which again points to biasedness of the parameter estimates in the two-sided type II tobit. Similarly to Benchmark regression I, the Hausman test shows that the parameters in the two-sided type II tobit are inconsistent (at the 1% significance level – see Table 6).

The problem of biased estimates can also be seen by comparing the parameters of the OLS with those of the 2S-CNREG procedure. In both Benchmark regressions, the Hausman test suggests misspecification in the OLS estimates: p-values = 0.00 in both regressions.[20] The tests confirm the issue of biased parameter estimates in Taylor-type rules when estimated by the available conventional estimation methods.

The findings, in addition, are supported by the first-order autocorrelation statistics (see Table 6). The Durbin *h* statistic for Benchmark regressions I and II, respectively, takes values of 11.41 and 9.9 for the two-sided type II tobit and 4.96 and 3.26 for OLS. These values suggest autocorrelation at the 5% significance level, which contrasts with the statistics for 2S-CNREG, where the same statistics are 0.25 and 1.02, respectively, implying no first-order autocorrelation.

[20] In Benchmark regression II, the statistically insignificant variable y_{t-1} was dropped for evaluation of the Hausman test statistics.

7. Conclusion

This paper has contributed to the literature on monetary policy rule estimation by exploring the biases that might arise from censoring in conventionally estimated policy rules. In order to fully account for the effects of the censoring rule, the paper develops an estimation procedure (combining ordered probit and censored regression methods) that, in principle, should address the concerns.

I provide evidence, based on the Czech inflation targeting experience, of an apparent inconsistency between the tight fit of Taylor-type rules to historical data and, at the same time, the failure of the financial markets to predict well future short-term market rates. Such a conundrum can be reconciled if one accepts that the estimates of the Taylor rule are severely biased. This conjecture is verified using the new methods advocated in the paper.

I analyze two policy episodes. For the policy experience in the Czech Republic I confirm that the parameters in a Taylor-type rule estimated by ordinary least squares are inconsistent. Using data on the United States I find that the new method delivers significant parameters with intuitive sign, compared to the conventional estimators.

The systematic difference in the parameter point estimates is large enough to have considerable policy implications. In particular, using a simulation with the policy framework of the Czech National Bank (the QPM), I find excessive inflation, output gap and policy rate levels at the monetary policy horizon as compared to the benchmark (the actual model and the model with parameters from the new estimation method).

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