Central Banks, adjustment costs and interest rate policy*

Kasper Roszbach
Stockholm School of Economics†

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Abstract

The main instrument of monetary policy in industrialized countries is currently a short-term interest rate. It typically remains unchanged during long spans of time. This paper tries to answer three questions. Why do Central Banks change targeted interest rates so seldomly? How should we estimate Central Banks' reaction functions? And what are the driving forces behind rate changes? This paper takes the point of view that Central Banks face a fixed cost when adjusting the targeted interest rate and therefore smoothe the targeted interest rate by using a discrete policy rule. In the estimation of the reaction function this discrete nature is taken into account by applying a grouped data model to a Swedish data set. Probabilities of the target rate being raised, lowered or kept constant are computed and compared with actual interest rate behavior. The model has a prediction rate of 88% versus 78% for the best naive estimator.

Key words: central banks, reaction functions, interest rate policy, censored variables, grouped data model

JEL classification: C34, E43, E52, E58

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†*Address:* Department of Economics, Box 6501, S 113 83 Stockholm, Sweden. *Email:* nekr@hhs.se

A central banker walks into an Italian restaurant to order a pizza. When the pizza is done, he goes up to the counter to get it. There a clerk asks him :
– Should I cut it into six or eight pieces?
The central banker replies :
–I'm feeling rather hungry right now. You'd better cut it into eight."
http : //www.etla.fi/pkm/joke.html

1 Introduction

In recent years, the main instrument of monetary policy in most industrial countries has been a very short interest rate controlled by the Central Bank. Despite the often explicitly stated final goal of price stability, monetary policy in many countries has in practice also been employed for the purpose of reducing fluctuations in short-term interest rates. For the U.S., for example, a number of studies has presented evidence for the thesis that interest rates became substantially more persistent and less volatile and ceased to exhibit the pattern of wide irregular and seasonal fluctuations after the foundation of the Federal Reserve System in 1914.[1] Recent empirical work on monetary policy, like Bernanke and Blinder [5], Brunner [6], Cecchetti [7], Christiano and Eichenbaum [8] and Hamilton [15] has also taken the view that the federal funds rate, an overnight rate targeted by the Federal Reserve Bank, is the Fed's foremost policy instrument.

Since very short Central Bank rates like the repo rate in Sweden and the federal funds rate in the U.S. form an important building-stone for term structure theory, they are of interest to us not only from a monetary economic but also from a financial economic perspective. Rudebusch [22] is one of those who linked together these two different perspectives.

Maybe the most salient feature of a policy instrument like the federal funds rate target in the U.S. and the repo rate in Sweden is their constancy over long lapses of time despite changes in the economic environment.[2] Surprisingly, except for Rudebusch [22], all authors modeling them have consistently ignored this property. Khoury [16] and Brunner [6] offer good overviews of the single equation OLS and VAR based reaction functions that have been estimated.

Until today, and to my knowledge, no attempt has been made to build a theoretical framework that explains why Central Banks follow discrete decision rules for their interest rate policy instrument. The first to recognize the empirical relevance of this feature and treat the interest rate targeted by the Central Bank as a discrete dependent variable was Rudebusch [22]. He applied a non-parametric hazard rate estimator on the spells between changes in the daily U.S. federal funds rate target and found that "after a target [rate] change, there is a greater likelihood of another target change in the same direction." [3] The hazard functions were also found to

[1] Cukierman [9] pp. 111-115 summarizes some of the evidence.

[2] For an in-depth description of U.S. monetary policy, see Goodfriend [13]. Hamilton [15] gives a detailed description of the workings of the federal funds market. For Sweden, see [19] and [20].

[3] A random-walk characterization of the federal funds rate, for which Cukierman [9] argued, would thus be incorrect.

Durations separating two target rate increases were found to have the same distribution as those separating two target rate decreases (see: Rudebusch [22]). Likewise, spells between a negative and a succeeding positive display duration dependence. During the first 25 business days after a change, the target rate is more likely to move once more in the same direction than in the other direction. After the fifth week the duration dependence has ebbed away. Thereafter, the target rate displays the behavior of a random walk.

In the earlier mentioned work with reaction functions estimated with VARs or single equation OLS the above described censored behavior of the interest rate has been removed by using monthly data. Those models can be employed to produce consistent forecasts of the targeted interest rate one or more months ahead. However, doing so does not add very much to our comprehension of when and why the Central Bank will move to change interest rates *within* any monthly period; they cannot explain the factors underlying the behavior found by Rudebusch at weekly frequencies.

Rudebusch's conclusions are liable to some qualifications, however. Firstly, a quick glance at Figure 1 suggests that the size of a target rate change does depend on the sign of the change: decreases tend to be bigger than increases. A test on the means, for example, cannot reject the null that cuts in the repo rate target are at least 1/4 percent larger than rises.[4]

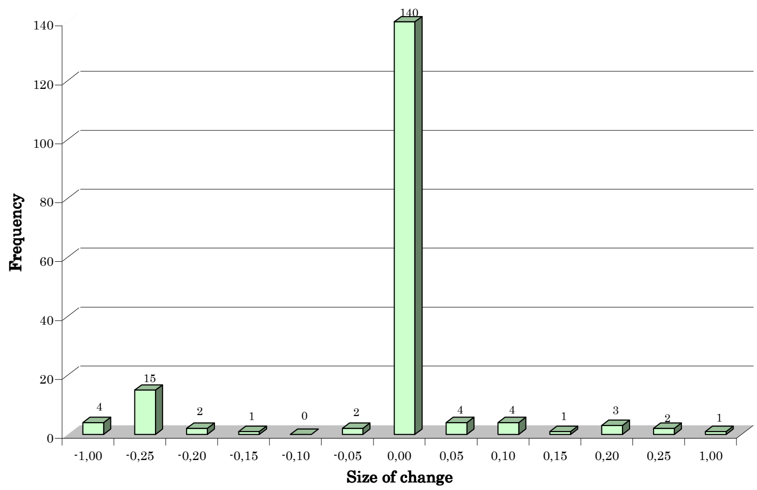

Figure 1. Changes (in perc. points) in the Swedish repo rate, weekly data, 24/11/92 - 30/4/96

Secondly, due to the nature of duration models, Rudebusch was unable to compose one model that explains both increases and decreases in the funds rate. Instead, he estimated two separate models, one for each type of change.

Apart from that, he assumed that target rate changes can be well described by a hazard rate that doesn't depend on any covariates - thus making the funds rate behavior independent of the macro-economic environment. Thereby he conveniently circumvented the data problem that economists faced in earlier work - namely that statistics on financial, and sometimes monetary data are abundantly available at weekly or even daily frequencies, while information on most real economic aggregates is so only at monthly frequency.

rate change have the same distribution as spells between a positive and succeeding negative target rate change. However, durations between changes of the same sign are drawn from a different distribution than the ones between changes of different sign. Because a one-to-one relationship exists between hazard ratios and probabilities, this implies that $P^{--} = P^{++} \equiv P^s$ and $P^{-+} = P^{+-} \equiv P^d$, but $P^d \neq P^s$ where P^{-+} is the probability of successive changes being first downward and then upward, etc.

[4] An identical test on U.S. data used by Rudebusch cannot reject the null that decreases are 1/16 percent bigger than increases.

The above qualifications combined with the stylized facts on the distribution of target rate changes provided in Figure 1, raise a number of questions about the way in which monetary policy is conducted and how we can estimate a Central Bank's policy function.

Firstly, why do Central Banks change targeted interest rates so seldomly? Secondly, when changes occur, should we expect an asymmetry in the reaction function, that is: are increases and decreases differently sized? Thirdly, what are the driving forces behind changes in the interest rate? Finally, if one could describe the hazard rates in terms of covariates, would we then still be able to find any duration dependence or asymmetries?

This paper is made up of two parts, a theoretical and an empirical. In section 2, I formulate a simple model of interest rate policy, that casts some light on the underlying properties of Central Banks' discrete, and asymmetric, policy rules. There, a monetary authority with quadratic preferences incurs a fixed cost of changing the interest rate. With the size of the cost depending on the direction of the change, the optimal interest rate rule is both discrete and asymmetric. That section also contains a sketch of the conditions under which the model and its implications would generalize to a dynamic environment. The main objective of section 3 is to formulate econometric models that can accurately describe the discrete behavior of the targeted short term interest rate for Sweden and the U.S. These models form the basis for the empirical analysis in section 4.

2 Interest rate targeting with costly adjustment

In this section, I first review a selection of studies that have offered either evidence that Central Banks face an adjustment cost when changing interest rates or an explanation for their policy of smoothing interest rates. After that, I formulate a simple model that provides us with some basic insights into the mechanisms that cause monetary authorities to change interest rates so seldomly, and to do so asymmetrically.

Although I am not aware of any paper offering a rationale for Central Banks' following discrete decision rules, a few papers have attempted to either explain the persistence in interest rates or discuss the consequences of interest rate smoothing policies. Goodfriend [12] and Barro [2] assumed some form of interest rate smoothing as an objective of monetary policy, and then pursued this goal with money as the instrument. Goodfriend started from the premiss that Central Banks seek to minimize price level forecast errors and the variation in inflation expectations. As a direct result smoothing nominal interest rates becomes the optimal means "to maintain 'orderly money markets"'. In Barro's paper, the starting point is a monetary authority that dislikes deviations of both the nominal interest rate from its target value and the price level from people's expectations. In such a model, both monetary growth and inflation are more volatile than the nominal interest rate.

Cukierman [9] has been a proponent of the view that the Fed engages in interest rate smoothing to maximize the stability of the financial sector - one of its explicitly stated tasks. Big profits generally provide financial companies with a buffer against losses and therefore further stability. To capture this mechanism, Cukierman added a banking sector to a stripped version of Goodfriend's [12] model. Under the presumption that interest rates on loan contracts are set prior to the determination of the cost of funds to banks, the best the Central Bank then can do is to supply money in such a way that shocks to the market rate of interest are smoothed.

Finally, an explanation that has regularly been brought forward but has not been explored in any formal theoretical framework, is that Central Banks loose credibility when they alter the stance of monetary policy. In this view, frequent rate changes are an expression of the Central

Bank's lacking understanding of, or control over, the economy. One way to think of this loss of credibility goes as follows: when commercial banks match their borrowing and lending, they assume a certain amount of uncertainty in future rates of interest. The perceived uncertainty is a function of the Central Bank's force of conviction, which the financial sector measures, among other things, by the frequency of interest rate changes. When a Central Bank changes the centrally determined rate of interest after a longer period with a constant rate, financial institutions experience an increase in uncertainty. Due to the greater uncertainty, commercial banks require a bigger risk premium and thus widen the margin between lending and borrowing rates, thereby reducing equilibrium lending to private businesses. Central Banks, although aware of this mechanism, cannot perfectly infer the cost of their actions. Instead, they use a rule of thumb, a simpler function (possibly duration - and state-dependent), to infer the cost of adjusting interest rates. This mechanism could also account for the duration dependence found by Rudebusch if the adjustment cost increases with the number of weeks since the latest rate change and reaches its maximum after some time.

The most concrete empirical evidence for the hypothesis that Central Banks incur a fixed cost when adjusting short term interest rates has been reported by Cecchetti [7]. After comparing the simulated interest rate patterns implied by two different objective functions with actual interest rates, he concluded that [U.S.] interest rates have been so smooth over the last 10 years that policymakers must have been "attaching a cost to actually moving the federal funds rate".

The main interest of this paper is to investigate if it is possible to incorporate the mechanism through which this adjustment cost affects the implementation of monetary policy in an econometric model and match the actual interest rate behavior with the latter. For that reason, I will set up a model of Central Bank behavior in a very simple environment with adjustment costs. This closely follows Obstfeld [21], who analyzed the adjustment of exchange rate pegs in the presence of fixed adjustment costs in a Barro-Gordon [4] economy, and Alexius [1], who used the same structure to model escape clauses for inflation rules. I let the adjustment cost that the Central Bank incurs be a fixed one, as a short-cut for the more complicated, possibly state-dependent, adjustment cost the Bank would face in a full scale general equilibrium model. Thereby, I abstract from any possible interaction between the adjustment cost and the state variables. Since the main objective of this paper is to model weekly interest rate behavior with a reduced form equation, the absence of a theory-based parametrization of the cost function will not constrain the analysis.

Let y be the natural logarithm of GNP and $\overline{y}$ its steady state level. The increment in the interest rate is denoted by $\triangle\, i$ and its expectation by $\triangle\, i^e$, while ϵ represents a random disturbance with mean zero and variance σ_ϵ^2. I^+ is an indicator function that takes the value 1 if $\triangle\, i > 0$ and zero otherwise, while I^- takes the value 1 if $\triangle\, i < 0$ and zero else. Suppose that the adjustment costs are independent of the state of the economy, but contingent on the sign of the change. So $\overline{c}$ and $\underline{c}$ are the costs associated with an increase respectively a decrease in the interest rate. GDP follows a Lucas inspired supply curve. The only difference is that income deviates from its steady state level due to unexpected interest changes rather than unexpected inflation.

$$y = \overline{y} + \alpha\,(\triangle\, i - \triangle\, i^e) - \epsilon \tag{1}$$

To change an inflation based Phillips curve into (1) one would need a link between the interest rate and inflation. Although it is conceptually very easy, I do not formalize that link here for reasons of algebraical simplicity. The Central Bank dislikes both deviations of income from its preferred level $\overline{y}$ and changes in the interest rate, with the cost having both a fixed and a variable component. Consequently, it faces the following optimization problem:

$$\min_{\{\triangle\ i\}} \frac{1}{2} \left\{ (y-\overline{y})^2 + \beta (\triangle\ i)^2 + \overline{c} \cdot I^+ + \underline{c} \cdot I^- \right\} \tag{2}$$

which it solves by setting the interest rate given interest rate expectations $\triangle i^e$.[5,6]

This very simple model implies the discrete type of optimal interest rate policy that we actually observe. The Central Bank's decision rule will be discrete and non-symmetric around zero if adjustment costs are asymmetric:[7]

$$\triangle\ i \ = \ \begin{cases} 0 & if \quad \underline{\epsilon} \leq \epsilon \leq \overline{\epsilon} \\ \frac{\epsilon}{\alpha^2+\beta} & if \quad not \end{cases} \tag{3}$$

where

$$\underline{\epsilon} = -\frac{1}{\alpha}\sqrt{\underline{c}\,(\alpha^2+\beta)} \qquad \overline{\epsilon} = \frac{1}{\alpha}\sqrt{\overline{c}\,(\alpha^2+\beta)} \tag{4}$$

Only when the economy is exposed to big, unexpected shocks and the steady state interest rate comes to differ too much from the optimal rate, will the Central Bank adjust the interest rate. The circumstances under which this happens depend on the parameters that describe the economy, the objective of the Central Bank and the size of the adjustment costs.

Although this model is a crude abstraction of reality, its quintessential property will generalize to more complicated, dynamic settings. If the Central Bank forms its optimal decision rule in a dynamic economy then its interest rate policy could well be a function of both simultaneous and lagged values of macroeconomic and financial variables. However, even then, if one accepts the existence of some adjustment cost, will the monetary authorities' optimal policy follow a discrete, possibly non-symmetric, decision rule. In the presence of adjustment costs, the interest rate will not change when the optimal frictionless rate change is small. First when the gain of the optimal interest rate change is bigger than the cost of adjustment will the Central Bank decide to increase or decrease the interest rate. This mechanism is independent of the variables determining the optimal frictionless rate change.

Suppose $\mathbf{X}_t$ is a vector containing all relevant variables *observed* by the Central Bank, $\boldsymbol{\beta}$ a vector of structural parameters and ε_t a random disturbance, that is unrelated to ϵ above, with zero mean and σ^2 variance. Let $i_t^* = \widetilde{h}(\boldsymbol{\beta}, \mathbf{X}_t, \varepsilon_t)$ be the optimal interest rate in the absence of adjustment costs, where the * indicates that the variable is unobserved. I will restrict myself to functions $\widetilde{h}(\cdot)$ with an additive disturbance, so that $i_t^* = h(\boldsymbol{\beta}, \mathbf{X}_t) + \varepsilon_t$. In this dynamic macroeconomic context the Central Bank's interest rate policy rule, in the presence of an adjustment cost like the one in the model $(1)-(2)$, would be of the form:

$$\triangle\ i_t \ = \begin{cases} i_t^* - i_{t-1} & if \quad i_t^* < \underline{a} + i_{t-1} \\ 0 & \text{''} \quad \underline{a} + i_{t-1} \leq i_t^* \leq \overline{a} + i_{t-1} \\ i_t^* - i_{t-1} & if \quad \overline{a} + i_{t-1} < i_t^* \end{cases} \tag{5}$$

or equivalently, in a notation more similar to that in (3):

[5] If we let i^{ss} be the steady state level of interest, then $\triangle i = i - i^{ss}$ in this static model, just as in Obstfeld [21]. For the same reason, we could also write $\triangle i - \triangle i^e = (i - i^{ss}) - (i^e - i^{ss}) = i - i^e$.

[6] It is tempting but confusing to talk about discretion versus rules instead of adjustment versus non-adjustment. Since both full discretion and following a rule can imply that adjustment is optimal, I prefer the latter terminology. The adjustment regime I use here is a full discretion policy.

[7] Derivations are provided in Appendix B.

$$\triangle\, i_t \;=\begin{cases} h(\boldsymbol{\beta},\mathbf{X}_t)+\varepsilon_t-i_{t-1} & if \;\; h(\boldsymbol{\beta},\mathbf{X}_t)+\varepsilon_t<\underline{a}+i_{t-1} \\ 0 & if \;\;\; \underline{a}+i_{t-1}\leq h(\boldsymbol{\beta},\mathbf{X}_t)+\varepsilon_t\leq\overline{a}+i_{t-1} \\ h(\boldsymbol{\beta},\mathbf{X}_t)+\varepsilon_t-i_{t-1} & if \;\; \overline{a}+i_{t-1}<h(\boldsymbol{\beta},\mathbf{X}_t)+\varepsilon_t \end{cases} \tag{6}$$

In other words, in the presence of adjustment costs $\triangle\, i_t$ will be non-zero only for values of i_t^* outside the range $[\underline{a}+i_{t-1}\;,\;\overline{a}+i_{t-1}]$. The parameters $\underline{a}$, $\overline{a}$, analogous to $\underline{\epsilon}$ and $\overline{\epsilon}$ in (4), are a function of the economy's parameters, the Central Bank's preferences and the adjustment cost. A difference from the static model is that the limits that i_t^* has to exceed, in order for a *change* in i_t to be optimal, now vary over time.

It is not the notion of Central Banks incurring some kind of adjustment cost that I consider being controversial, given our observation of their following discrete policy rules. Rather, as it has been in all earlier work in the adjustment cost literature, the issue really at stake is what the adjustment cost originates in. Moreover, are $\underline{a}$, $\overline{a}$ constants or are they a function of the state of the economy, $\underline{a}(\mathbf{X}_t)$, $\overline{a}(\mathbf{X}_t)$? Here, I will not go into this subject any deeper and suffice with a reference to the literature I reviewed in the beginning of this section.

The next step will be to test if a decision rule like (5) can accurately describe monetary policy. For this purpose, I will use a grouped data model. In addition, I will assume a specific functional form for $h(\boldsymbol{\beta},\mathbf{X}_t)$. Section 3 reviews previous econometric work on reaction function estimation and discusses the underlying assumptions and the workings of the methods proposed here. Section 4 contains the empirical results.

3 Econometric modeling

There already exists an extensive literature on the estimation of reaction functions, that broadly breaks up into two categories. Papers of the first type generally consist of ordinary least squares regressions of single equation reaction functions. Khoury [16] offers the most complete survey of this line of research. Studies in the second group usually employ a VAR approach. Brunner [6] is a recent, representative and interesting paper in this category, that contains some new insights about U.S. monetary policy between 1959 and 1993. Most importantly, he found in his study on American monetary policy that the federal funds rate is the best *indicator* of the stance of monetary policy - even in periods when the Fed was reportedly targeting reserves.[8] In the literature, this view has also been supported by Bernanke and Blinder [5]. Christiano and Eichenbaum [8] on the other hand preferred a reserve measure. Brunner also demonstrated that the federal funds rate is predetermined with respect to other reserves market variables and general macroeconomic variables. Moreover, the monetary authority does not have direct information about economic activity in the current week or month. Hence, it is permitted to estimate the reaction function by OLS regression of the target rate on the appropriate lagged variables in the Central Bank's information set.[9]

[8] The argument consists of two steps. First, open market operations are shown to be predominantly determined by deviations in the federal funds rate from its target and much less by deviations in non-borrowed reserves. Thus, the federal funds rate has been the Fed's *operational* target - even in periods when reserves were reported to play that role. Next, variance decomposition reveals that more than 86 percent of the variance of the federal funds rate is due to monetary policy shocks , while the portion of the variance of nonborrowed reserves due to policy shocks amounts to a mere 7 percent. Conditional on the identifying assumptions made by Brunner, this confirms that even to the extent that non-borrowed reserves *were* targeted, they weren't quantitatively important.

[9] Combined with the results mentioned in the preceding footnote, this also means that such a regression is the best means to uncover monetary policy shocks.

Both approaches suffer from the same weakness, having consistently ignored the high frequency behavior of interest rates. Figure 1 in section 1 clearly displayed how the Swedish repo rate typically is constant during long periods of time. An econometric model estimated on monthly data is not fit to explain Central Bank behavior at higher frequencies. Interest rates, especially rates for very short maturities, can make jumps in response to changes in the Central Bank's interest rate instrument, that are especially important directly after their occurrence. Since the OLS estimator is inconsistent when the dependent variable is censored, the size and timing of the jumps in daily or weekly series of the federal funds rate target and the repo rate can't possibly be explained by the OLS or VAR based models that have been used. Some authors conveniently circumvented this problem, for example by utilizing the daily federal funds rate - which fluctuates around its target - rather than the target itself. Such a daily rate is typically a market rate, however, whereas the target is a pure policy rate. Most likely the variables that cause fluctuations in the daily rate around its target, and the way in which they do this, are very different from those determining movements in the target itself.

The objective of this paper is to explain fluctuations in the targeted interest rate at weekly frequencies. Therefore one needs to take the censored nature of the interest rate data explicitly into account in order to obtain consistent estimates of the parameters in the reaction function. I estimate the Swedish Riksbank's reaction function with a grouped data model.[10]

The data might have allowed us to estimate the model with a Tobit model with both an upper and lower censoring threshold. This is less attractive, however, for at least three reasons. First, there are merely 40 uncensored obervations in the Swedish data, making it unrealistic to expect great predictive power *within* the uncensored range. Second, many of the uncensored observations take round values like 0.05, 0.10, 0.15, etc., and there is very little reason to believe that the remaining uncensored observations (only 8) differ in any systematic way from the others. Third, as will be illustrated in section 4, efficiency considerations require the model choice to be determined by the purpose it has to serve. As I mentioned above, the scarcity of uncensored observations means we should expect little from the model's ability to make point forecasts for the interest rate. However, the model may have a good potential to predict increases and decreases, possibly even for different intervals. On these grounds, grouping the observations seems to be the best way to handle the data. This is illustrated in figure 3.1. The 45° line represents all changes in the repo rate that are actually observed - without indicating relative frequencies of the various changes. Only values very close to zero are not observed. Instead of using the actual values, I group the changes according to size and maximize the likelihood that the observations belong to their respective intervals. Cuts bigger than a_1 are assigned to interval $(-\infty\ ,\ a_1)$, decreases smaller than a_1 but bigger than a_2 are assigned to the interval $[a_1\ ,\ a_2)$ etcetera - as is illustrated in the third quadrant. I will let the models' performance determine the number of groups that we will allocate the observations to.[11]

Let us assume that the underlying, unobserved, interest rate is linear in the explanatory variables and has an additive normally distributed disturbance. Then the model from section 2 where $i_t^* = h(\boldsymbol{\beta}, \mathbf{X}_t) + \varepsilon_t$ will simplify into

$$i_t^* = \boldsymbol{\beta}'\mathbf{X}_t + \varepsilon_t\ ,\ \varepsilon_t \sim N\left(0, \sigma^2\right) \tag{7}$$

[10] Greene [14] contains a compact description of both the ordered probit and the grouped data model. Stewart [23] describes the latter model more extensively.

[11] Group probabilities obtained from a model with for example 7 groups can simply be summed to calculate the probabilities for bigger groups, that contain one or more of these 7 groups. However, a model that has been computed with observations split up into a smaller number of groups will make better predictions for that purpose.

where the $*$ indicates an unobserved variable. The matrix $\mathbf{X}_t$ could in principle even contain simultaneous values of the the explanatory variables. Since monetary authorities do not have direct information about economic activity in the current period, $\mathbf{X}_t$ will exclusively consist of lags of the regressors.

Although i_t^* is not observed, we can interpret (7) as the 'first best' or 'frictionless' interest rate: if there were no adjustment costs, the interest rate would adjust continuously and such a frictionless interest rate would follow a decision rule that is continuous in the explanatory variables.

Despite i_t^* being censored, we can observe the discrete variables i_t and $\triangle i_t$. These even inform us about the range in which $\triangle i_t^*$ falls when $\triangle i_t = 0$. We collect all changes and divide them into groups according to their size. The groups , or intervals, are ordered such that an observation in the second interval can be said to be greater than one in the first, those in the third interval are greater than the ones in the second, etcetera.

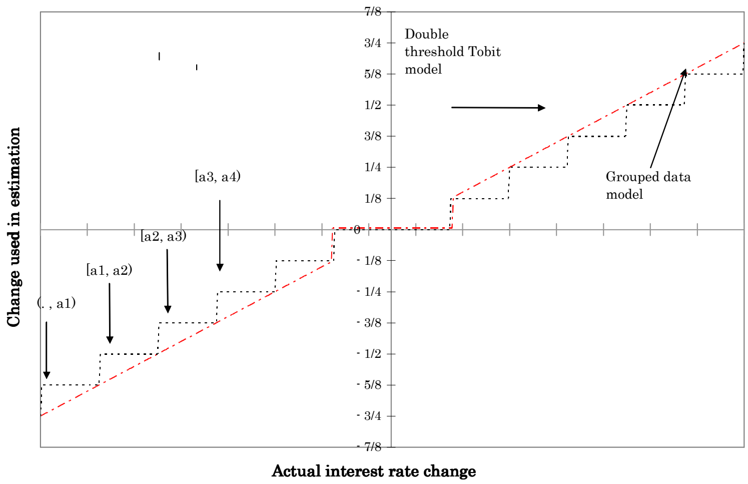

Figure 2. Grouping of observed interest rate changes in the grouped data model and a comparison with a double threshold Tobit model.

Consequently, we will be replacing the policy function (6)

$$\triangle\, i_t \;=\; \begin{cases} h(\boldsymbol{\beta},\mathbf{X}_t)+\varepsilon_t-i_{t-1} & if \;\; h(\boldsymbol{\beta},\mathbf{X}_t)+\varepsilon_t<\underline{a}+i_{t-1} \\ 0 & if \;\; \underline{a}+i_{t-1}\le h(\boldsymbol{\beta},\mathbf{X}_t)+\varepsilon_t\le\overline{a}+i_{t-1} \\ h(\boldsymbol{\beta},\mathbf{X}_t)+\varepsilon_t-i_{t-1} & if \;\; \overline{a}+i_{t-1}<h(\boldsymbol{\beta},\mathbf{X}_t)+\varepsilon_t \end{cases}$$

with the following structure, that we will find easier to estimate:

$$\triangle\, i_t \in \begin{cases} (-\infty,\; a_1) & if \quad i_t^*<i_{t-1}+a_1 \\ [a_1,\; a_2) & if \quad i_{t-1}+a_1\leqslant\; i_t^*<i_{t-1}+a_2 \\ . & \quad . \quad . \\ . & \quad . \quad . \\ [a_{K-2},\; a_{K-1}) & if \quad i_{t-1}+a_{K-2}\leqslant\; i_t^*<i_{t-1}+a_{K-1} \\ [a_{K-1},\; \infty) & if \quad i_{t-1}+a_{K-1}\leqslant\; i_t^* \end{cases} \tag{8}$$

The corresponding likelihood function is

$$
\begin{aligned}
ln\ L = \quad & \sum_t d_t^1\ ln\ \Phi\left[\left(a_1 + i_{t-1} - \boldsymbol{\beta}'\mathbf{X}_t\right)/\sigma\right] + \\
\sum_{k=2}^{K-1} & \sum_t d_t^k\ ln\left\{\Phi\left[\left(a_k + i_{t-1} - \boldsymbol{\beta}'\mathbf{X}_t\right)/\sigma\right] - \Phi\left[\left(a_{k-1} + i_{t-1} - \boldsymbol{\beta}'\mathbf{X}_t\right)/\sigma\right]\right\} + \\
& \sum_t d_t^K\ ln\left\{1 - \Phi\left[\left(a_{K-1} + i_{t-1} - \boldsymbol{\beta}'\mathbf{X}_t\right)/\sigma\right]\right\}
\end{aligned}
\tag{9}
$$

where $\Phi(\cdot)$ is the standard normal cdf and d_t^k a dummy that takes value 1 if $\triangle\ i_t$ belongs to the k-th interval and zero otherwise. The number of groups K is exogenous in the estimation as are the the threshold values a_z. Note that one implicitly imposes an identifying restriction when assuming that the thresholds are exogenously given. In the estimation of (5) and (6) when i_t^* follows (7), $\underline{a}(\mathbf{X}_t)$, $\overline{a}(\mathbf{X}_t)$ are estimable in theory. However to be able to identify them, one would have had to parameterize these functions. Instead, what I have done now is to assume that $\underline{a}$ and $\overline{a}$, or a_1, a_2, ..., a_K if one so prefers, are exogenously given constants.

We can compute a conditional mean function in analogy to that in the Tobit model[12]:

$$
E\left[\ i_t^* \mid \mathbf{X}_t,\ a_{k-1} + i_{t-1} \leqslant\ i_t^* < a_k + i_{t-1}\right] = \boldsymbol{\beta}'\mathbf{X}_t + \sigma \cdot \frac{\phi\left(z_{t,k-1}\right) - \phi\left(z_{t,k}\right)}{\Phi\left(z_{t,k}\right) - \Phi\left(z_{t,k-1}\right)}
\tag{10}
$$

where $z_{t,k} = \left(a_k + i_{t-1} - \boldsymbol{\beta}'\mathbf{X}_t\right)/\sigma$ and $\phi(\cdot)$ is the standard normal pdf. Unfortunately, this is a prediction of the *un*observed variable conditional on both $\mathbf{X}_t$ *and* its group membership, and therefore a less interesting quantity[13]. Instead, as an alternative conditional forecast, one can calculate to which interval i_t belongs with the highest probability, conditional on observing $\mathbf{X}_t$. This can be used as a complement to the point estimator provided by (7).

Analogous to the calculation of the conditional forecast described above, it has been common in so called ordered probit models to use the marginal effect of changes in the explanatory variables on the *cell probabilities* - instead of on the point estimate (7) - as marginal effects:[14]

$$
\partial \text{Prob}\left[cell\ k\right]/\partial\mathbf{X}_t =
\begin{cases}
-\phi\left(\frac{a_1 + i_{t-1} - \boldsymbol{\beta}'\mathbf{X}_t}{\sigma}\right) \times \boldsymbol{\beta}/\sigma & k = 1 \\
\left[\phi\left(\frac{a_{k-1} + i_{t-1} - \boldsymbol{\beta}'\mathbf{X}_t}{\sigma}\right) - \phi\left(\frac{a_k + i_{t-1} - \boldsymbol{\beta}'\mathbf{X}_t}{\sigma}\right)\right] \times \boldsymbol{\beta}/\sigma & 2 \leq k \leq K-1 \\
\phi\left(\frac{a_{K-1} + i_{t-1} - \boldsymbol{\beta}'\mathbf{X}_t}{\sigma}\right) \times \boldsymbol{\beta}/\sigma & k = K
\end{cases}
\tag{11}
$$

One typically evaluates these marginal effects at the means of the explanatory variables.

In the evaluation of the grouped data one can again use this as a complement to the marginal effect on the unobserved variable $\boldsymbol{\beta} = \partial i_t^*/\partial\mathbf{X}_t$. Note that (11), unlike the marginal effects in the linear model, can take very different values, even opposite signs, across both observations and cells. In the first cell the marginal effect will always have a sign opposite to that of the estimated coefficient vector whereas it will have the same sign as $\boldsymbol{\beta}$ in cell K. For the interjacent groups, the marginal effect can be either positive or negative depending on the values of $\mathbf{X}_t$ and i_{t-1}. It is thus important to be careful when interpreting the parameter estimates.

[12] The analogy derives its origin from the grouped data model's being a special case of the Tobit model - namely where the range of the dependent variable is completely censored.

[13] This can be compared to the case of the standard Tobit where the uncensored range of the dependent variable is the object of the conditional mean function. Also, observe that in the grouped data model $E\left[\triangle\ i_t^* \mid \mathbf{X}_t\right]$ once again simply equals $\boldsymbol{\beta}'\mathbf{X}_t$.

[14] The only difference between the ordered probit and the grouped data model is that the threshold values a_z are endogenous nuisance parameters that have to be estimated in the first model while they are exogenous in the second. This creates a difference in the efficiency of the parameter estimates when the dependent variable is not only ordered but even measurable on a cardinal scale.

Finally, it is important to stay aware of the conditions under which one can estimate the reaction function (7)-(8) consistently. Both Bernanke and Blinder [5] and Brunner [6] have advanced ample evidence in favor of the thesis that the target rate is predetermined with respect to other reserves market variables and macroeconomic variables in the U.S. They did *not* find any compelling reasons for macroeconomic variables not to depend simultaneously on the target rate or each other. This, however, combined with the fact that monetary authorities do not have direct information about economic activity in the current period, is enough to be able to consistently, although not efficiently, estimate the reaction function (7)-(8) while disregarding the equations that rule the evolution of the macro variables included in $\mathbf{X}_t$. Since I am primarily interested in the monetary authority's reaction function, I can and will hereafter disregard the equations that govern the motion of the macro variables in $\mathbf{X}_t$.

4 Empirical results

In this section, I will address two questions. Firstly, is it possible to accurately represent and explain monetary policy in Sweden by means of a discrete decision rule like (6)? Secondly, if one can, then what are the driving forces behind changes in the policy interest rate? And thirdly, is there any evidence for pure duration dependence? In other words: is time itself an explanatory variable once one describes the hazard rates for increases and decreases in the repo rate in terms of exogenous variables?

To make the step from the static, theoretical model (3) to a dynamic form that we can estimate, like (6) or $(7)-(8)$, one needs to identify the matrix of explanatory variables that compose the information set of the Swedish Riksbank in any week in the period 1992/50-1996/16. I have chosen weekly frequencies because changes in the repo rate have generally been announced on Tuesday morning by the Riksbank. Here, I will take $\mathbf{X}_t$ to consist of a set of commonly used financial and macro-economic variables. The full list of variables that I employ is provided in the table below.

Variable	**Definition** W = weekly data, M = monthly data
$Srepo$	Swedish repo rate (W)
$Tdown$	Weeks since last rate reduction (zero if last change was up)
Tup	Weeks since last rate increase(zero if last change was down)
CPI	Annual growth rate consumer price index (M)
IP	Annual growth rate of indust. production (M)
$Retail$	Annual growth rate of retail sales (M)
U	Unemployment rate (M)
$L2hh$	Annual growth rate of bank lending to households (M)
$USffr$	US federal funds rate (W)
$Grepo$	German repo rate (W)
$SKDM$	SEK/DEM exchange rate (W)
$SKUS\$$	SEK/USD exchange rate (W)

The two censored time variables have been included to test if Rudebusch's [22] finding of duration dependence in the hazard rate exists in Sweden and to see if it is a robust finding or just a by-product of the exclusion of covariates from the model.[15]

[15] Of course, this tests for a linear type of duration dependence.

Real and monetary variables including the CPI are expressed in annual growth rates, exchange and interest rates in levels. The motive for choosing this specific transformation of the macro aggregates - rather than taking their levels, which are more common in the VAR literature - is fourfold. First, a widely used work horse model in macro theory like the neoclassical growth model implies an equilibrium relationship between the real interest rate and the growth rate of consumption or GDP.[16] Variations on the basic model include the cash-in-advance economy of Stockman [24], in which equilibrium implies a relationship between the interest rate and the growth rate of money. Next, the treatment of economic news flows in the media strongly suggests that the public has little or no interest for the levels of real and monetary variables. Although the logic behind this behavior can be questioned, economic decision making appears to based on an information set consisting of growth rates of real and monetary variables plus levels of exchange and interest rates. Third, growth rates have the advantage over levels of being scale-free. Last of all, in arguing against the use of levels in the regression, one ought to keep in mind that the VAR literature, being a-theoretical by nature, doesn't offer any convincing theoretical justification for its choice of variable transformation.

In order to exploit all relevant data in the Swedish Riksbank's information set, we have used both weekly and monthly data in the estimation of the reaction function. Using the release dates for all relevant macro-economic and financial series, we have composed the Swedish Riksbank's information set for every week in the period December 1992 - May 1996. The data are described in greater detail in Appendix A.

The results for Sweden from the grouped data estimation of (7)-(8) for K=3 are summarized in tables 1 and 2. With the smallest increases and decreases being 0.03 percent, the thresholds were somewhat arbitrarily set at $a_1 = -0.025$ and $a_2 = 0.025$. Moving them closer towards 0.03 did not affect the results, however.

Although each explanatory variable shows up significantly in the regression at some lag length, they do so for only one or two lags, and most of them at the 10 % level. I also estimated the model for K = 5, 7, and 13 but found that the model's explanatory power decreased with increasing K. This is a consequence of the small number of rate changes in the sample, which is makes it difficult for the exogenous variables to predict interest rate changes more exactly than just "up", "unchanged" or "down".

There are two potential explanations for this result. Firstly, the sample used here is rather short, maybe too short to do any inference. Below, however, we will see that there are variations of the model that with much higher significance levels for the estimated parameters. Secondly, the model described above, although adequately embodying the discrete character of the monetary policy rule, may have failed to capture some other aspect Central Bank behavior. To investigate in what direction we should look for modifications in the specification, I estimated an ad-hoc variant of the model (7)- (8) in which I regress the *change* in the federal funds rate on *changes* in the exogenous variables $\mathbf{X}_t$. In other words, I replaced (7) by

$$i_t^* - i_{t-1} = \boldsymbol{\beta}' \triangle \mathbf{X}_t + \xi_t \ , \ \xi_t \sim N\left(0, \widetilde{\sigma}^2\right) \tag{12}$$

while maintaining (8) as the observation rule.

Such a hypothesis was brought forward and tested for the U.K. by Eichengreen et al. [11], who estimated the Bank of England's policy function during the interbellum. The simple rule of thumb assumed here, in analogy to Eichengreen et al., is that unobserved changes in the

[16] For some examples, see Barro and Sala-i-Martin [3].

Central Bank's target rate of interest are determined by changes in the growth rates of some macroeconomic variables and changes in interest and exchange rates.[17]

Maybe somewhat surprisingly, Table 2 shows that this model actually performs rather well, especially compared to the model (7)-(8) above. Except for Tup and the krona-dollar exchange rate, all explanatory variables are significant at the 1 or 5 percent level, some of them at two or three different lags. The Riksbank is responsive to changes in the German repo rate 2 weeks earlier and reacts both simultaneously and with a one week lag to changes in the US federal funds rate. The krona-deutschemark exchange rate influences the equilibrium repo rate simultaneous as well as with a 3-week lag. Unemployment is significant at lag 1 only, while the CPI, retail sales, industrial production and credit growth are significant at 2 different lags each. There also appears to be a significant duration dependence effect, since Tdown is significant at the 1% level.

On the basis of these results, I proceed to evaluate the model's predictive power. The most straightforward means of assessing the model's performance is to compare its predictive power with that of a naive predictor. An intuitively attractive predictor would be to 'expect the same as last week' to happen. As is shown in table 3, this predictor correctly forecasts 125 out of 177 observations (70%). Table 4 demonstrates that the most efficient naïve predictor for our sample is to 'always predict that rates will stay constant'. This has a success rate of 139 out of 178 (78%).

The grouped data model does a much better job [18] and correctly predicts 156 out of 178 observations, giving it a success rate of 88%. As one can see in Figure 4, among the remaining 22 misses, there are another two pairs of observations where an unforecasted 'down' (constant) is immediately followed by an incorrectly predicted 'down' (constant) in the first or second period after.

Of course, as holds for all models with discrete dependent variables, an ideal measure of fit would weigh the errors by their importance. Since the model correctly predicts a rare event, its gain over the naive estimator is likely to be larger than 10 percentage points. At the margin, the cost of failing to correctly forecast any change is likely to be very high.

[17] A subtle difference exists between the ways in which the model (12) on the one hand and the reaction function in Eichengreen et al. [11] on the other hand are formulated and estimated. Eichengreen et al. [11] replace (12) by $\triangle\, i_t^* = \boldsymbol{\beta}'\triangle\mathbf{X}_t + \zeta_t$, with $\zeta_t \sim N\left(0, \overline{\sigma}^2\right)$, $\triangle i_t^* = i_t^* - i_{t-1}^*$. Their unobserved variable $\triangle i_t^*$ represents *changes in* the 'frictionless' rate, while $i_t^* - i_{t-1}$ in this paper stands for *deviations of* the 'frictionless' rate from the currently charged rate. The former interpretation seems less attractive, since deviations of a 'frictionless' rate from the currently charged rate - not first differences in the 'frictionless' rate itself - should intuitively be the driving force behind interest rate adjustments. More importantly, using $\triangle i_t^*$ in favor of $i_t^* - i_{t-1}$ has the effect of significantly complicating the likelihood function and the estimation of the reaction function, because the econometric model then consists of one equation in first differences ($\triangle\, i_t^* = \boldsymbol{\beta}'\triangle\mathbf{X}_t + \zeta_t$) and one in levels (equation (8)). See pp. 734-35 and the appendix of Eichengreen et al. [11] for details.

[18] The prediction rule is $E\left[\triangle\, i_t\right] \;=\; \underset{\triangle\, i_t}{argmax}\; P\left(\triangle\, i_t\right)$, $\triangle\, i_t \in \{\text{up, unchanged, down}\}$

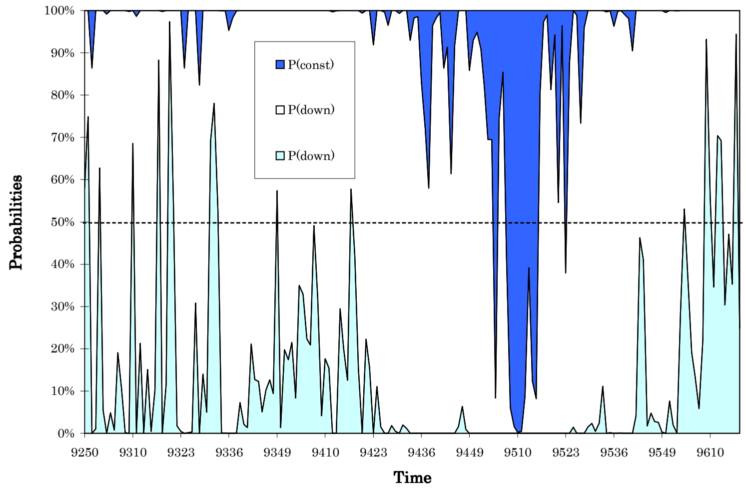

Figure 3. Implied probabilities of the Swedish repo rate being reduced, raised or kept constant.

Figure 3 shows the probabilities of the Swedish repo rate increasing, staying constant or decreasing during the sample period December 1992 - April 1996. By comparing Figures 3 and 4 one can easily see that the model, for part of the incorrectly forecasted observations, implies probabilities of the correct change taking place that are very high and sometimes only marginally under 0.5. A non-binary measure of fit would also take such predictive power into account in its evaluation of the model.

In view of the caution that is required when interpreting the marginal effects in the grouped data model, it is rather difficult to impute the shift from high odds of a rate cut between late 1992 and early 1994 to a high probability rate increase in early 1995, and then back again in 1996, to any specific variables. It may be helpful in understanding these shifts to inspect the broad pattern of economic changes that took place between early 1994 and early 1995.

Inflation, generally considered to be one of the most important determinants of interest rate policy, dropped below 2 percent in Sweden in 1994, then rose by about a percent in 1995 to fall back under the 2 percent level in 1996. Sales in the retail industry, one of the two indicators of economic activity in the model, lost ground uninterruptedly during the 1992-94 period. In 1996, after a period of growth in the preceding year, retail sales fell sharply. Industrial production grew modestly from the the third quarter of 1993 and quite rapidly from the first quarter of 1994 until the last quarter of 1995. It then lost speed and stagnated in the beginning of 1996. The monetary indicator used here, lending to households, shrank during the complete sample period, but experienced half a year of relative stability in early 1995. Foreign interest rates displayed quite different patterns of behavior. The German repo rate dropped from about 9 percent in late 1992 to 5 percent in mid 1994 and continued its decline a little less than a year later. In the U.S. the federal funds rate rose most of the time, but started falling and kept pace with the German repo rate from the second half of 1995.

Together the above events give us an impression of an economy where many indicators pointed upward at the end of 1994 and in the beginning of 1995: industrial production and inflation went up, the repo rate in Germany had stopped falling whereas the federal funds rate in the U.S. continued rising. In the first half of 1995 many of these variables reversed sign: production growth and inflation flattened, retail sales continued their plunge while interest rates were lowered abroad and this deterioration in the economic climate was accompanied by a shift from a high probability rise to a high probability cut in the repo rate in Sweden.

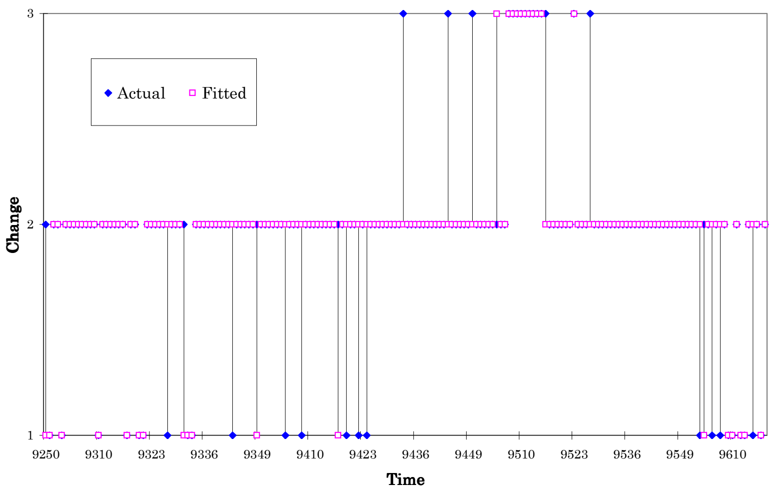

Figure 4. Conditional forecasts from the 3 cell grouped data model;1=repo down, 2=repo constant, 3=repo up. Vertical lines indicate an incorrect forecast

Finally, the discussion in section 3 about the interpretation of i_t^* created some hope about our ability to obtain implicit calculations of the 'frictionless' rate of interest. Figure 5 displays the outcome of these calculations for a grouped data model with 3 cells. [19] The general impression we get from Figure 5 is that the model is not able to produce the same size of changes in the repo rate as we observe in reality. The conditional forecast of $i_t^* - i_{t-1}$ is *always* smaller in absolute value than $i_t - i_{t-1}$ in periods when the repo rate is actually changed. In other words, actual changes in the repo rate are always bigger than the ones implied by the 'frictionless' rate.

This should not surprise us, however. The grouped data model, as other likelihood based discrete choice models, does not maximize the model's fit in the sense of minimizing the sum of squared residuals. It maximizes the likelihood of observing the censored variable in different intervals. As a consequence, the model is less likely to produce good conditional (point) forecasts of the dependent variable than any least squares based model. Moreover the model was estimated with observations split up into 3 groups - up, constant and down. Its ability to make quantitatively accurate forecasts of rate changes should therefore be expected to be small. The real bottleneck preventing the production of accurate conditional forecasts is most likely not the model's intrinsic inability to do so, however, but rather the small number of rate changes in the available sample.

[19] I computed the implicit frictionless rate for models with 3, 5, 7, 9 and 13 groups. The qualitative results were not affected by the number of cells.

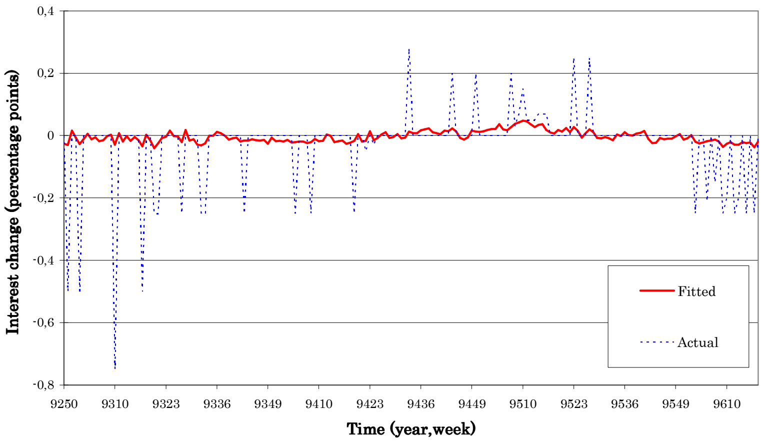

Figure 5. Fitted frictionless changes and actual changes in the repo rate.

5 Conclusions

The main instrument of monetary policy in industrialized countries is currently a very short interest rate. Such an interest rate, like the repo rate in Sweden, forms the building-stone for all term structure theory and is therefore of interest from both a monetary economic and a financial economic perspective. A typical feature of this interest rate, that has consequently been ignored by monetary economic theory, is that it remains unchanged during long spans of time.

This paper has tried to answer 3 questions. Why do Central Banks change targeted interest rates so seldomly. Moreover, what are the driving forces behind a change? And finally, is there any sign of duration dependence? For this purpose a simple theory has been developed that can explain why Central Banks smoothe this short interest rate through discrete decision rules. It argues that Central Banks face some cost when adjusting the interest rate. One possible interpretation of the adjustment cost is that financial institutions perceive that uncertainty is related to the frequency of interest rate changes. In face of an adjustment cost, the Central Bank's optimal policy is to follow a discrete interest rate rule.

The estimation of a Central Bank's policy rule, or reaction function, has traditionally been done with monthly data - often of a market rate with the same maturity as the targeted rate - and has therefore failed to explain the discrete jumps in the targeted interest rate. Moreover, the factors causing fluctuations in such an interest rate are likely to be very different from those determining movements in the target rate.

In this paper this discrete behavior has been taken into account in the estimation of the reaction function. A grouped data model has been used to estimate Swedish Riksbank's reaction function. It turns out that the Bank's decision rule is better represented in terms of *changes in* growth rates of macroeconomic variables and *changes in* exchange rates and interest rates than in their respective growth rates and levels - as implied by the theory. Probabilities of the repo rate being raised, lowered or kept constant have been computed. These show that repo rate cuts had likelihoods close to one in mid 1993 and early 1996, while increases had such likelihoods in early 1995. The model correctly predicts 88 percent of the observations and 23 out 39 interest rate changes. It thereby clearly outperforms the best 'naive' estimator, which has a success rate of 78 percent and predicts 'no change' for all observations. The model has no strong ability, however, to make good quantitative predictions of the changes. This is likely to be much better in a bigger sample, where the model can be estimated with more than three cells - as was done here .

A Data appendix

Data were obtained from Statistics Sweden (SCB), the Bank of Sweden (Riksbanken, RB), the annual report of Federal Reserve Bank of New York (NY Fed), and Dextel Findata AB

Variable	**Definition** W = weekly data, M = monthly data	**Source**
$Srepo$	Swedish repo rate (W)	RB
$Tdown$	Weeks since last rate reduction (zero if last change was up)	-
Tup	Weeks since last rate increase(zero if last change was down)	-
CPI	Annual growth rate consumer price index (M)	SCB
IP	Annual growth rate of indust. production (M)	SCB
$Retail$	Annual growth rate of retail sales (M)	SCB
U	Unemployment rate (M)	SCB
$L2hh$	Annual growth rate of bank lending to households (M)	RB
$USffr$	US federal funds rate (W)	NY Fed
$Grepo$	German repo rate (W)	Findata
$SKDM$	SEK/DEM exchange rate (W)	Findata
$SKUS\$$	SEK/USD exchange rate (W)	Findata

While composing the data set, the following has been taken into account. Changes in the repo rate are announced by the Swedish Riksbank on Tuesdays at 10 A.M. Any economic data released before that time is assumed to be in the information set that is taken into consideration in the decision to raise or lower the repo rate. Figures released after that time are assumed to be new information next week. List with release dates and times for all monthly data series were provided by Statistics Sweden and the Bank of Sweden. Foreign interest rates and exchange rates were directly available at daily and weekly frequencies.

B Mathematical appendix

In the absence of any fixed cost the FOC's of problem (1) - (2) imply that

$$\triangle\, i = \frac{\alpha\left(\epsilon + \alpha\ \ \triangle\, i^e\right)}{\alpha^2 + \beta} \tag{13}$$

Given interest rate expectations $\triangle i^e$, this would imply equilibrium income of

$$y = \overline{y} - \frac{\beta.\epsilon + \alpha\beta \triangle\, i^e}{\alpha^2 + \beta} \tag{14}$$

We can then evaluate the loss function both when the interest rate is adjusted and when not. Using (14) and (1) we find that

$$L^{adjust}\left(\triangle i^e\right) = \frac{\alpha}{\alpha^2 + \beta}\left(\epsilon + \alpha \triangle\, i^e\right)^2 \tag{15}$$

and

$$L^{const}\left(\triangle i^e\right) = \left(\epsilon + \alpha \triangle\, i^e\right)^2 \tag{16}$$

Interest rate changes are optimal only if

$$\begin{array}{ll} L^{adjust}(\triangle i^e) + \overline{c} < L^{const}(\triangle i^e) & \Leftrightarrow \quad \epsilon > \overline{\epsilon} \\ \text{or} & \\ L^{adjust}(\triangle i^e) + \underline{c} < L^{const}(\triangle i^e) & \Leftrightarrow \quad \epsilon < \underline{\epsilon} \end{array} \tag{17}$$

Define

$$\begin{array}{rcl} \Xi(\triangle i^e) & = & \{\epsilon \in R \mid \;\; L^{adjust}(\triangle i^e) + \overline{c} \geq L^{const}(\triangle i^e) \;\; \textit{and} \\ & & \qquad\qquad L^{adjust}(\triangle i^e) + \underline{c} \geq L^{const}(\triangle i^e)\} \\ & = & [\underline{\epsilon}, \overline{\epsilon}] \end{array} \tag{18}$$

Thus we find that

$$\begin{array}{rcl} \underline{\epsilon}(\triangle i^e) & = & -\frac{1}{\alpha}\sqrt{\underline{c}(\alpha^2+\beta)} - \alpha \triangle i^e \quad \text{and} \\ \overline{\epsilon}(\triangle i^e) & = & \frac{1}{\alpha}\sqrt{\underline{c}(\alpha^2+\beta)} - \alpha \triangle i^e \end{array} \tag{19}$$

For simplicity we assume that ε is uniformly distributed over the interval $(-\omega, \omega)$ Using 13 and assuming that $\underline{\varepsilon} > -\omega$ and $\overline{\varepsilon} < \omega$ it follows that

$$\begin{array}{rcl} E[\triangle i] & = & E[\triangle i \mid \epsilon > \overline{\epsilon}] \,.\, \Pr(\epsilon > \overline{\epsilon}) + E[\triangle i \mid \epsilon < \underline{\epsilon}] \,.\, \Pr(\epsilon < \underline{\epsilon}) \\ & = & \frac{\alpha^2}{\alpha^2+\beta} \triangle i^e \end{array} \tag{20}$$

The unique fixed point of this equation leads us to the equilibrium interest rate expectations: $\triangle i^e = 0$. Any other solution would imply an ever increasing or decreasing interest rate. Substituting this into (14) and (19) gives that

$$y = \left\{ \begin{array}{ll} \overline{y} - \epsilon & \text{if } \; \underline{\epsilon} \leq \epsilon \leq \overline{\epsilon} \\ \overline{y} - \frac{\beta}{\alpha^2+\beta}\epsilon & \text{otherwise} \end{array} \right. \tag{21}$$

and

$$\triangle i = \left\{ \begin{array}{ll} 0 & \text{if } \; \underline{\epsilon} \leq \epsilon \leq \overline{\epsilon} \\ \frac{\epsilon}{\alpha^2+\beta} & \text{otherwise} \end{array} \right. \tag{22}$$

where

$$\underline{\epsilon} = -\frac{1}{\alpha}\sqrt{\underline{c}(\alpha^2+\beta)} \text{and } \overline{\epsilon} = \frac{1}{\alpha}\sqrt{\underline{c}(\alpha^2+\beta)} \tag{23}$$

C Table appendix

Table 1 : Maximum likelihood estimators from grouped data regression (3 groups) of $istar_i$ on $\mathbf{X}_t$ and lags if i_t. Standard errors in parentheses. Underlined style for coefficients significant at the 10% level, bold for the 5% level and both underlined and bold for the 1% level.

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4
Constant	0.93384E-01 (0.18255)				
Tup	0.18970E-03 (0.39532E-03)				
Tdown	0.20362E-03 (0.81061E-03)				
Grepo	0.12083E-01 (0.21582E-01)	-0.20928E-01 (0.28611E-01)	0.44884E-01 (0.27860E-01)	0.13033E-01 (0.28176E-01)	0.20978E-01 (0.22569E-01)
USffr	**0.31051E-01** **(0.16171E-01)**	-0.21381E-01 (0.18532E-01)	0.31599E-01 (0.18787E-01)	0.36896E-02 (0.16090E-01)	-0.45899E-01 (0.16676E-01)
SKDM	**0.56353E-03** **(0.28868E-03)**	0.890804E-04 (0.29191E-03)	-0.30121E-03 (0.27934E-03)	0.48419E-03 (0.31096E-03)	0.21897E-03 (0.24986E-03)
SKUS$	0.53429E-02 (0.16294E-01)	-0.31535E-01 (0.17934E-01)	-0.58964E-03 (0.15979E-01)	**0.37361E-01** **(0.17399E-01)**	-0.61547E-02 (0.14588E-01)
Srepo		**0.52735E-01** **(0.18048E-01)**	0.51648E-02 (0.18229E-01)	0.14230E-01 (0.15843E-01)	-0.36915E-04 (0.57912E-04)
U	0.54499E-02 (0.42323E-02)	**0.86308E-02** **(0.39348E-02)**	-0.80819E-02 (0.43528E-02)	**0.78225E-02** **(0.40684E-02)**	
CPI	**0.78021** **(0.37411)**	-0.67875 (0.50894)	-0.20893 (0.56787)	-0.42392 (0.52330)	
Retail	0.20032 (0.12471)	0.10126 (0.10522)	0.88143E-01 (0.11784)	0.68749E-01 (0.10653)	
IP	0.89463E-01 (0.10222)	-0.23582E-01 (0.94516)	0.15292E-01 (0.90984E-01)	0.14597 (0.88678E-01)	
L2hh	-0.21105 (0.34605)	0.70695 (0.40368)	0.38889 (0.44781)	0.45853 (0.27076)	

Number of observations 178
Iterations completed 6
Log likelihood function -49.62734
Standard error of regression 0.82220E-02 *(0.12444E-02)*

Table 2 : Maximum likelihood estimators from grouped data regression (3 groups) of $istar_i$-i_{t-1} on $\Delta\mathbf{X}_t$. Standard errors in parentheses. Underlined style for coefficients significant at the 10% level, bold for the 5% level and both underlined and bold for the 1% level.

	contempor.	Lag 1	Lag 2	Lag 3	Lag 4
Constant	0.36180E-02 (0.32689E-02)				
Tup	-0.46104E-04 (0.28891E-03)				
Tdown	**-0.17440E-02** **(0.55181E-03)**				
Grepo	0.20159E-01 (0.18975E-01)	-0.10977E-01 (0.21486E-01)	**0.39895E-01** **(0.17283E-01)**	0.31052E-01 (0.23848E-01)	0.34048E-01 (0.21269E-01)
USffr	**-0.47090E-01** **(0.13181E-01)**	**-0.42342E-01** **(0.14604E-01)**	-0.12637E-01 (0.13105E-01)	-0.47222E-02 (0.11572E-01)	-0.13104E-01 (0.15160E-01)
SKDM	**0.23810E-02** **(0.12369E-02)**	0.12474E-02 (0.12419E-02)	-0.12117E-03 (0.10422E-02)	**-0.31943E-02** **(0.10528E-02)**	-0.63020E-03 (0.98794E-03)
SKUS$	0.55878E-03 (0.10633E-02)	-0.17393E-02 (0.11005E-02)	-0.17490E-02 (0.97284E-03)	0.17861E-02 (0.98278E-03)	0.12235E-02 (0.93527E-03)
U	-0.10979E-02 (0.25883E-02)	**0.80244E-02** **(0.28512E-02)**	0.39249E-02 (0.31095E-02)	0.19024E-02 (0.21858E-02)	
CPI	**0.10911E-01** **(0.30579E-02)**	-0.39718E-02 (0.29819E-02)	-0.11086E-02 (0.31416E-02)	**-0.76154E-02** **(0.32375E-02)**	
Retail	0.65910E-03 (0.82445E-03)	0.13269E-02 (0.10984E-02)	**0.19694E-02** **(0.95057E-03)**	**0.15100E-02** **(0.65623E-03)**	
IP	**0.18190E-02** **(0.69626E-03)**	**0.14991E-02** **(0.76423E-03)**	0.10722E-02 (0.68925E-03)	**0.17766E-02** **(0.63219E-03)**	
L2hh	0.26055E-03 (0.21668E-02)	**0.46153E-02** **(0.23114E-02)**	**0.52282E-02** **(0.23838E-02)**	0.15559E-02 (0.24482E-02)	

Number of observations 178
Iterations completed 6
Log likelihood function -56.06951
Standard error of regression 0.80632E-02 *(0.12290E-02)*

Table 3.
Actual and predicted outcomes from Figure 4 in tabular form. The predicted outcomes are computed with the probabilities that are displayed in Figure 3.

Actual outcome	Predicted outcome *down*	*constant*	*up*	
down	13	11	0	24
constant	3	133	3	139
up	0	5	10	15
	16	149	13	178

Table 4.
Actual outcomes compared with the predictions of a naïve estimator that equals the predicted action to last periods actual action.

Actual outcome	Predicted outcome *down*	*constant*	*up*	
down	4	20	0	24
constant	20	112	6	138
up	0	6	9	15
	24	138	15	177

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