# Estimating Price Elasticities on the Hungarian Consumer Lending and Deposit Markets: Demand Effects and Their Possible Consequences

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*In this paper, we use bank product and consumer level data and estimate a random coefficient logit model (RCL) to calculate price elasticities on the Hungarian consumer lending and retail deposit markets in line with the most recent developments in the literature on discrete choice demand estimation. The findings indicate that, on average, demand for domestic currency-denominated loans is more price sensitive than demand for foreign currency loans. The results also suggest that there is an asymmetric substitution effect toward foreign currency-denominated loans as a result of a price increase of domestic currency-denominated loans (i.e. a rise in interest rates on HUF-denominated loans increases the demand for foreign currency loans more than a rise in interest rates on foreign currency loans increases the demand for HUF-denominated loans). Finally, as the substitution effect toward foreign currency-denominated loans is stronger, it might weaken the effectiveness of the interest and exchange rate channels of monetary transmission.*

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## 1 Introduction

Banks play a significant role in economic processes, but their function is especially important for countries where economic agents have limited possibilities to obtain other forms of financing (i.e. where capital markets are underdeveloped). In such economies, the pricing decisions of financial institutions may considerably influence the consumption and investment behavior of depositors and borrowers and, finally, the evolution of GDP and inflation, the degree of which depends inter alia on the strength of the price sensitivity effects on loan and deposit markets.

In this paper, we examine the most recent developments in the discrete choice demand estimation[2] literature – e.g. Berry (1994), Berry, Levinsohn and Pakes[3] (1995), Nevo (2001), Ho (2007) and Zhou (2007) – and estimate a random coefficient logit (RCL) model to calculate own- and cross-price elasticities in the Hungarian consumer lending and retail deposit markets. Moreover, we try to discover the possible consumer loan demand, retail deposit demand and monetary policy implications of these price sensitivity effects.

Banks' decisions about the interest rates on their assets and liabilities influence the real economy through three main mechanisms. The first comprises the so-called own-price and cross-price elasticity effect, i.e. the effect of price changes on the demand for certain deposit and loan products themselves and on the demand

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[2] *The roots of discrete choice demand estimation go back to the logit demand model of McFadden (1973), which was developed further by Goldberg (1995).*

[3] *Hereinafter referred to as BLP.*

for alternative deposit or loan products (i.e. substitutes), and the real economic consequences of these price sensitivity effects (e.g. a less price-sensitive deposit or loan demand does not remarkably influence the consumption, saving and investment behavior of economic agents). The second mechanism is the income effect, i.e. the changes in the earnings and expenditures of economic agents that result from varying interest rates. The change in the realized yields on deposits and debt-servicing costs can be mentioned as an example for a direct income effect, while those multiplicator mechanisms that are induced by credit-financed consumption and investment qualify as indirect effects. Finally, the last mechanism is the wealth effect, i.e. the changes in the value of economic agents' real and financial assets.

When speaking of the monetary policy consequences of interest rate changes, we primarily think of how the strength of the two main monetary transmission channels (i.e. the interest rate and exchange rate channels) might be affected by the intensity of the own-price sensitivity of loan demand and the substitution of domestic currency-denominated loans by foreign currency-denominated loans and vice versa.

The consequence of the mutual substitution of domestic and foreign currency-denominated loans can be a portfolio denomination realignment effect as a result of the price increase of loans denominated in either currencies (i.e. the relative prices of domestic and foreign currency-denominated loans change and, as a result, demand for these loans changes as well). The changing currency composition of the portfolio can react to the effectiveness of both the interest and exchange rate channels of domestic monetary transmission. If the portfolio share of foreign currency debt rises due to the increasing interest rates on domestic currency-denominated loans, then the effectiveness of the interest rate channel weakens, while in the short run the exchange rate channel might attenuate as well. As a result of restrictive domestic monetary policy actions, for instance, the exchange rate appreciates, the debt-servicing costs for holders of foreign currency debt decrease and their consumption possibilities expand, which can convey short-run inflation risks.

Substitutability between domestic and foreign currency-denominated loans also has implications on financial stability. On the one hand, Holló and Papp (2007) showed that as a result of the denomination structure of Hungarian households' loan portfolio, its quality is sensitive to exchange rate depreciation.[4] On the other hand, the relatively high share of foreign currency debt can be further increased by a strong substitution toward foreign currency-denominated products, thereby further increasing the exposure of households' loan portfolio to direct exchange rate risk and indirect credit risk (i.e. changes in households' debt-servicing costs as a result of exchange rate movements).

The novelty of this study is that it employs – for the first time, to our knowledge – the random coefficient logit (RCL) methodology to calculate substitution patterns between various consumer credit and retail deposit products. The main reason for the application of this framework lies not in its computational simplicity, but rather in its other important and favorable properties, which are often neglected in demand estimations. These are as follows:

[4] *Foreign currency-denominated loans accounted for 59% of the total household loan portfolio in Hungary at the end of 2007 (Source: Financial accounts of Hungarian households for 2007).*

– The RCL methodology handles the problem of representative agent models, as the estimation captures individual or consumer heterogeneity (differences in tastes).[5]
– It enables us to aggregate up individual purchases from the observed distribution of consumer characteristics without observing "true" individual purchase decisions;
– It handles the dimensionality problem of the earlier literature on differentiated product demand systems by projecting the products onto a space of characteristics;
– Finally, and most importantly, as a result of the above it produces more realistic price elasticities of demand compared to standard neoclassical differentiated product demand models.

In addition to its favorable attributes, the RCL methodology also has some weaknesses that might be restrictive in some cases. Its two main shortcomings relate to multiple choices and dynamic demand. The impact of these factors, however, depends upon the market analyzed and the issues the researcher focuses on. Regarding the first factor, we do not think that it imposes a true restriction as neither consumer loans nor retail deposits are typically products of which more than one is "consumed" at the same time.[6]

The problem of dynamic demand usually occurs with either durable, storable or experience goods. Models that are appropriate for dynamic demand estimation can become quite complex, since they often require forward-looking consumers whose behavior depends on the possible distribution of future as well as current offerings of goods. In addition, these future offerings would, in turn, depend on producers' perceptions of consumer demand (for an application of dynamic demand estimation, see e.g. Hendel and Nevo, 2002).

In our case, neglecting dynamics (especially the dynamic pricing behavior of banks) is the main drawback of the employed framework. However, whether it is a "true" limitation or not depends on the share of forward-looking agents (i.e. banks and customers), which is a conundrum.

All in all, we believe that the favorable attributes of the RCL methodology more than offset its weaknesses, which is also supported by the following policy-relevant main empirical findings:

– The estimation results provide empirical evidence that on average the demand for domestic currency-denominated consumer loans is more price sensitive than the demand for foreign currency consumer loans;
– In addition, the results show that there is an asymmetric substitution effect between domestic and foreign currency-denominated consumer loans. This means that the demand reaction of foreign currency loans to the price change of domestic currency loans is stronger than the change in demand for domestic currency-denominated products that results from interest rate variations in foreign currency loans;

[5] *The economic and policy implications of a demand model which does not reflect individual heterogeneity and one that explicitly captures this factor (i.e. the RCL model) might be substantially different, since differences in tastes necessarily affect product and firm level demand and, as a result, market shares.*

[6] *Although there might be situations in which clients take on multiple credit products – either if they encounter payment difficulties or if new claims arise – but from our point of view, it is the timing of these actions that matters, and usually clients do not take on multiple loans at the same time.*

– Finally, as the substitution effect toward foreign currency-denominated consumer loans is stronger, it might weaken the effectiveness of the interest and exchange rate channels of monetary transmission.

The remainder of this paper is organized as follows: In section 2 the empirical methodology is presented, section 3 discusses the empirical results and, finally, section 4 offers a concluding summary.

## 2 Model Setup

In this section, we provide a technical overview of the employed random coefficient logit demand model.

### 2.1 The Random Coefficient Logit (RCL) Demand Model

Consider a market (or time period) with $J$ different products; each product $j$ has observed and unobserved (by the econometrician) characteristics and a price. Unobserved characteristics are, inter alia, unobserved promotional activity, brand and/or firm equity or systemic demand shocks. Depending on the data structure, some unobserved components can be captured by product and/or market (time)-specific dummy variables. Following Nevo's (2001) notation, the conditional indirect utility for consumer $i$ from consuming one unit of product $j$ in market (or time period) $t$ in the RCL framework can be expressed as follows:

$$u_{ijt} = \beta_i x_{jt} - \alpha_i p_{jt} + \xi_{jt} + \varepsilon_{ijt} \tag{1}$$

where $x_{jt}$ and $p_{jt}$ (price) are observed product characteristics, $\xi_{jt}$ are unobserved product characteristics, $\varepsilon_{ijt}$ is a mean-zero stochastic term and $\alpha_i$ and $\beta_i$ are individual-specific coefficients.

Observed characteristics vary with the product analyzed. The RCL model describes how consumer preferences vary as a function of individual characteristics, which means that the distribution of individual taste parameters (i.e. $\alpha_i$ and $\beta_i$) must be modeled. Similarly to brand characteristics, individual characteristics can be either observed or unobserved. We refer to demographic characteristics as observed, denoted by $D_i$, and additional attributes as unobserved, denoted by $v_i$. In respect of observed demographic characteristics, we can either have information about the distribution of the selected attributes from population or consumer surveys or, if such information is not available, but we know the important moments of these demographic characteristics such as the mean and standard deviation, a parametric distribution can be assumed. Unobserved attributes $v_i$ might include factors that may influence consumers' decision-making processes, but are unobserved by the econometrician (such attributes may include an individual's relation to risk or the general financial situation of individuals that influence their participation in the credit market, etc.).

Consumers' taste parameters for the observed product characteristics can be modeled as follows:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma v_i \qquad v_i \sim \mathrm{P}_{\mathrm{v}}^{*}(v) \qquad D_i \sim \hat{\mathrm{P}}_{\mathrm{D}}^{*}(D) \tag{2}$$

where $D_i$ is a $d \times 1$ vector of demographic variables, $v_i$ are the unobserved demographic characteristics discussed above, $\mathrm{P}_{\mathrm{v}}^{*}(v)$ is a parametric distribution (usually type I extreme value[7]), $\hat{P}^*_D(D)$ is either a parametric or a nonparametric distribution, $\Pi$ is a $(K+1)\times d$ matrix of coefficients and measures how the taste characteristics vary with demographic characteristics, and $\Sigma$ is a scaling matrix. The demand system specification is completed with the introduction of an outside option, i.e. consumers may decide to choose services of other financial institutions. The indirect utility from this option is as follows:

$$u_{i0t} = \xi_0 + \pi_0 D_i + \sigma_0 v_{i0} + \varepsilon_{i0t} \tag{3}$$

The mean utility (i.e. $\xi_0$) from the outside option is normalized to zero. The advantage of normalization is that it does not change the order of preferences over goods. The coefficients $\pi_0$ and $\sigma_0$ are not identified separately from the individual specific constant term in equation (1). After combining equations (1) and (2), we obtain the following:

$$\begin{aligned} u_{ijt} &= \delta_{jt}\left(x_{jt}, p_{jt}, \xi_{jt}; \alpha, \beta\right) + \mu_{ijt}\left(x_{jt}, p_{jt}, v_i, D_i; \Pi, \Sigma\right) + \varepsilon_{ijt} \\ \delta_{jt} &= \beta x_{jt} - \alpha p_{jt} + \xi_{jt}, \mu_{ijt} = \left[p_{jt}, x_{jt}\right]\left(\Pi D_i + \Sigma v_i\right) \end{aligned} \tag{4}$$

Based on equation (4), the indirect utility is expressed as a sum of the mean utility level which is common to all consumers $\delta_{jt}$ (i.e. it is independent of consumer characteristics), and the last two terms $\mu_{ijt}+\varepsilon_{ijt}$ represent the mean-zero heteroskedastic deviation from the mean utility, which captures the effects of the random coefficients.

Consumers, by assumption, purchase one unit of a good which provides the highest utility. As within this framework, the individual is defined as a vector of demographic characteristics and product-specific shocks, the set of individual attributes leading to the choice of product $j$ can be formulated as follows:

$$A_{jt}\left(x_{.t}, p_{.t}, \delta_{.t}; \Pi, \Sigma\right) = \left\{ \begin{matrix} \left(D_i, v_i, \varepsilon_{i0t}, \ldots\ldots, \varepsilon_{iJt}\right) \middle| u_{ijt} \geq u_{ilt} \\ \forall l = 0,1,\ldots\ldots\ldots, J \end{matrix} \right\} \tag{5}$$

where $x_{.t} = \left(x_{lt}, \ldots\ldots\ldots, x_{Jt}\right)'$, $p_{.t} = \left(p_{lt}, \ldots\ldots\ldots\ldots, p_{Jt}\right)'$ and $\delta_{.t} = \left(\delta_{lt}, \ldots\ldots\ldots, \delta_{Jt}\right)'$ are observed product characteristics, prices and mean utilities of all the products.

As a firm's pricing decision is based on its expectation about the demand for its products, the expected market share for the firm's product $j$ (firm indices are neglected for notational simplicity) can be expressed as an integral over the mass of consumers in the region $A_{jt}$, that is:

$$\begin{aligned} s_{jt}\left(x_{.t}, p_{.t}, \delta_{.t}; \Pi, \Sigma\right) &= \int_{A_{jt}} dP^*\left(D, v, \varepsilon\right) = \\ = \int_{A_{jt}} dP^*\left(\varepsilon \middle| D, v\right) dP^*\left(v \middle| D\right) dP^*_D\left(D\right) &= \int_{A_{jt}} dP^*_\varepsilon\left(\varepsilon\right) dP^*_v\left(v\right) d\hat{P}^*_D\left(D\right) \end{aligned} \tag{6},$$

where $P^*(.)$ denotes the population distribution function. In expression (6), Bayes' rule is applied, i.e. the independence of $D$, $v$ and $\varepsilon$ is assumed. For a given para-

[7] *The type I extreme value distribution (also known as Gumbel distribution) is usually employed to model the distribution of a number of samples coming from various distributions. The demographic data used in our estimation came from Hungarian household surveys conducted between 2003 and 2008 (for further details, see the data description part in section 3.1). With this distribution it is possible to compute unobserved demographic characteristics that relate to the employed sample of observed demographic characteristics. For a detailed description of the Gumbel distribution, see e.g. Willemse and Kaas (2007).*

meter set (i.e. $\alpha$, $\beta$, $\Pi$, $\Sigma$), the integral predicts the market share ($s_{jt}$) of each bank product in each market (or time period) as a function of product characteristics ($x_{jt}$), prices ($p_{jt}$), demographic characteristics ($D_i$, $v_i$) and other unknowns.

The intuition behind the model is quite simple, namely it is (implicitly) assumed that firms' observed market shares[8] ($S_{jt}$) in time period $t$ represent realized optimal consumer decisions. This means the reason why a consumer chooses product $j$ in time period $t$ from a given firm is simply because the firm's product provides the highest utility. Thus, the bank product level market shares are "constructed" from these individual preference-driven optimal choices. The main goal of our estimation is to recover the individual taste parameters (i.e. $\alpha_i$ and $\beta_i$) that will be used for the computation of demand elasticities. This can be done by matching the observed market shares ($S_{jt}$) with the market shares predicted by the model (i.e. $s_{jt}$ in (6)) as closely as possible.

### 2.1.1 Estimation

If firm product level data and consumer survey information (either explicit survey data or summary statistics) on the selected demographic characteristics are available, the RCL estimation procedure can be summarized as follows:

– **Step I.** Draw vectors of selected consumer characteristics from population or consumer surveys for each year of the estimation period for a predefined number of individuals (each individual is a vector of demographic characteristics and product-specific shocks). This must be done prior to estimation;
– **Step II.** Determine the choice that each of the selected individuals would make for a given value of the parameter vector. This means we give initial values to the parameter vector $\theta=(\alpha,\beta,\Pi,\Sigma)$ and compute purchase probabilities for each "simulated" individual, then sum these probabilities up and arrive at a prediction of market shares conditional on the parameter vector (i.e. we approximate numerically the integral given in (6));
– **Step III.** Then we apply a search routine that matches the predicted market shares computed in Step II ($s_{jt}$) with the observed market shares ($S_{jt}$). If the difference between the predicted and observed market shares exceeds a predefined threshold, the parameter values ($\alpha$, $\beta$, $\Pi$, $\Sigma$) are modified and the predicted market share and the difference are recomputed. If the difference falls below the predefined threshold, the parameters that "generated" the optimal choices are found. More formally, the search routine finds the unique values of $\delta_{jt}$ (the mean utility level) that make the predicted market shares ($s_{jt}$) for a given parameter vector $\theta=(\alpha,\beta,\Pi,\Sigma)$ as close as possible to the observed market shares ($S_{jt}$). The iteration equation the search routine employs is as follows: $\delta_{jt}^{h+1}=\delta_{jt}^{h}+\ln(S_{jt})-\ln\left(s_{jt}\left(p_{jt},x_{jt},\delta_{jt}^{h},\Pi,\Sigma\right)\right)$, where $\ln\left(s_{jt}\left(p_{jt},x_{jt},\delta_{jt}^{h},\Pi,\Sigma\right)\right)$ is the natural logarithm of the predicted market share in iteration $h$ *(h=0,......,H)* and time period *t=1,.........,T, ln(S*$_{jt}$*)* is the natural logarithm of the observed market share in time period $t$ and $\delta_{jt}^{h}$ is the approximation of the mean utility level ($\delta_{jt}$) in time period $t$ and in the $h^{th}$ iteration. If $\left\|\delta_{jt}^{h+1}-\delta_{jt}^{h}\right\|$ falls below the predefined tolerance level in iteration $h$, the parameters that "generated" the optimal deci-

[8] *Observed market shares were computed as follows:* $S_{kjt}=\frac{RV_{kjt}}{RV_t}$, *where* $RV_t$ *is the total consumer loan or deposit stock of MFIs in time period t and* $RV_{kjt}$ *is the stock of the consumer loan or deposit product j (j=1,....,J) of bank k (k=1,....,K) in time period t.*

sion are found.[9] Then, equation (4) implies $\omega_{jt} = \delta_{jt}\left(S_{jt}, \Pi, \Sigma\right) - \left(\beta x_{jt} + \alpha p_{jt}\right) \equiv \xi_{jt}$, that is the unobserved product characteristics ($\xi_{jt}$) are expressed as a function of parameters, $\theta = (\alpha, \beta, \Pi, \Sigma)$ and the employed data ($x_{jt}, p_{jt}, S_{jt}$).

– **Step IV.** Finally, the General Method of Moments (GMM) procedure is used to estimate our RCL model. We interact $\xi_{jt}$ with the function of instruments $Z$ and find the exact value of $\theta = \left(\alpha, \beta, \Pi, \Sigma\right)$ that makes the sample moments as close as possible to zero.[10]

Section 2.2 provides details on the employed instrumental variables.

### 2.1.2 Elasticities

As mentioned in the introduction, one of the main advantages of the RCL framework is that it allows for flexible substitution patterns by introducing utility shocks that are correlated across products. These shocks will ensure that the borrower in question will be more likely to take a loan with attributes similar to his or her first choice if the price of the first choice increases. By examining equation (4), this correlation can be generated either through $\varepsilon_{ijt}$ or $\mu_{ijt}$. The latter captures the effect of both observed $D_i$ and unobserved $v_i$ demographic characteristics. We turn our attention to modeling the correlation between choices obtained through the observed demographic characteristics in $\mu_{ijt}$. That is, we assume that the correlation of "utility shocks" is a function of product and borrower characteristics, which will ensure that products with similar attributes and borrowers with similar demographic characteristics will have similar product rankings and, therefore, similar substitution patterns.

The price elasticities of the market shares defined by equation (6) can be calculated as follows:

$$\eta_{jkt} = \frac{\partial s_{jt} p_{kt}}{\partial p_{kt} s_{jt}} = -\frac{p_{jt}}{s_{jt}} \int_{A_{jt}} \alpha_i s_{ijt} \left(1 - s_{ijt}\right) d\hat{P}_D^*\left(D\right) dP^* \text{ if } i = j \tag{7}$$

$$\text{and } \eta_{jkt} = \frac{\partial s_{jt} p_{kt}}{\partial p_{kt} s_{jt}} = \frac{p_{kt}}{s_{jt}} \int_{A_{jt}} \alpha_i s_{ijt} s_{ikt} \, d\hat{P}_D^*\left(D\right) dP_v^*\left(v\right) \text{ if } i \neq j$$

where $s_{ijt} = \dfrac{\exp\left(\delta_{jt} + \mu_{ijt}\right)}{1 + \sum_{k=1}^{K} \exp\left(\delta_{kt} + \mu_{ikt}\right)}$ is the probability that individual $i$ purchases product $j$. Now elasticities are determined by the price sensitivity of each borrower, which will be averaged to mean price sensitivity using the purchase probabilities of simulated individuals as purchase weights. Since the RCL model allows for flexible substitution patterns (i.e. the composite random shock $\mu_{ijt} + \varepsilon_{ijt}$ is not independent of product and consumer characteristics), this flexibility will ensure that in the event of changing product prices, borrowers will be more likely to switch to products with similar characteristics.

[9] *See BLP (1995) for further details.*

[10] *For a detailed technical description, see BLP (1995) and Nevo (2001).*

### 2.2 Instruments

The price variable $p_{jt}$ is very likely correlated with unobserved product characteristics, i.e. the price variable is not strictly exogenous, which leads to biased and inconsistent parameter estimates. This problem can be handled by the instrumental variable (IV) approach. In order to estimate the demand equation for both consumer credit and deposit markets, the following set of instruments is used to identify the price coefficients:

(8) *Z=(administrative costs to total assets, credit risk, liquidity, rival employee per branch, rival branch number, rival salary per employee)*

The instruments consist of several cost shifters, which are, theoretically, valid instruments because they affect prices but are not related to unobserved product characteristics. The first cost shifter is the ratio of administrative costs (including all noninterest expenses) to total assets. Credit risk can also be considered a cost shifter since high credit risk may entail higher operation costs due to monitoring and auditing, therefore higher credit risk might shift up the cost function. Credit risk is proxied by the ratio of loan loss provisions to total loans. Furthermore, liquidity variables might be informative about credit risk and, thus, about the cost function. Banks' liquidity is proxied by the ratio of cash and negotiable instruments to total assets.

Mark-up shifters were also used as instruments; they include other banks' characteristics such as the competitors' number of employees per branch, their branch number and salary per employee.[11] Given that the product characteristics are exogenous, these instruments are orthogonal to unobserved product characteristics.

## 3 Empirical Analysis

In this section, we first describe the data set and define the variables used. We then present the empirical results of the credit and deposit demand estimations.

### 3.1 Data and Variable Description

Estimating the model previously described requires bank product level data such as information on market shares, prices of consumer loans and deposits as well as product characteristics (in our case bank characteristics) such as a bank's number of branches and age. These data stem from Magyar Nemzeti Bank's banking database and cover the period between March 2004 and August 2007 for consumer loans,[12] and between January 2003 and August 2007 for retail deposits. Data were adjusted for revaluation effects caused by exchange rate changes.

In our analysis, we defined 15 consumer lending and 3 retail deposit submarkets. The consumer lending submarkets are as follows: hire purchase HUF-denominated loans with short maturities and maturities up to five years; personal HUF- and CHF-denominated loans with short maturities, maturities up to five

[11] *The "competitors' salary per employee" indicator might reflect service quality through an indirect channel, namely employees' quality. If a bank pays high salaries, the best qualified employees can be expected to choose to work there.*

[12] *Our analysis of the consumer credit market covers the period between March 2004 and August 2007, since the denomination composition of the various loan products is only available from March 2004.*

years and maturities over five years; overdraft, home equity HUF- and CHF-denominated loans with short maturities, maturities up to five years and maturities over five years. In Hungary, the aforementioned lending products are considered consumer loans. These loans vary in purpose and in whether they are secured or not. Hire purchase loans are designated for the consumption of durable goods, personal and overdraft loans can be employed either for durable goods consumption or for managing temporary liquidity problems. Home equity loans also belong in this category and have become very popular over the past three to four years mainly due to their secured nature and the related price advantage compared to the aforementioned unsecured products and their versatile utilization possibilities (house, car, durable goods purchase). Regarding retail deposit submarkets, we considered three different types: demand deposits (without maturity), short-term deposits (maturities up to two years) and long-term deposits (maturities over two years) as these are the main retail deposit products provided by banks in Hungary. These types of deposits account for approximately 40% to 50% of Hungarian households' financial savings.[13] Descriptive statistics of the consumer loan and retail deposit products analyzed in this paper can be found in table A1 in the annex.

Bank product level market shares, which were computed separately for the consumer credit and retail deposit submarkets for each month of the estimation period, constitute one of the main model variables. For each submarket in time period $t$ we divided consumer loan or retail deposit stocks at the bank product level by the total consumer loan or retail deposit stocks of MFIs in time period $t$ (for a more formal description, see footnote 8).

The most important explanatory variables are the price proxies. As a loan price proxy, we use the monthly interest rate on stocks, while prices for deposits are calculated as the difference between monthly deposit interest rates on stocks and service fees for deposits. The latter are approximated by the ratio of revenues from fees and commissions to the retail deposit stock. A relevant part of the required data set consists of product characteristics, which play an important role in our estimation as, on the one hand, they explain the mean utility level $\delta(.)$ and, on the other hand, they drive the substitution patterns $\mu(.)$ in equation (4). We choose bank attributes based on data availability and observability to consumers as observed characteristics, namely banks' branch number and age. These characteristics represent the service quality provided by banks, such as the convenience of local branches, and capture factors such as reputation, experience and reliability.

Finally, information about the distribution of demographic characteristics $\hat{P}_D^*$ is important for the RCL demand estimations. We choose three demographic attributes that might have relevance for influencing consumer decisions: customers' disposable income (in HUF), age (in years) and level of education (elementary, secondary, higher). For the RCL estimation, we need information about the joint distribution of these demographic characteristics for each year of the respective estimation period (2004 to 2007 for consumer loans and 2003 to 2007 for retail

[13] *Source: Financial accounts of Hungarian households between 2004 and 2007.*

deposits). For this purpose, 500 individuals were selected randomly from household surveys conducted in Hungary between 2003 and 2008.[14]

## 3.2 Estimation Results

### 3.2.1 The Consumer Credit Market

Estimation results for the preferred consumer credit demand specification can be found in table 1 below.

The means of the distribution of marginal utilities (alpha and betas) are presented in the second column. All of the coefficients are statistically significant. Estimates of heterogeneity around these means are presented in columns 3 to 6. Among the interactions with demographic characteristics, the interaction between interest rate and customers' income, interest rate and customers' education, and the number of bank branches and customers' education proved to be significant.[15] The price variable has the expected sign, which means an increase in the interest rate decreases the quantity demanded in the consumer credit submarkets and thus the bank's market share. Both the size of the branch network and the age of the financial institution positively influence the product's utility for an average consumer. The former can be explained by the significant role bank branches still play as distribution channels. The latter might indicate that people trust "old," safe and experienced financial institutions more and, as a result, clients are more likely to resort to financial services provided by these "older" banks.

The interpretation of parameter estimates is straightforward. The marginal valuation of prices (i.e. interest rates), for instance, increases with income, denoting that wealthier consumers are less price sensitive, but decreases with education,

Table 1

**Coefficient Estimates of the Consumer Credit Demand Model**

| | | | Interaction terms | | |
|---|---|---|---|---|---|
| Variable | Mean (alpha and betas) | Standard deviation (sigmas) | Customers' income | Customers' age | Customers' education |
| Interest rate | −33.05 (13.56) | 1.83 (9.07) | 16.58 (8.20) | −0.63 (1.29) | −0.06 (0.025) |
| Number of bank branches | 1.36 (0.28) | 0.01 (1.84) | 0.02 (0.89) | – | 3.28 (0.21) |
| Age of bank | 1.15 (0.07) | 0.004 (1.79) | −1.29 (0.99) | – | 0.60 (0.64) |
| Constant | −7.04 (0.28) | 0.49 (2.76) | 13.33 (7.81) | – | – |

*Source: Author's calculations.*

*Note: The regression includes bank product dummies, time dummies and, as instruments, cost and mark-up shifters. The instruments used proved to be valid according to Hansen's J-statistic in the framework of a simple logit model (IV validity cannot be explicitly tested in the RCL model; results are not reported here, but available upon request). Asymptotically robust standard errors are given in parentheses.*

[14] *Individuals were selected from GfK household surveys for Hungary for the years 2003, 2004 and 2005, while for 2006 and 2007 we used the surveys conducted by the MNB in January 2007 and 2008, respectively (the data in the MNB surveys contain information on households' financial situation, loans and demographic characteristics for 2006 and 2007). In the numerical calculation of the integral given in equation (6), we employed the same 500 randomly selected individuals both for the consumer credit and retail deposit markets. The accuracy of the results was also checked by simulating 800 and 1,100 individuals, respectively. However, except for the running time of the program code, the parameter estimates did not show substantial qualitative differences.*

[15] *Several interaction relationships were tested, but only a few provided economically meaningful results. The interactions depicted in table 1 proved to be the only ones of several relationships tested that were both statistically and economically significant.*

which suggests that more educated persons are more sensitive to loan interest rate fluctuations than less educated persons. It may be true that better-educated people are more able to collect and synthesize information and, as a result, are more conscious in their decision-making (i.e. they react more sensitively e.g. to product price fluctuations). Furthermore, the estimate of the standard deviation (sigma is not statistically significant) suggests that most of customers' heterogeneity is explained by the selected demographic characteristics.[16]

Table 2 presents the own- and cross-price elasticities for the most relevant consumer loans, which account for a dominant share within the consumer loan category. The most relevant consumer loan products are as follows: hire purchase

Table 2

**Own- and Cross-Price Elasticities on the Hungarian Consumer Credit Market**

| Consumer loans (denomination, maturity) | Hire purchase loans (HUF, short maturity) | Hire purchase loans (HUF, maturity up to 5 years) | Personal loans (HUF, maturity over 5 years) | Own-price elasticities |
|---|---|---|---|---|
| | *August 2007* | *August 2007* | *August 2007* | *2004–2007* |
| Hire purchase loans (HUF, short maturity) | *–2.30* | **0.46** | 0.40 | *–3.64* |
| Hire purchase loans (HUF, maturity up to 5 years) | 0.20 | *–2.12* | 0.20 | *–3.59* |
| Personal loans (HUF, maturity over 5 years) | 0.30 | 0.30 | *–2.52* | *–4.19* |
| Overdraft loans (HUF) | 0.32 | 0.30 | 0.30 | *–4.17* |
| Home equity loans (HUF, maturity over 5 years) | 0.22 | 0.20 | 0.21 | *–2.95* |
| Home equity loans (CHF, short maturity) | 0.40 | 0.10 | 0.10 | *–3.52* |
| Home equity loans (CHF, maturity over 5 years) | 0.24 | 0.21 | 0.24 | *–3.55* |
| | Overdraft (HUF) | Home equity loans (HUF, maturity over 5 years) | Home equity loans (CHF, short maturity) | Own-price elasticities |
| Hire purchase loans (HUF, short maturity) | 0.41 | 0.35 | 0.40 | *–3.64* |
| Hire purchase loans (HUF, maturity up to 5 years) | 0.20 | 0.17 | **0.39** | *–3.59* |
| Personal loans (HUF, maturity over 5 years) | 0.30 | 0.30 | 0.20 | *–4.19* |
| Overdraft loans (HUF) | *–2.23* | 0.29 | 0.26 | *–4.17* |
| Home equity loans (HUF, maturity over 5 years) | 0.21 | *–2.37* | 0.30 | *–2.95* |
| Home equity loans (CHF, short maturity) | 0.10 | 0.10 | *–1.41* | *–3.52* |
| Home equity loans (CHF, maturity over 5 years) | 0.22 | 0.24 | 0.43 | *–3.55* |
| | Home equity loans (CHF, maturity over 5 years) | Home equity loans (CHF, maturity up to 5 years) | Personal loans (CHF, maturity up to 5 years) | Own-price elasticities |
| Hire purchase loans (HUF, short maturity) | 0.20 | 0.25 | 0.28 | *–3.64* |
| Hire purchase loans (HUF, maturity up to 5 years) | 0.25 | 0.30 | 0.16 | *–3.59* |
| Personal loans (HUF, maturity over 5 years) | 0.24 | 0.24 | **0.40** | *–4.19* |
| Overdraft loans (HUF) | 0.30 | 0.29 | **0.40** | *–4.17* |
| Home equity loans (HUF, maturity over 5 years) | **0.40** | **0.40** | 0.29 | *–2.95* |
| Home equity loans (CHF, short maturity) | **0.51** | 0.49 | 0.10 | *–3.52* |
| Home equity loans (CHF, maturity over 5 years) | *–1.12* | **0.44** | 0.29 | *–3.55* |

*Source: Author's calculations.*

*Note: Field values (except in the right-hand column) indicate the elasticity of the column brand with respect to changes in the price of the row brand. Bold numbers denote the strongest demand reaction of the column brands to a price increase of the row brand. Numbers in italics show own-price elasticities.*

[16] *Frequency distribution charts of the estimated coeffcients (i.e. interest rate, number of branches, age of bank) of the consumer loan demand model are available upon request. These charts show the distribution of the valuation of respective product characteristics across the population.*

loans (denominated in HUF with short maturities and with maturities up to five years), personal loans (denominated in HUF with maturities over five years), overdraft and home equity loans (denominated in HUF with maturities over five years and denominated in CHF with short maturities and maturities over five years).[17]

Own-price elastic loan demand can be observed in every case (own-price elasticities of demand are greater than one in absolute value). The mean own-price sensitivity across the 15 lending submarkets (personal, home equity, hire purchase and overdraft loans with different maturities and denominatons) considered was –3.7 between 2004 and 2007 (i.e. a 1% price rise decreases the demand for consumer loans by 3.7% on average). If we make a distinction between domestic and foreign currency-denominated loans and compute the average own-price elasticities separately across these submarkets, it seems that the demand for HUF-denominated consumer loans is on average more price sensitive than the demand for foreign currency loans. In the case of HUF-denominated loans, a 1% rise in interest rates on HUF-denominated consumer loans decreases the demand for this type of loans by 3.78% on average, while for foreign currency consumer loans the mean demand decrease of a 1% rise in interest rates on foreign currency consumer loans is 3.55%. The asymmetric own-price effect between HUF- and foreign currency-denominated products is more pronounced if the averages are computed without home equity loans. In this case, the mean own-price elasticity of HUF-denominated consumer loans is –4, while for foreign currency-denominated consumer loans it is –3.58.

The quantitative differences between foreign currency- and HUF-denominated products' own-price elasticities computed with and without home equity loans can be explained by the below-average own-price sensitivity of home equity loans. At least two explanations can be given for these differences. First, as home equity loans are secured products, it is easier for wealthier clients to have access to these credits (as they have their own houses or flats to use as collateral) and, as suggested by the estimation results presented in table 1, wealthier clients are less price sensitive. Second, there might be an interest rate level effect. Namely, due to the secured nature of home equity loans, their interest rates are lower than those on other consumer loans. Therefore, a 1% price rise from a lower interest rate level might reduce the demand for these loans to a lesser extent than a 1% price increase from the higher interest rate level of other consumer loans decreases the demand for these unsecured products.

Table 2 also shows cross-price elasticities.

Substitution effects were analyzed along three dimensions: loan denomination, loan type (secured or unsecured) and maturity. Similarly to the case of own-price elasticities, mean cross-price sensitivities were computed separately across all the HUF and foreign currency lending submarkets considered and excluding home equity loans. The estimated cross-price elasticities indicate that the substitution effect between loans denominated in different currencies is asymmetric. The average cross-price elasticities between HUF and foreign currency-denominated con-

[17] *These products account for approximately 80% to 90% of the total consumer loan stock in Hungary. Results of own- and cross-price elasticities for all the consumer loans included in the estimation are available upon request. The mean own- and cross-price effects mentioned in this paper were computed for all the consumer lending submarkets considered.*

sumer loans is 0.28. This means that a 1% rise in interest rates on HUF-denominated consumer loans increases the demand for foreign currency-denominated consumer loans by 0.28% on average. By contrast, a 1% rise in interest rates on CHF-denominated loans increases the demand for HUF loans by 0.2% on average. If home equity loans are excluded from the calculation of mean cross-price elasticities, the previous results do not change substantially; substitution is still asymmetric and of similar size. The respective results are 0.3% and 0.19% instead of 0.28% and 0.2%, respectively. This suggests that whether a loan is secured or not seems to be irrelevant from the point of view of the strength of cross-price effects in the loan denomination dimension.

The results given above have implications on monetary policy: They show that substitution among domestic and foreign currency loans can result in a portfolio realignment effect toward foreign currency-denominated debt as a consequence of the "price" increase of domestic currency-denominated credit (i.e. the relative prices of and, as a result, the demand for domestic and foreign currency-denominated loans changes). This can weaken the effectiveness of the interest rate channel due to the rising share of foreign currency debt and might, at the same time, also have an influence on financial stability. The reason for this latter possibility is that exchange rate developments directly impact the debt-servicing cost for foreign currency debt holders and their payment ability. Beside the interest rate channel, the exchange rate channel is of particular importance in monetary transmission in Hungary (Vonnák 2007). However, the effectiveness of the exchange rate channel might also be affected by the realignment toward foreign currency debt. A restrictive domestic monetary policy, for instance, leads to an exchange rate appreciation which, in turn, is favorable for both long-run inflation prospects and the evolution of debt-servicing costs for foreign currency debt holders. However, in the short run restrictive monetary policy action might induce inflationary pressure as it directly mitigates the debt-servicing costs of foreign currency debt holders and as a results expands their consumption possibilities.

Substitution was analyzed in the secured/unsecured dimension as well. Average cross-price elasticities were computed between unsecured (hire puchase, personal, overdraft) and secured (home equity) consumer loans across all maturities and denominations. The results thus obtained indicate that the demand for secured loans increases more (by 0.26% on average) if the prices of unsecured loans increase by 1% than the demand for unsecured loans increases (by 0.2% on average) as a result of a 1% price rise of secured consumer loans. This finding can be explained by the differences in the interest rate levels of secured and unsecured products. Even if the interest rates on home equity products rise, they might be still significantly below the average interest rate on unsecured loans; it is therefore not worthwhile to substitute a home equity loan for an unsecured loan.

Furthermore, substitution operates not only among products of different denominations or types (secured/unsecured), but also among products with different maturities. For instance, a CHF-denominated home equity loan with a maturity of over five years is most sensitive to the price change of HUF-denominated home equity loans with a maturity of over five years (cross-price elasticity of 0.4) and of CHF-denominated home equity loans with short maturities (cross-price elasticity of 0.51). At the same time, the same type of loan is found to be least sensitive to a change in the price of hire purchase loans denominated in HUF with short maturities (cross-price elasticity of 0.2).

### 3.2.2 The Deposit Market

Estimation results for the retail deposit demand model can be found in table 3 below. The means of the distribution of marginal utilities (alpha and betas) are given in the second column and estimates of heterogeneity around these means are presented in columns 3 to 6.

Considering the interaction of interest rates, branch number and bank age with demographic characteristics, that of interest rates and customers' income, branch number and customers' age, bank age and customers' income and, finally, bank age and customers' age prove to be significant.[18] The sign of the price variable indicates that an increase in deposit interest rates increases the demand for deposits and thereby increases the bank's market share on the retail deposit markets. The size of a bank's branch network positively influences the utility for an average consumer, while a bank's age negatively influences average consumer utility.[19] The latter finding might indicate that when opening a deposit account at a bank, average consumers mainly base their decision on the deposit interest rates offered.

The marginal valuation of deposit interest rates increases with income, suggesting that wealthier consumers are less sensitive to deposit interest rate fluctuations than less wealthy ones. Another interpretation might be that wealthier clients are hit to a lesser degree by a substantial deposit interest rate decline than consumers with limited financial resources. However, a comparison of the coefficients of the interactions between interest rate and income on retail deposit (0.99) and consumer credit markets (16.58) shows a substantial difference, which might indicate that although wealthier consumers are less price sensitive than less wealthy ones, their cost and revenue sensitivity differs and wealthier consumers are more cost than revenue sensitive. The estimate of the sigma (i.e. the standard deviation)

Table 3

**Coefficient Estimates of the Retail Deposit Demand Model**

| | | | Interaction terms | | |
|---|---|---|---|---|---|
| Variable | Mean (alpha and betas) | Standard deviation (sigmas) | Customers' income | Customers' age | Customers' education |
| Interest rate | 60.47 (23.24) | 3.51 (21.68) | 0.99 (0.31) | −1.19 (0.62) | 2.28 (27.97) |
| Number of bank branches | 3.62 (0.028) | 0.016 (0.35) | −0.22 (0.48) | 0.05 (0.012) | – |
| Age of bank | −0.29 (0.036) | 0.075 (0.25) | 1.62 (0.29) | 0.14 (0.017) | – |
| Constant | 1.24 (0.028) | 0.26 (0.29) | 7.23 (1.72) | – | – |

*Source: Author's calculations.*

*Note: The regression includes bank product dummies, time dummies and, as instruments, cost and mark-up shifters. The instruments used proved to be valid according to Hansen's J-statistic in the framework of a simple logit model (IV validity cannot be explicitly tested in the RCL model; results are not reported here, but available upon request). Asymptotically robust standard errors are given in parentheses.*

[18] *Several interaction relationships were tested, but only a few provided economically meaningful results. The interactions depicted in table 3 proved to be the only ones that were both statistically and economically significant.*

[19] *Frequency distribution charts of the estimated coefficients of the deposit demand model are available upon request.*

Table 4

**Own- and Cross-Price Elasticities on the Hungarian Retail Deposit Market**

| | Demand deposits (HUF, without maturity) | Short-term deposits (HUF, maturity up to 2 years) | Long-term deposits (HUF, maturity over 2 years) | Own-price elasticities |
|---|---|---|---|---|
| | *August 2007* | *August 2007* | *August 2007* | *2003–2007* |
| Demand deposits (HUF, without maturity) | *1.62* | –0.34 | **–0.35** | *1.49* |
| Short-term deposits (HUF, maturity up to 2 years) | –0.30 | *4.42* | **–0.44** | *3.24* |
| Long-term deposits (HUF, maturity over 2 years) | –0.24 | **–0.25** | *5.32* | *3.96* |

*Source: Author's calculations.*

*Note: Field values (except in the right-hand column) indicate the elasticity of the column brand with respect to changes in the price of the row brand. Bold numbers denote the strongest demand reaction of the column brands to a price increase of the row brand. Numbers in italics show own-price elasticities.*

is insignificant, indicating the relevant role the selected demographic characteristics play in the explanation of heterogeneity.

Table 4 shows the own- and cross-price elasticities by retail deposit product categories. Similarly to demand for consumer loans, the demand for deposits is also price elastic (i.e. the own-price elasticity is greater than one in absolute value), signifying that clients increase or decrease their deposit demand by more than 1% as a result of a 1% change in deposit interest rates.

Not surprisingly, the own-price elasticities of various deposit products are positive, while their cross-price elasticities are negative, indicating that the rise in deposit interest rates positively affects demand for the product itself and decreases demand for substitutes, albeit to a different degree. It can be observed that the demand reaction of long-term deposits to the price increase of short-term deposits is more pronounced than that of demand deposits, which can be explained by the fact that short- and long-term deposits are closer substitutes than either long-term and demand deposits or short-term and demand deposits.

## 4 Summary and Conclusion

In this paper, we use bank product and consumer level data to estimate a random coefficient logit (RCL) demand model in order to compute price elasticities on the Hungarian consumer lending and retail deposit markets and to derive the corresponding possible loan, deposit demand and monetary policy implications.

Our analysis covered a sample period from January 2003 to August 2007 for consumer loans and from March 2004 to August 2007 for retail deposits. By making a distinction between maturities, denomination structures and loan types (secured/unsecured), we defined 15 lending and 3 deposit submarkets.

We showed that the demand for HUF-denominated consumer loans is more price sensitive than the demand for foreign currency loans (i.e. asymmetric own-price effect): A 1% rise in interest rates on HUF-denominated consumer loans decreases demand for this type of loan by more (3.78% on average) than a 1% rise in interest rates on CHF-denominated loans decreases the demand for CHF-denominated loans (3.55% on average).

Furthermore, empirical evidence is found for an asymmetric substitution effect between domestic and foreign currency-denominated consumer loans, which means that the demand for foreign currency loans increases more strongly in response to a 1% price increase of HUF-denominated loans (0.28% on average) than the demand for HUF-denominated loans increases if the interest rate on CHF-denominated loans rises by 1% (0.2% on average).

Finally, the asymmetric substitution effect toward foreign currency loans impacts the strength of the interest and exchange rate channels of monetary transmission. The interest rate channel is directly influenced by the increasing portfolio share of foreign currency debt, while restrictive domestic monetary actions may weaken the exchange rate channel in the short run due to their exchange rate appreciation effect, which directly mitigates debt-servicing costs and expands the consumption possibilities of foreign currency debt holders and therefore may convey short-term inflation risks.

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## Annex

Table A1

### Descriptive Statistics of Consumer Loans, Retail Deposits and Selected Bank Characteristics in Hungary (2003–2007)

| | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|
| | *HUF million* | | | |
| **Consumer loans (bank level)** | | | | |
| Hire purchase loans (HUF, short maturity) | 1,023 | 1,559 | 1 | 6,700 |
| Hire purchase loans (HUF, maturity up to 5 years) | 7,689 | 13,471 | 1 | 46,519 |
| Personal loans (HUF, short maturity) | 395 | 1,203 | 1 | 5,394 |
| Personal loans (HUF, maturity up to 5 years) | 11,624 | 27,878 | 3 | 128,749 |
| Personal loans (HUF, maturity over 5 years) | 4,914 | 10,802 | 1 | 57,376 |
| Personal loans (CHF, short maturity) | 35 | 43 | 1 | 187 |
| Personal loans (CHF, maturity up to 5 years) | 7,049 | 10,423 | 1 | 37,921 |
| Personal loans (CHF, maturity over 5 years) | 5,568 | 7,376 | 1 | 40,309 |
| Overdraft loans (HUF) | 8,190 | 16,349 | 1 | 100,764 |
| Home equity loans (HUF, short maturity) | 77 | 107 | 1 | 336 |
| Home equity loans (HUF, maturity up to 5 years) | 340 | 436 | 2 | 2,644 |
| Home equity loans (HUF, maturity over 5 years) | 2,559 | 3,758 | 7 | 17,950 |
| Home equity loans (CHF, short maturity) | 334 | 1,108 | 1 | 4,641 |
| Home equity loans (CHF, maturity up to 5 years) | 809 | 976 | 1 | 5,060 |
| Home equity loans (CHF, maturity over 5 years) | 33,165 | 38,856 | 10 | 170,669 |
| **Retail deposits (bank level)** | | | | |
| Demand deposits (HUF, without maturity) | 52,451 | 114,935 | 4 | 660,446 |
| Short-term deposits (HUF, maturity up to 2 years) | 132,035 | 241,145 | 6 | 1,236,703 |
| Long-term deposits (HUF, maturity over 2 years) | 10,516 | 22,908 | 1 | 110,389 |
| **Bank characteristics** | | | | |
| Branch number | 94 | 116 | 1 | 432 |
| Age (years) | 29 | 21 | 6 | 85 |
| | % | | | |
| **Interest rates of consumer loans** | | | | |
| Hire purchase loans (HUF, short maturity) | 22.47 | 11.99 | 1.23 | 45.19 |
| Hire purchase loans (HUF, maturity up to 5 years) | 22.78 | 10.75 | 5.96 | 40.04 |
| Personal loans (HUF, short maturity) | 20.05 | 6.00 | 3.82 | 30.11 |
| Personal loans (HUF, maturity up to 5 years) | 20.47 | 4.83 | 8.29 | 31.57 |
| Personal loans (HUF, maturity over 5 years) | 19.86 | 5.04 | 6.86 | 30.23 |
| Personal loans (CHF, short maturity) | 15.26 | 4.82 | 5.97 | 23.80 |
| Personal loans (CHF, maturity up to 5 years) | 12.75 | 4.18 | 2.39 | 24.79 |
| Personal loans (CHF, maturity over 5 years) | 11.15 | 2.82 | 4.66 | 15.43 |
| Overdraft loans (HUF) | 17.62 | 7.26 | 3.36 | 35.92 |
| Home equity loans (HUF, short maturity) | 16.73 | 5.02 | 6.22 | 27.95 |
| Home equity loans (HUF, maturity up to 5 years) | 14.66 | 2.88 | 8.29 | 20.73 |
| Home equity loans (HUF, maturity over 5 years) | 15.45 | 3.23 | 8.29 | 22.00 |
| Home equity loans (CHF, short maturity) | 4.76 | 1.09 | 2.72 | 7.91 |
| Home equity loans (CHF, maturity up to 5 years) | 4.62 | 1.01 | 3.00 | 7.65 |
| Home equity loans (CHF, maturity over 5 years) | 4.41 | 1.08 | 1.49 | 6.85 |
| **Interest rates of retail deposits** | | | | |
| Demand deposits (HUF, without maturity) | 3.08 | 1.95 | 0.03 | 10.28 |
| Short-term deposits (HUF, maturity up to 2 years) | 7.18 | 2.05 | 2.38 | 12.11 |
| Long-term deposits (HUF, maturity over 2 years) | 6.90 | 2.21 | 1.71 | 13.03 |

*Source: Author's calculations.*