Interest Rate Sensitivity of Savings Accounts[1]

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Abstract

Interest rate risk measurement and management of non-maturity deposit balances presents a challenge for practitioners and academic researchers as well. The paper provides a review of several methodological approaches focusing on the area of savings accounts rate sensitivity modeling and estimation. The proposed interest rate sensitivity models are tested on a Czech banking sector dataset providing mixed results regarding the cointegration type models generally recommended in the literature. On the other hand, the analysis shows that simpler regression models may provide more robust results if the cointegration tests between the saving accounts rate and the market rate series fail. According to the empirical results, the sensitivity of the domestic savings rates is slightly higher for companies compared to rates for individuals, but in both cases well below 50%.

Keywords: *interest rate sensitivity, savings accounts, non-maturity deposits, cointegration, pass-through rate*

JEL Classification: C32, E43, E58, G21

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Introduction

Interest rate risk management of the banking book (IRRBB) is one of the core functions of a commercial bank. The bank collects client deposits mostly with short or non-defined maturity and provides loans to households and corporations

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mostly with longer maturity such as in case of mortgages. The mismatch between the interest rate costs and revenues represents potentially a significant risk both in terms of accrued net interest rate income as well as in terms of asset and liability fair value. The importance of the interest rate risk management has been underscored by the recently issued regulatory documents BCBS (2016) and EBA (2018).

The classical gap analysis approach to interest rate risk measurement, preceding any risk management decisions, is to classify assets and liabilities into time buckets, according to their interest rate repricing maturity, and, at the same time, to measure sensitivity of the banking book product interest rates with respect to market interest rates. A significant part of the measurement problem is the correct treatment of the non-maturity deposits (NMD), specifically of current and savings accounts that provide a major source of financing for a typical commercial bank. In case of current accounts with practically zero interest rate the situation may appear relatively simple. However, unexpected outflows of the current account deposits must be refinanced by taking the money market loans, or by selling liquid assets such as treasury papers. In both cases the zero interest rate cost jumps to the current market rate. Therefore, the current account interest rate modeling is closely related to the liquidity modeling (see e.g. Komárková et al., 2011 and Hejlová et al., 2020) with the goal of estimating the distribution of current account portfolio balances over time. The deposit volume is customarily (EBA, 2018) split into a stable and volatile parts, where the stable (core) part is treated as a long-term fixed (zero) interest rate liability while the volatile part as a short-term interest rate liability.

In case of saving accounts (SA), the modeling task becomes even more difficult because the deposit rates are positive and reflect the level of market interest rates in order to attract customers. Since the sensitivity with respect to the market rates is only partial, the stable deposit volume is, in addition, usually split to an interest rate sensitive part and a core part that is supposed to represent fixed-interest rate stable financing. The focus of this paper is the savings account interest rate sensitivity modeling which might be based on a simple regression between the actual SA interest rate and a market interest rate. Nevertheless, the relationship is more complex since the banks tend to delay their decision, in particular when interest rates are rising, and react depending on the market competition development. The goal of the modelling is to estimate the pass-through coefficient capturing not only the short-term, but also the medium and long-term impact of market interest rates shifts onto the savings account rates.

There is a relatively extensive literature on the loan products interest rate pass-through (see e.g. Horváth and Podpiera, 2012; Havránek et al., 2016; or Brož and Hlaváček, 2019). Nevertheless, the loan pass-through estimation is motivated rather from the macro-economic perspective (monetary policy transmission efficiency), while the savings account pass-through rate is mainly motivated from the microeconomic perspective (IRRBB). This can be explained by the fact that the IRRBB main goal is to analyze and manage the interest rate risk of the outstanding balance sheet where loan rates are either fixed or float (linked to the reference rates), while SA rates change (immediately) depending on the internal (or banking market) SA rate development.

In spite of the practical importance, the academic literature on the topic of savings accounts rate pass-through is relatively scarce. Jarrow and van Deventer (1998) model the deposit rate as a function of both the level of market rates and the change in market rates. They derive an analytical valuation formula for a portfolio of non-maturity deposits in the non-arbitrage but segmented market framework conditional on the deposit rate and volume using a Vasicek-like short-rate model. O'Brien (2000) analyzes the U.S. retail deposit rates with a regression model where the deposit rates adjustments depend on the difference between an equilibrium long-term rate and the actual rate. The estimated model allows for different speeds between the downside and upside adjustment. Maes and Timmermans (2005) analyze the Belgian NMD balance and rates dynamics. They focus on the concept of deposit duration, outline the idea of static and dynamic NMD portfolio replication, and of a Monte Carlo valuation approach. Strnad (2009) provides a thorough overview of the models and discusses the accounting issues related to the applications of different approaches. He points out that it is virtually impossible to hedge the economic value and at the same the profit-loss due to different accounting treatment of the deposit liabilities and hedging derivative instruments. Džmuráňová and Teplý (2015; 2016) describe the replicating portfolio procedure and discuss its advantages compared to more classical IRRBB methods. Hejdová et al. (2017) analyze the dynamics of volumes and client rates of non-maturing bank products in the Czech Republic in the 1993 – 2015 period. They conclude that non-maturing liabilities exhibit interest rate sensitivity of volumes, while non-maturing assets are largely insensitive. Gerlach et al. (2018) estimate the VAR model with both the change in the composition of the deposits and the deposit rates on the U.S. banking system data. In contrast to other academic research, they find little evidence of asymmetry in the sensitivity of deposit rates to market rates. Blöchlinger (2019) proposes a coherent Monte Carlo valuation approach in which the bank's NMD pricing behavior is modeled using ordered logit regression and Blöchlinger (2021) provides a closed-form solution replacing the Monte Carlo simulation based on a generalization of the Jarrow and van Deventer (1998) model. Wang et al. (2019) propose a pass-through rate model and the error-correction regression approach that is applied to Hong Kong banking sector data. They show that the long-term pass-through ratio equals to the cointegration coefficient. The pass-through model also allows to allocate the NMD funds to more buckets according to the modeled gradual pass-through of a market rate shock to the deposit rates.

The goal of this paper is to compare several parsimonious regression models and the error-correction model on a Czech banking system dataset that distinguishes the SA deposit interest rates for households and the rates for companies. The rates for companies are expected to react more quickly to changes of markets rates, having a more direct access to alternative money market instruments, and so we perform the analysis separately for the two segments. The paper is organized as follows: after the introduction, Section 1 summarizes the methodology, Section 2 describes the data and presents the empirical results, and the last section concludes.

1. NMD Sensitivity Modeling

Let $\langle x_t \rangle$ denote the time series of market rates such as IBOR (Interbank Offered Rate, for example Libor, Pribor, etc.), interest rate swap, or treasury rates, and $\langle y_t \rangle$ the time series of SA deposit rates, where the time *t* is typically measured in months. The SA deposit rates might be specific for a bank or may represent an average across the banking sector. The key question we want to answer is what is the expected change in the deposit rates when the market rates jump up or down *N* basis points, for example, due to a central bank decision. If the expected change over a given time horizon can be expressed as βN basis points, then the coefficient $0 \le \beta \le 1$ represents *the pass-through rate* and can be used to allocate the stable SA portfolio balance into the interest rate gap short-term (depending on the time horizon) and long-term buckets in the proportion $\beta:(1-\beta)$. The pass-through rate estimated over different time horizons might be used to refine the allocation of SA balance into more than two time buckets.

We implicitly assume that the rates are nonnegative (which is the case of Czech interest rates used in the empirical study), however, the proposed models admit negative interest rates as well (e.g., in case of EUR interest rates). In our analysis, we do not consider other macroeconomic indicators similarly to other authors (see e.g. Wang et al., 2019) focusing on the interest rate sensitivity.

It should be noted that the estimation problem depends on the way, in which the SA rates are set. For example, if the SA rates $\langle y_t \rangle$ were determined by a specific bank using a mechanical rule, for example setting y_t to be the market rate or its moving average minus a spread, then there would be nothing to estimate –

the rule exactly determines the dependence between the SA and market rates. The bank may also a priory determine a strategy how to invest the SA funds and set the SA rate equal to the reinvestment portfolio yield minus a margin – in this case, again, there is not much to estimate. However, in our analysis, we are focusing on the situation when the individual bank's SA rates are not set mechanically, but follow more or less the rates set up by the competition and various business and marketing factors. Therefore, the sensitivity model should depict the behavior patterns of the banks setting the SA rates and their dependence on the money market rates.

Since the interest rate time series can hardly be expected to be stationary, we should rather focus on the differenced series $\Delta x_t = x_t - x_{t-1}$ and $\Delta y_t = y_t - y_{t-1}$, and in the simplest approach regress the change in deposit rates Δy_t on the changes in the market rates Δx_t, e.g. as

$$\Delta y_t = \gamma_0 \Delta x_t + u_t \tag{1}$$

The problem of this model is that the deposit rates tend to be "sticky", i.e. the banks hesitate before a change in the deposit rate is approved waiting for a possible return of the markets rates to their previous level, competitors' reaction etc. Therefore, the estimated coefficient γ_0 might significantly underestimate the true pass-through rate, or could be even non-significant in spite of positive pass-through rate, and so we should take also lagged differences into account

$$\Delta y_t = \alpha + \gamma_0 \Delta x_t + \cdots + \gamma_k \Delta x_{t-k} + u_t \tag{2}$$

This model might better estimate the pass-through rate as $\beta \approx \gamma_0 + \cdots + \gamma_k$. To explain this, let us assume that $\Delta x_t = \Delta x$ while $\Delta x_s = 0$ for $s \neq t$. Then $E[\Delta y_{t+i}] = \gamma_i \Delta x$ for $i = 0, \ldots, k$ according to (2), and so $E[y_{t+k} - y_{t-1}] = (\gamma_0 + \cdots + \gamma_k)\Delta x$. Since the model is linear, we can generally conclude that an unexpected change Δx (impulse) of the market rate causes a response $(\gamma_0 + \cdots + \gamma_k)\Delta x$ in the SA rate over the (k +1)-month horizon including the month when the impulse took place. The estimated coefficients can be used to allocate the stable saving accounts portfolio balance to interest rate gap (duration based) time buckets: γ_0 to the 1st month bucket, γ_1 to the 2nd month bucket, …, and $1 - \sum \gamma_i$ to the long or medium-term bucket (e.g. 5 years).

In spite of its simplicity, the model (2) is still problematic since the delays, with which banks react to the market rate shocks, vary over different time periods, depend on the level of market competition and other factors. Therefore, it might happen that none of the coefficients is estimated as significant in spite of a positive overall pass-through rate. Thus, we will also consider another parsimonious model where the deposit rate changes $\Delta_m y_t = y_t - y_{t-m}$ are regressed in terms of market rate changes $\Delta_m x_t = x_t - x_{t-m}$ over a longer period (e.g. 6 months),

$$\Delta_m y_t = \gamma_0 \Delta_m x_t + \gamma_1 \Delta_m x_{t-m} + \cdots + \gamma_k \Delta_m x_{t-km} + u_t \tag{3}$$

Another possible solution is to introduce a time-varying deposit equilibrium rate depending on the market, for example in the form $bx_t - a$ as proposed in O'Brien (2000) and regress the deposit rate changes with respect to the deviation from the equilibrium rate, i.e.

$$\Delta y_t = \Theta_1 \left(b x_{t-1} - a - y_{t-1} \right) + u_t \tag{4}$$

The idea of an equilibrium rate leads to the more general concept of cointegration between the deposit and market rates, i.e. employing the Engle and Granger (1987) 2-step univariate error-correction model (ECM) applied as in Wang et al. (2019),

$$\Delta y_t = \alpha + \gamma_0 \Delta x_t + \cdots + \gamma_k \Delta x_{t-k} + \Theta_1 e_{t-1} + u_t \tag{5}$$

possibly with lagged terms of e_t, where the error-correction term $e_t = y_t - b_1 x_t - b_0$ is obtained by regressing

$$y_t = b_0 + b_1 x_t + e_t \tag{6}$$

and testing for stationarity of the residuals e_t using the standard Engle and Granger (1987) test.

The estimated models described above will be compared in terms of the standard RMSE (root-mean-square error between the prediction and the target variable) and the passthrough-rate. The pass-through rate over h periods defined as $\beta_h = \frac{dE\left[y_{t+h}\right]}{dx_t}$ can be expressed analytically based on the ECM model (5) as follows. Let us firstly express the equation (5) for $h = 0$ in the form

$$y_t = c_0 + c_1 y_{t-1} + c_2 x_t + c_3 x_{t-1} + u_t$$

where $c_0 = \alpha - \theta_1 b_0, c_1 = 1 + \theta_1$, $c_2 = \gamma_0, c_3 = -\gamma_0 - \theta_1 b_1$. Then $\frac{dE\left[y_t\right]}{dx_t} = c_2$ and for $h \geq 1$,

$$\frac{dE\left[y_{t+h}\right]}{dx_t} = c_1 \frac{dE\left[y_{t+h-1}\right]}{dx_t} + \left(c_2 + c_3\right)$$

where we implicitly assume that a jump in the market rate at time t causes the same increases in the future, i.e. $\frac{dE[x_{t+h}]}{dx_t}=1$. Applying the equation recursively, we obtain the following result for the h-period pass-through rate:

$$\beta_h=\frac{dE[y_{t+h}]}{dx_t}=c_1^h c_2+(c_2+c_3)\frac{1-c_1^h}{1-c_1} \tag{7}$$

Note that the error-correction term coefficient θ_1 is expected to be negative, $-1<\theta_1<0$, and so $0<c_1<1$ implying that

$$\lim_{h\to\infty}\beta_h=\frac{c_2+c_3}{1-c_1}=\frac{-\theta_1 b_1}{-\theta_1}=b$$

Therefore, the asymptotic pass-through rate β turns out to be simply equal to the cointegration coefficient b_1. The formula (7) can be generalized in a straightforward way for the ECM model (5) with lagged market rate differences $(k>0)$. The asymptotic pass-through ratio will be still the cointegration coefficient b_1 in line with the result of Wang et al. (2019). The same algebra can be applied to the model (4), for which $c_0=-\gamma a, c_1=1-\gamma, c_2=\gamma b$, and $c_3=0$, and so the asymptotic pass-through again turns out to be equal to the sensitivity of the equilibrium deposit rate with respect to the market rate, i.e. $\beta=b$.

However, in practice the deposit rate adjustment to a shock in market rates is assumed to take place over a limited time period, e.g. 12 months, and so the partial pass-through rate such as β_{12} is used as the final sensitivity estimate. It should be noted that the partial pass-through rates β_h approach the asymptotic pass-through rate β and cannot be interpreted as the coefficients in (2). Provided $\beta_0=\gamma_0<b_1=\beta$, in the notation of model (5), the series $\beta_0<\beta_1<\cdots$ is increasing and can be used to allocate the SA portfolio stable balance into interest rate gap time buckets in the following proportions: β_0 to the O/N (over-night) bucket, $\beta_1-\beta_2$ to the 1M bucket,…, $\beta_{12}-\beta_{11}$ to the 12M bucket, and $1-\beta_{12}$ to the long-term bucket assuming the 12M pass-through horizon.

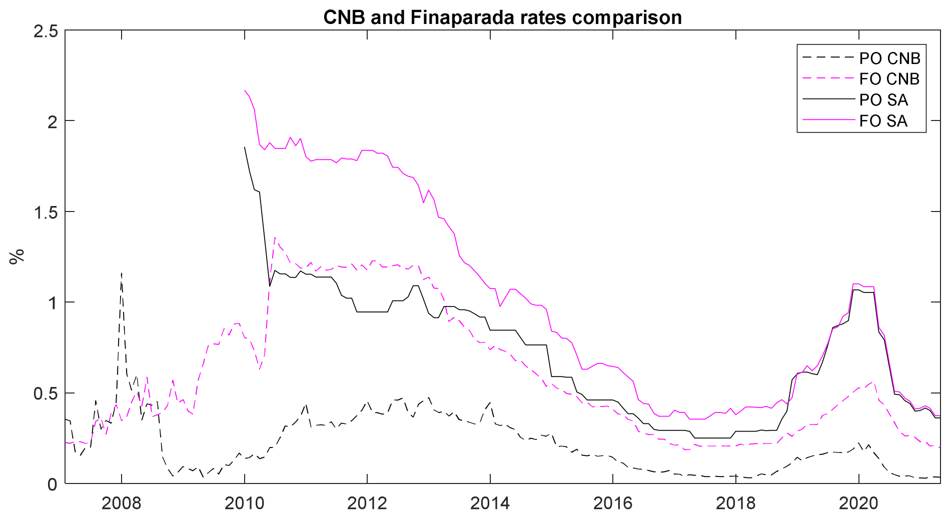
2. Data and the Empirical Results

The models described in the previous section will be empirically tested on a Czech banking sector dataset provided by the web retail financial information servis <www.finparada.cz>. The dataset covers the period 12/2009 – 4/2021 and gives end-of-months averages of savings accounts rates offered to individuals (FO SA) and to companies (PO SA) by 20 banks on the market including the top 5 banks.[2] The averages are equally weighted (i.e. not volume weighted) based on the SA rates announced by the banks offering the product. The SA rates have been collected separately for SA products for individuals (FO) and companies (PO) until 10/2019 and after this date only an average rate represented by the "Finparada Sporoindex" has been provided. We have used the index and its ratio with respect to FO SA and PO SA rates in 11/2018 – 10/2019 to extend the dataset until 4/2021 so that the sensitivity of the two types of rates can be analyzed separately.

Alternative data sources such as CNB ARAD database or ECB Statistical Data Warehouse provide average over-night (NMD) rates and do not explicitly distinguish between the current and savings accounts for outstanding amounts (and do not provide individual bank rates). Nevertheless, the CNB ARAD statistics offers current account (CA) rates for new deposits only. In this case, the SA rates can be calculated based on the overall over-night rates and the CA rates.

Figure 1

A Comparison of FO SA and PO SA Rates (12/2009 – 4/2021) and the Rates Obtained from CNB ARAD Over-Night and Current Account New Deposit Rates (1/2007 – 4/2021)



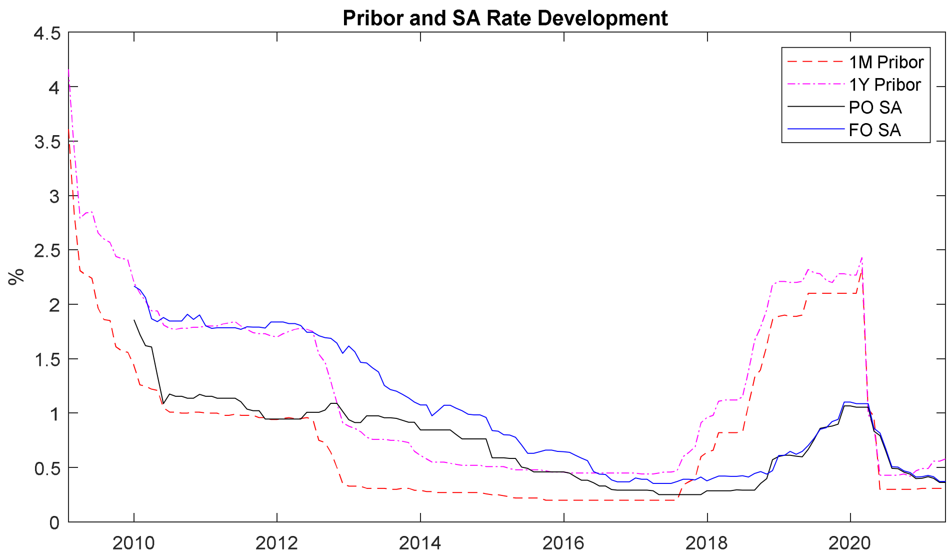
Source: CNB ARAD and Finaparada data.

[2] The dataset records the SA rates of the Czech banks offering the SA product for a given month, and so the number of recorded rates is variable ranging from 12 in12/2019 to 19 in 4/2021. For example, Citibank has been offering the SA products since 12/2019 only until 1/2016.

Figure 1 shows a comparison between the rates based on the CNB statistics (PO/FO CNB for companies and individuals) and the rates based on Finparada data (PO/FO SA). The time series follow similar patterns with CNB rates being systematically lower than the Finparada rates. This can be explained by the construction of the rates: the rates reported by CNB are volume weighted, while the Finparada rates are equally weighted averages of the individual bank rates. Since the largest domestic banks generally have excess of liquidity and tend to offer low or negligible savings rates, the volume weighted average rates are lower than the equally weighted rates, where the rates offered by smaller banks have a relatively larger weight. The smaller banks with scarcer financial resources are also forced to react to market rate changes faster than the large banks that can rely on their large market share and sufficient liquidity. The equally weighted average can be compared to the calculation of the reference rates (e.g. Pribor) representing the marginal rate of financing. Therefore, we have decided to use for our analysis the PO/SA rates that can be also interpreted as marginal savings account deposit rates (the clients that decide to change the bank may achieve higher rates).

Figure 2

The Development of FO SA and PO SA Rates (12/2009 – 4/2021) Compared to 1M and 1Y Pribor (1/2008 – 4/2021)



Source: CNB ARAD and Finaparada data.

Figure 2 shows the development of the SA rates in the period 2010 – 2021. The market rates represented by 1M and 1Y Pribor are shown over the period

2008 – 2021 in order to illustrate the “stickiness” of the SA rates. In the period 2008 – 2016 of steadily declining market rates the SA rates were declining with a delay staying mostly above 1M Pribor or above 1Y Pribor. On the other hand, in the period 2016 – 2020 when the market rates were steadily increasing, the SA rates stayed substantially below the Pribor rates and were adjusting to the market rate increase very slowly until the beginning of the Covid when the market rates fell to technical zero again.

Before starting the regression analysis, we have certainly tested stationarity of the time series. The PO SA and FO SA monthly time series do not pass the standard ADF (Augmented Dickey-Fuller) test with linear trend, i.e. existence of the unit root is not rejected, while the monthly differenced series do pass the tests, i.e. both series are first-order integrated. Although the interest rates are generally mean reverting, we included the liner trend due to the limited time period where the interest rate levels have been mostly decreasing. The same applies to the 1M Pribor monthly time series that we will use as representative market rates. We have also inspected other rates such as 14D Pribor, 1Y Pribor, CNB Repo or 2Y swap rates with similar outcomes, and so we will report only the results based on the 1M Pribor rate series.

The estimates of the linear regression models (1) and (2) based on the monthly differences without lag or with one or more lags are shown in Table 1 (SA for companies) and Table 2 (SA for individuals). We have estimated the models with no lag, with 2 lags (3 monthly differences), 5 lags (6 monthly differences), and 11 lags (12 monthly differences). The column $\sum \gamma_i$ shows the estimated pass-through rate conditional on the model and highlights the dilemma of the model choice. The model (1) where the SA rate monthly change Δy_t is explained only by the current month market rate change Δx_t apparently underestimates the effect since the SA rates react to market rate changes with a delay. On the other hand, in models (2) with the current month change Δx_t and k lagged changes Δx_{t-i} most of the estimated coefficients turn out to be non-significant (on 10% level). For example, for PO SA with $k = 5$ only lag 1 and lag 4 coefficients γ_1 and γ_4 are tested as significant. Based on the full model, the estimated pass-through coefficient ($\sum \gamma_i$) is 38.6%, while after removing the non-significant lags (and re-estimating the model) the estimated pass-through coefficient falls to 32.1%. In the model with 12 monthly market rate differences, only three parameters remain significant (PO SA, lag 1, 4, and 11) and the estimated pass-through coefficient turns out to be 37.8% (after eliminating the non-significant lags). To conclude, the PO SA rates adjustment over a six-month or one-year horizon measured by the pass-through coefficient has been estimated by this type of model in the interval 32 – 38%. The same approach for FO SA pass-through coefficient gives the estimates around 28 – 33% confirming a slightly higher sensitivity of SA rates for companies that might have a better access to regular market deposit instruments.

T a b l e 1

Monthly Difference Models (1) and (2) Estimates for PO SA
(s.e. in parenthesis, significance * 10%, ** 5%, *** 1%).
RMSE Shows the Root Mean Squares Error of the Model in Percentage Units

Model	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	γ_{11}	RMSE	$\sum\gamma_i$
(1)	0.071** (0.035)	–	–	–	–	–	–	0.057	0.071
(2), $k = 2$	0.040 (0.031)	0.190*** (0.030)	0.062* (0.033)	–	–	–	–	0.050	0.293
(2), $k = 5$	0.051 (0.031)	0.168*** (0.031)	0.011 (0.033)	0.055 (0.033)	0.123*** (0.031)	–0.028 (0.031)	–	0.047	0.386
(2), lag 1 and 4	–	0.189*** (0.029	–	–	0.131*** (0.029)	–	–	0.048	0.321
(2), lag 1, 4 and 11	–	0.188*** (0.028)	–	–	0.123*** (0.028)	–	0.066*** (0.024)	0.047	0.378

Source: CNB ARAD and Finaparada data; own calculations.

T a b l e 2

Monthly Difference Models (1) and (2) Estimates for FO SA
(s.e. in parenthesis, significance * 10%, ** 5%, *** 1%)

Model	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	γ_{11}	RMSE	$\sum\gamma_i$
(1)	0.043 (0.032)	–	–	–	–	–	–	0.520	0.043
(2), $k = 2$	0.007 (0.029)	0.178*** (0.027)	0.077*** (0.029)	–	–	–	–	0.044	0.262
(2), $k = 5$	0.013 0.028	0.161*** 0.028	0.042 0.030	0.041 0.031	0.083*** 0.028	–0.009 0.028	–	0.043	0.333
(2), lag 1 and 4	–	0.178*** (0.026)	–	–	0.101*** (0.026)	–	–	0.043	0.278

Source: CNB ARAD and Finaparada data; own calculations.

Due to the problem of non-significant monthly difference variables, we are also going to investigate the model (3) based on longer period, e.g. quarterly or semiannual, changes. We will focus on the model based on the quarterly differences since the series $\Delta_3 y_t$ and $\Delta_3 x_t$ remain stationary (pass the ADF and PP tests) while the semiannual differenced series unfortunately do not pass the stationarity tests.

Table 3 and Table 4 show that model with one lag ($k = 1$) gives significant estimates of both coefficients γ_0 and γ_1 for PO SA as well as for FO SA. The totals 36.7% and 33.2% can be considered as relatively reliable estimates of the six-month horizon pass-through coefficients for PO SA and FO SA. If we increase the number of lags to $k = 3$, only three coefficients (lag 0, 1, and 3) remain significant with the totals 43.4% for POSA and 41.7% for PO SA that can be interpreted as the one-year horizon pass-through coefficients. For example, in case of PO SA, based on the model, 15.3% of the stable balance should be allocated to the 1st quarterly time bucket, 19.9% to the 2nd quarterly bucket, 8.2% to the 4th quarterly bucket, or rather to the (7 – 12)-month bucket, and the remaining part, i.e. 56.6% to a longer-term bucket such as 5-year.

Table 3

Quarterly Difference Models (1) and (2) Estimates for PO SA
(s.e. in parenthesis, significance * 10%, ** 5%, *** 1%)

Model	γ_0	γ_1	γ_2	γ_3	RMSE	$\sum\gamma_i$
(3), $k = 0$	0.214*** (0.034)	–	–	–	0.109	0.214
(3), $k = 1$	0.159*** (0.030)	0.209*** (0.030)	–	–	0.094	0.367
(3), $k = 2$	0.157*** (0.030)	0.194*** (0.031)	0.054* (0.029)	–	0.093	0.404
(3), lag 0, 1 and 3	0.153*** (0.029)	0.199*** (0.029)	–	0.082*** (0.027)	0.091	0.434

Source: CNB ARAD and Finaparada data; own calculations.

Table 4

Quarterly Difference Models (1) and (2) Estimates for FO SA
(s.e. in parenthesis, significance * 10%, ** 5%, *** 1%)

Model	γ_0	γ_1	γ_2	γ_3	RMSE	$\sum\gamma_i$
(3), $k = 0$	0.190*** (0.031)	–	–	–	0.100	0.190
(3), $k = 1$	0.139*** (0.028)	0.193** (0.027)	–	–	0.086	0.332
(3), $k = 2$	0.136*** (0.027)	0.173** (0.028)	0.074** (0.026)	–	0.084	0.383
(3), lag 0, 1 and 3	0.133*** (0.027)	0.171*** (0.027)	0.057** (0.027)	0.056*** (0.026)	0.082	0.417

Source: CNB ARAD and Finaparada data; own calculations.

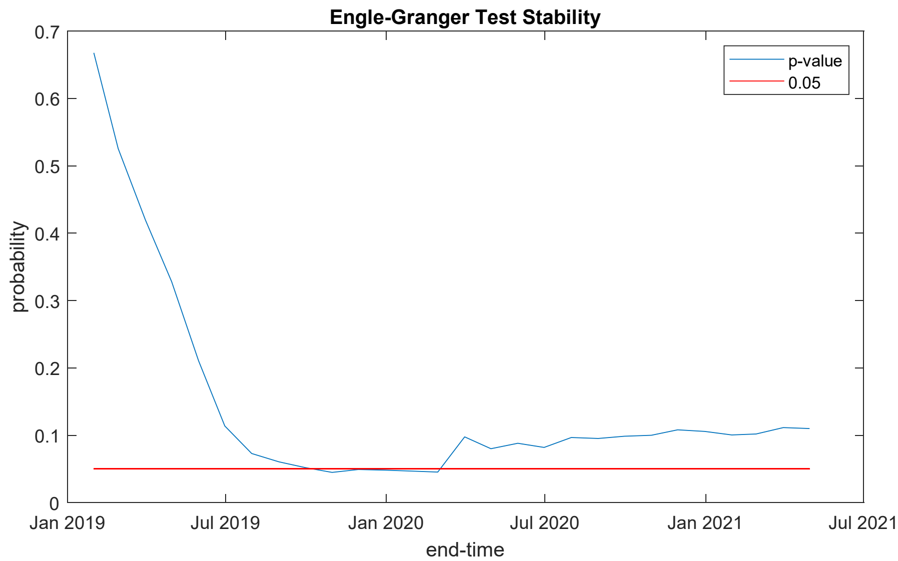
Finally, we want to apply the O'Brien (2000) and the ECM models. In both cases, we need to test for cointegration between the SA and market rates series. Starting with PO SA and 1M Pribor series the Engle-Granger (1987) test p-value 0.11 based on the full time period indicates only a weak cointegration (Table 5).

The weak cointegration relationship is also illustrated by Figure 3 which shows the Engle-Granger test p-values based on the time period starting 12/2021 and ending at different points time from 1/2019 until 4/2021. It shows that, if we evaluated the test around 1/2020, the non-stationarity of the cointegration relationship residuals (ADF unit root test) would be rejected.

F i g u r e 3

Engle-Granger Test p-values for the PO SA Rates Series with Time Window Ranging from 12/2009 to the End-date Shown on the x-axis

(the red line indicates 5% significance level)



Source: Own calculations.

In spite of the weak evidence of cointegration (EG test p-value 0.11), the results of the O'Brien (4) and ECM model (5) are shown in Table 5. The O'Brien's model is in fact the ECM model with omitted Δx_t terms (i.e., $\gamma_0 = \gamma_1 = 0$) and without the intercept ($\alpha = 0$). The parameter $\beta_{12} = 0.136$ represents the one-year pass-through coefficient estimated based on (7). The remaining four ECM models reported use the same cointegration coefficients $b_0 = 0.558$ and $b_1 = 0.232$ but include the market rate monthly difference Δx_t and its lagged values. Besides the basic no-lag model, we report the models with $k = 1, 4, 11$ lags and the significant parameters only (with the exception of $k = 0$). The coefficient γ_0 is not significant on the 10% level in the no-lag model and only weakly significant in the one-lag model with (with the lagged difference Δx_{t-1}), where the estimated coefficient $\gamma_1 = 0.156$ turns out to be strongly significant similarly to the results reported in Table 1. While the pass-through coefficient β_{12} estimate remains low for the O'Brien's or no-lag ECM models, it goes up substantially to the value 0.211 in the one-lag ECM model. Note that the asymptotic pass-through coefficient equals to $b_1 = 0.232$, which is a substantial difference compared to the results reported in Table 1 and Table 3 indicating that the pass-through coefficient is around 38 – 43%. However, if we include the estimates of the model with 4 or 11 lags, the pass-through coefficient β_{12} increases to 27 – 32% which is close, but still below the monthly or quarterly models estimates. In addition, the coefficient β_k is in fact maximal for $k = 12$ and converges to asymptotic pass-through level (23%) for larger time horizons as illustrated by Figure 4.

Table 5

Engle-Granger Test and the Cointegration Model Coefficients for PO SA Series 1M Pribor Series (s.e. in parenthesis, significance * 10%, ** 5%, *** 1%)

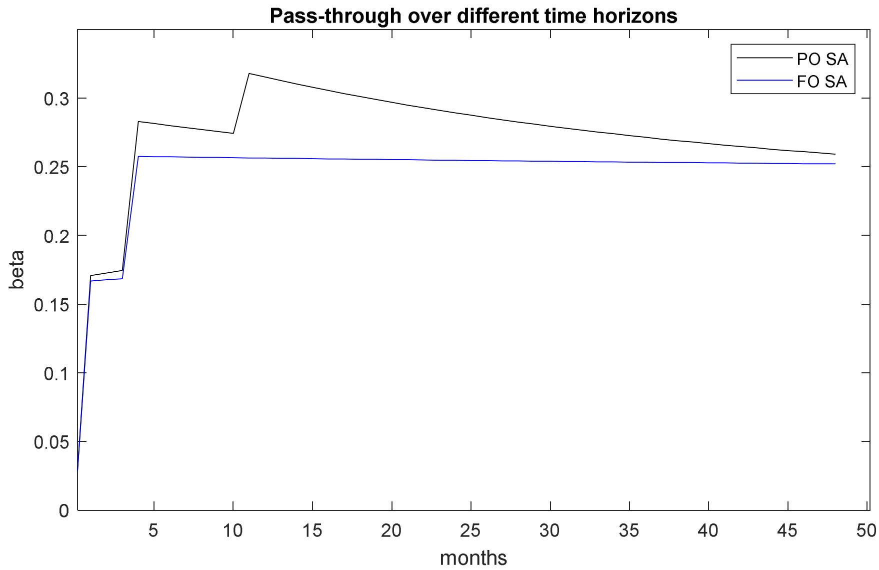
Series	EG test p-value	b_0	b_1
POSA, Pribor 1M	0.110	0.558*** (0.044)	0.232*** (0.047)

Model	α	γ_0	γ_1	γ_4	γ_{11}	θ_1	RMSE	β_{12} eq. (7)
O'Brien, (4)	–	–	–			–0.070*** (0.014)	0.052	0.136
ECM (5), $k = 0$	–0.011** (0.004)	0.031 (0.033)	–			–0.067*** (0.014)	0.052	0.145
ECM (5), $k = 1$	–0.009** (0.004)	0.038* (0.030)	0.156*** (0.030)			–0.045*** (0.014)	0.048	0.211
ECM (5), $k = 4$	–0.008** (0.004)	–	0.159*** (0.030)	0.108*** (0.029)	–	–0.038*** (0.013)	0.046	0.270
ECM (5), $k = 11$	–0.007* (0.004)	–	0.163*** (0.029)	0.107*** (0.028)	0.045* (0.025)	–0.031*** (0.014)	0.046	0.315

Source: CNB ARAD and Finaparada data; own calculations.

Figure 4

The Pass-through Coeffcient Over Different Time Horizons and for the PO SA Rates (ECM model with lags 1, 4, and 11) **and FO SA Rates** (ECM model with lags 1 and 4)



Source: Own calculations.

Similar conclusions can be reached when we combine the cointegration term with the quarterly differences, however, in this case the cointegration term becomes non-significant when the lagged quarterly differences are included. Since the cointegration evidence is weak we should rather accept the results of the parsimonious short-term dependence models, but we should keep in mind that the simple monthly or quarterly difference models do not consider the fundamental cointegration relationship between the two series and might tend to overestimate the pass-through coefficient.

In case of FO SA rates for individuals the evidence of cointegration is even weaker. The unit root test of residuals is not rejected by the Granger-Engle test (EG test p-value 0.731). In spite of the weak cointegration evidence (based on fundamental arguments rather than on the statistical test result) we report the O'Brien and ECM models results in Table 6.

The conclusions are similar to PO SA pass-through analysis. The one-year horizon pass-through coefficients estimated by the O'Brien and the no-lag ECM models are very low, while the ECM model with one-lag monthly market rate difference gives a more realistic estimate $\beta_{12} = 0.198$ which gets closer to the asymptotic pass-through $b_1 = 0.243$ implied by the cointegration model. However, this value is still substantially smaller than the pass thorough estimates around 33 – 40% reported in Table 2 and Table 4.

As above, the twelve-month pass-through increases to 26% when we estimate the model with 4 lags, nevertheless in this case the coefficient of the cointegration is very small (in fact, non-significant on 10% level), which means that the pass-through coefficient converges to the asymptotic level very slowly as illustrated in Figure 4.

The estimated coefficients for larger number of lags are not significant, and so we do not report the model with $k = 11$ as for PO SA. Again, since the cointegration evidence is weak, we should accept rather the results of the parsimonious short-term dependence models, but keep in mind that the simple models might tend to overestimate the true pass-through rate.

If we decide to choose a model, its stability should be tested in the sense of looking on the variability of the estimates over time. For example, Figure 5 shows the pass-through estimates based on the quarterly model with one lag on over the time window starting always in 12/2009 and ending in a month going from 1/2019 to 4/2021. The figure shows that the estimates have been quite stable, especially during the last 12 months.

Therefore, the estimates from Table 3 and Table 4 (36.7% for PO SA and 33.2% for FO SA) can be considered as relatively robust.

T a b l e 6

Engle-Granger Test and the Cointegration Model Coefficients for PO SA and FO SA Series versus 1M Pribor and Repo Series

(s.e. in parenthesis, significance * 10%, ** 5%, *** 1%)

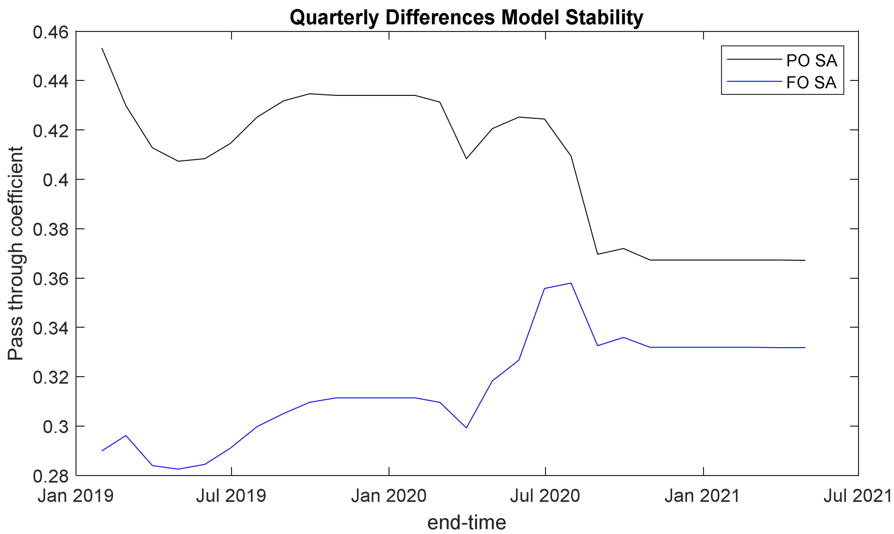
Series	EG test p-value	b_0	b_1
POSA, Pribor 1M	0.731	0.834*** (0.074)	0.243*** (0.079)

Model	α	γ_0	γ_1	γ_4	γ_{11}	θ_1	RMSE	β_{12} eq. (7)
O'Brien, (4)	–	–	–	–	–	–0.24*** (0.008)	0.500	0.061
ECM (5), $k = 0$	–0.013** (0.004)	0.024 (0.030)	–	–	–	–0.023*** (0.008)	0.049	0.077
ECM (5), $k = 1$	–0.011*** (0.004)	0.023 (0.027)	0.136*** (0.027)	–	–	–0.014* (0.007)	0.044	0.198
ECM (5), $k = 4$	–0.011*** (0.004)	–	0.164*** (0.026)	0.088*** (0.026)	–	–0.011 (0.007)	0.042	0.256

Source: CNB ARAD and Finaparada data; own calculations.

F i g u r e 5

Passed Through Coefficients for PO SA and FO SA Based on the Quarterly Model with One Lag (k = 1) and with the Time Window Ranging from 12/2009 to the End-date Shown on the x-axis



Source: Own calculations.

Conclusion

Interest rate risk measurement and management of savings accounts balances presents a challenge for practitioners and academic researchers as well. The modeling can be approached in the framework of derivatives valuation, based on the portfolio replication idea, or using a more classical analysis of the volatility and interest sensitivity of the savings account portfolio balances. In our study, we have focused on the latter approach, and in particular on the interest rate sensitivity estimation exercise. The purpose of the interest rate sensitivity estimation is to allocate the stable SA portfolio balance into short-term and long-term interest rate gap time buckets, i.e. to hedge the interest rate risk optimally. Consequently, the goal is to obtain non-biased sensitivity estimates since both underestimation or overestimation of the true sensitivity means that the bank is still exposed to the interest rate risk, even after hedging based on a (biased) estimation. This is not the same as in case of liquidity measurement and management where banks and regulators tend to be rather conservative allocating larger (liability) amounts to the short-term liquidity buckets.

We have summarized several relatively simple regression models, where the SA rate changes are regressed on market rate changes, and the error-correction model assuming a cointegration relationship between the SA and market rates. The models have been tested on a Czech banking sector dataset of SA rates offered to companies and individuals and covering the period 12/2009 – 4/2021.

The SA rates in our dataset are calculated as average rates offered by individual banks where the smaller banks have a relatively larger weight compared to the volume weighted averaged that could be obtained from CNB ARAD data. The equally weighted averages (analogously to the reference rates) better represent the marginal SA deposit rates that can be achieved by clients willing to change the bank and open a new SA account with a bank offering a higher SA rate. The market rates were represented by the 1M Pribor. We have also inspected other rates such as 14D Pribor, 1Y Pribor, CNB Repo or 2Y swap rates with similar outcomes. Our analysis did not consider other macroeconomic indicators, or bank specific explanatory variables due to aggregate character of the data.

The results have demonstrated a significant model risk of the estimation exercise with the estimated pass-through ratio (interest rate sensitivity) ranging from 4% to 43% depending on the model assumptions and the segment (individual and companies). After a selection of the best candidates the one-year pass-through estimate still ranges between 37% and 43% for companies (PO SA) rates and between 33% to 40% for individuals (FO SA) rates based on the parsimonious quarterly changes regression model. However, the cointegration model estimates give a significantly lower one-year (31% for PO SA and 26% for PO SA) and asymptotic (23% for PO SA and 24% for PO SA) pass-through coefficient estimates. Since the evidence of cointegration is rather weak, our recommendation would be to accept the one-lag quarterly regression model estimates, but rather at the lower end of our confidence interval (i.e. 37% for PO SA and 33% for

FO SA) due to the missing cointegration effect in the quarterly models that should, in spite of failed statistical cointegration tests, fundamentally hold over a longer-time horizon. We have back-tested stability of the quarterly model estimates with acceptable results. The estimated pass-through rates can be intuitively interpreted as the long-term effect of 1% move of the market rates on the SA rates (37bps for company SA rates and 33bps for individual SA rates). The risk management implication for the banks is to offset this SA deposit interest rates sensitivity by a corresponding sensitivity on the asset side of the balance sheet.

Besides the conclusions specific to the analyzed dataset, the discussion and the empirical study have shown that some models proposed in literature, namely the O'Brien (2000) model, are not appropriate at all, while the fundamentally acceptable error-correction model suggested in Wang et al. (2019) does not have to provide reliable results due to a failure of the cointegration tests. In this case, our recommendation is to use a parsimonious model where SA changes (generally over a longer period than just one month) are regressed on market rate changes with possible lagged terms involved.

The measurement of SA stable balances interest rate sensitivity is only one component of the interest rate risk measurement and management problem. The other part of the problem lies in volatility modelling of the SA balances. The balance volatility modeling is basically the key part of the interest rate sensitivity analysis in case of current accounts bearing technically zero interest rates. A study of possible methodological approaches to this problem, their relationship to SA interest rate modeling, and a comparison with alternative methods, in particular with the portfolio replication and non-arbitrage valuation approaches, present a possible direction of future research.

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