Quantifying Inertia in Retail Deposit Markets

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By FLORIAN DEUFLHARD*

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This paper investigates inertia within and across banks in retail deposit markets using detailed panel data on consumer choices and account characteristics. In a structural choice model, I find that costs of inertia are around one third higher for switching across compared to within banks. Observable measures of switching costs (number and type of additional financial products) explain most of this excess inertia, while search costs (online banking use) affect both inertia components. On the supply side, I provide evidence that banks discriminate based on inertia by underpricing older accounts with a higher share of existing consumers. Counterfactual policies reducing overall inertia shift market share to more competitive smaller banks but only eliminating inertia within banks already results in high potential gains in consumer welfare. The results suggest that facilitating bank switching alone might be insufficient to improve consumer choices.

* Department of Economics, Goethe University Frankfurt. Email: florian.deuflhard@hof.uni-frankfurt.de. I especially thank my advisors Roman Inderst and Christine Zulehner for their guidance on this project. I also thank Gregory Crawford, Francesco Decarolis, Liran Einav, Tülin Erdem, Dimitris Georgarakos, Jozsef Molnar, Helena Perrone, Konrad Stahl, as well as participants of the 2015 Summer School 'Empirical Analysis of Markets with Incomplete Information' of the University of Mannheim and the Ph.D. Empirical IO Seminar in Frankfurt for helpful comments and discussions. I am grateful to a major Dutch bank for providing interest rate data on savings accounts in the Netherlands, to CentERdata for providing additional information on financial product holdings and bank relationships of DNB survey participants, as well as to SpaarInformatie for providing data on restrictions of Dutch savings accounts.

I. Introduction

In retail banking markets, consumers often stick to their choices in the presence of better alternatives. This inertia is widely believed to negatively impact competition by affecting incumbent pricing strategies and modifying entry conditions.[1] Low switching rates in deposit markets have, thus, been a long-standing concern of regulatory authorities. In 2009, the Dutch central bank noted that:[2]

> ...by offering higher deposit interest rates, new entrants might be able to attract quantities of savings that are relevant to them, but this has as yet not resulted in large shifts in the savings market as a whole. [...] the majority of Dutch savers seem thereby relatively interest rate-indifferent.

Measuring inertia and its determinants is important for the design of effective policies to improve consumer choices. If, for example, choice complexity is the problem, independent comparison websites might help consumers. If, however, high effort costs prevent switching, then services such as account number portability might be more effective.[3] Despite the importance of deposit markets, prior structural work on consumer demand has relied on aggregate data without considering choice frictions.[4] Several reduced-form studies associate low switching rates observed in micro data with observable proxies for switching costs but lack important information on prices and volumes.[5]

In this work, I use detailed panel data on deposit account choices of Dutch consumers to measure inertia within and across banks and link it to observable consumer characteristics and related choices. I use these estimates to evaluate the impact of counterfactual policies reducing inertia. My results indicate that only removing inertia within banks results in around one third of the welfare gains from an overall elimination of inertia for the average consumer. To my knowledge, this is the first paper that quantifies heterogeneous inertia in this market based on consumer-level transitions over time.

My primary data source is the DNB household survey from 2005 to 2008. The data contain information on all savings accounts held by consumers including bank and account names as well as account volume. In addition, I observe information on consumer demographics, online banking usage, risk aversion, and bank information on additional financial products such as checking accounts and mortgages. I complement the survey with data from a comparison website containing information on interest rates

[1] See Farrell and Klemperer (2007) for a survey of the theoretical literature on switching costs.
[2] See De Nederlandse Bank (2009)
[3] This has, for example, been suggested for checking accounts in the Payment Services Directive of the European commission. See, e.g., http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32014L0092
[4] Examples include Dick (2007, 2008) and Molnar, Violi and Zhou (2013).
[5] See, e.g., Kiser (2002), Brown, Guin and Morkoetter (2013) or Brunetti, Ciciretti and Djordjevic (2015).

for all Dutch banks which for some accounts vary with invested volume. Moreover, the data contain information on additional account restrictions.

Several key features of the Dutch deposit market make it well suited for the research question at hand. First, there are potential gains from switching across banks due to a set of aggressively pricing smaller banks. Second, there are also gains from switching within banks as banks offer multiple differentiated accounts. Third, the relative attractiveness of the available accounts shifted over time due to differential pass-through of ECB rate increases and the regular introduction of new accounts. Despite this, account switching within and across banks remains at 6% to 8% per year. While this could suggest the presence of inertia, the observed patterns are also consistent with persistent consumer preference heterogeneity.

To precisely separate these two competing explanations, I develop a structural choice model allowing for inertia within and across banks, differential price sensitivities over several volume brackets, and heterogeneous account preferences.[6] While several economic explanations might generate inertia, I model it as an implied monetary premium on the default account and default bank relative to alternative options.[7] The richness of the data allows me to construct the individual choice set of consumers depending on their available volume. As I cannot observe the choice process from the start, I model inertia conditional on the initial conditions extending the approach by Wooldridge (2005) to the mixed logit model used in this paper.

The choice model estimates reveal substantial costs of inertia and large heterogeneity over different volume brackets. The monetary costs of inertia within banks are around €576 or 6.6% of invested volume annually for the average consumer. Investors with volumes between €2,500 and €10,000 forgo €333 or 6.1% per year, while investors with volumes between €25,000 and €45,000 forgo €905 or 2.9% within banks. Inertia costs across banks are around one third higher for all volumes categories. I provide several robustness checks to show that my results are stable across different specifications.

I then continue to investigate potential determinants of the estimated inertia.[8] My results indicate that switching costs as measured by multi-banking and the presence of additional financial products at the main bank, as well as risk aversion explain most of the inertia premium for switching across banks, while search costs as measured by online banking usage affect both inertia components. The remaining unexplained inertia, in

[6] These volume types are €0 - €2,500, €2,500 - €10,000, €10,000 - €25,000, €25,000 - €45,000, and €45,000 - max.

[7] This compares to the modelling approach taking in the literature on the structural estimation of switching costs. Alternative explanations might imply different choice models, while in this work I take the approach to analyze the contribution of proxies for several micro foundations of inertia to the default premium.

[8] The theoretical literature offers both rational frictions and behavioral explanations as potential explanations for inertia. The former include, for example, search, switching, or learning costs, while examples for the latter are inattention, loss aversion, or procrastination. Thaler and Sunstein (2008) summarize the behavioral research on choice inadequacies.

particular within banks, suggests that unmeasured behavioral explanations might also be important drivers of inertia.

On the supply side, I provide reduced-form evidence that banks price discriminate based on inertia once accounts reach a certain maturation point. Older accounts pay progressively lower rates than newer accounts with increasing account age across all volume categories.[9] In addition, larger banks offer lower interest rates on average conditional on account restrictions and account age consistent with the idea that banks with a larger customer base should have stronger incentives to exploit inertia.

In two counterfactual exercises, I study how potential policy interventions impact market outcomes in a partial equilibrium framework holding prices fixed. In the first counterfactual, I find that reducing inertia shifts market shares from larger to more competitive smaller banks resulting in large potential gains in consumer welfare. In a second counterfactual, I study how the composition of inertia impacts consumer choices. I find that allowing for costless optimization within banks, holding inertia across banks fixed, leads to gains in consumer welfare amounting to almost a third of the gains from an overall elimination of inertia.

This paper relates to two distinct strands of literature. First, it adds to a growing literature quantifying consumer inertia and related phenomena using micro panel data. Recent examples include Handel (2013), Polyakova (2015), and Ho, Hogan and Morton (2015) for health insurance plans, Barone, Felici and Pagnini (2011) for corporate loan decisions, Goettler and Clay (2011) for grocery delivery plans, Sudhir and Yang (2014) for rental cars, or Grubb, Osborne et al. (2015) for cellular-service plans. Shum (2004) and Dubé, Hitsch and Rossi (2009, 2010) are examples of a related literature in marketing studying the effect of brand loyalty or state dependence. Some recent papers, in addition, disentangle different sources of inertia in a structural framework. Honka (2014) and Kiss (2014) separate switching from search costs or inattention, respectively, in auto insurance markets. Luco (2014) analyzes the relative importance of decision and enrollment costs in the market for pension funds. In deposit markets, Honka, Hortaçsu and Vitorino (2015) disentangle awareness, consideration, and choice stage using cross-sectional data on all three stages for retail bank accounts. As I only observe the choice stage, my estimated inertia implicitly captures costs incurred on all stages. The richness of the data allows me, however, to link the estimated inertia to multiple dimensions of observable heterogeneity. In addition, the availability of panel data allows me to disentangle inertia and persistent preference heterogeneity.

Second, this study relates to reduced-form work providing indirect evidence of switching costs in deposit markets without quantifying its monetary value. Sharpe (1997),

[9]For example, five years old accounts pay on average 0.64% and seven years old accounts 1.1% less than just introduced accounts for a volume of €10,000.

Hannan and Adams (2011), and Carbo-Valverde, Hannan and Rodriguez-Fernandez (2011) find that areas with higher in-migration, and, thus, a supposedly higher share of people choosing without default option, offer higher deposit rates on average. Alternatively, Anderson, Ashton and Hudson (2014) find that older accounts pay lower interest rates than newer accounts on average suggesting banks price discriminate between old and new customers. Several authors analyze instead determinants of switching costs in deposit markets using survey data. Kiser (2002) provides descriptive evidence that household relocation, service, and price factors are the most frequent reasons to switch. Brown, Guin and Morkoetter (2013) find that proxies for switching costs including the total number of accounts, the existence of credit relationships with a bank, or the distance to a non-distressed bank impact deposit withdrawals from distressed Swiss banks. Brunetti, Ciciretti and Djordjevic (2015) find that also education and financial literacy matter for the propensity to switch of Italian households.[10] This work differs from the latter literature as it explicitly quantifies inertia and uses the structural estimates to study the effect of counterfactual policies improving individual choices.[11] In addition to proxies for switching costs as shown in the previous literature, I find that online banking usage and risk aversion can partly explain the estimated inertia.

The rest of the paper is organized as follows. Section II presents the data and summary statistics. Section III provides preliminary evidence of inertia. Section IV introduces the empirical framework, while Section V presents the structural choice model estimates, robustness checks, evidence on sources of inertia. Section VI analyzes implications for bank pricing. Section VII performs counterfactual simulations. Section VIII concludes.

II. Data and Environment

A. Choice Data

My main data source is the DNB Household Survey (DHS) from 2005 to 2008. The DHS is an annually conducted survey of around 2,000 Dutch households containing extensive information on demographic characteristics, asset and debt holdings, housing, work, health and income, as well as economic and psychological concepts. The survey is representative of the Dutch population and is conducted via the Internet.[12] One key feature of the survey is that it asks detailed information on all savings accounts held by

[10]Similarly, Deuflhard, Georgarakos and Inderst (2014) show that financial literacy matters for the interest rate earned on savings accounts.

[11]The only exception is Shy (2002) who estimates switching costs in the Finnish deposit market using highly aggregate data on prices and market shares. See also Kim, Kliger and Vale (2003) using a similar approach in the Norwegian loan market.

[12]The survey provides equipment to households without Internet access in order to compensate for this form of bias. See Teppa and Vis (2012) for a detailed description of the DHS.

each household member, including bank and account name, as well as invested volume on each account.[13] The data also contains information on bank names of other financial products such as checking accounts and mortgages as well as online banking usage, and a measure of risk aversion. All asset amounts and bank information are reported as of December 31st of the year preceding the interviews.

I complement this data set with additional information on savings account characteristics from two sources. I use data on annual interest rates for savings accounts of all Dutch banks from December 2004 to December 2007 provided by a major Dutch financial institution. The data set covers in total 40 banks offering 140 savings accounts. For each savings account, it contains the weekly interest rate for eleven different amount brackets ranging from €0 - €1,000 to €45,000 or more.[14] In addition, I use data on the existence of various savings account restrictions provided by the Dutch Internet comparison website 'SpaarInformatie'. These restrictions can be roughly partitioned across two dimensions. First, accounts are either internet managed or not. Internet accounts are fully managed online by the depositor and offer only limited banking services. Second, accounts are either restricted or not. The information from the comparison website allows to distinguish in total six main restrictions such as balance requirements or withdrawal limitations.[15]

I match these data sources on account-volume-year-level as follows. As the DHS reports the holdings of financial assets as of December 31 of the year prior to the survey, I match interest rates for the last week of December of each year to the DHS data based on bank name, account name and invested volume on each individual account.[16] For each savings account held by a member of a household, the matched data ultimately contain the invested volume, account name, bank name, and the applicable interest rate.[17]

[13]In the regular panel, participants are provided with a list of seven possible answers when asked at which bank they hold each of their savings accounts: ABN Amro, Postbank, Rabobank, ING, Fortis, SNS Bank, and 'Other'. In case participants indicate ownership in the category 'Other', they are further asked to provide the name of the bank. This latter information along with account names held in 'Other' banks is not available in the public version of the dataset, but has been recovered from additional data that were made available to me by CentERdata. Appendix B provides more details.

[14]The exact amount brackets are €0 - €1,000, €1,000 - €2,500, €2,500 - €3,500, €3,500 - €4,500, €4,500 - €7,000, €7,000 - €8,000, €8,000 - €9,000, €9,000 - €10,000, €10,000 - €25,000, €25,000 - €45,000, and more than €45,000. As some of these volume thresholds might fall within these ranges, I manually recover the exact amount thresholds whenever possible.

[15](1) Accounts with minimum amount requirements offer either very low base rates or zero interest rate up to a certain volume threshold and higher rates above that threshold. (2) Accounts with lowest balance bonus give a bonus rate on the lowest account balance within a year or a quarter and yield a base rate on the remaining balance. (3) Accounts with balance growth bonus yield a bonus rate if the balance grows by a specified percentage amount per month or year. (4) Accounts with fixed deposit require a specified absolute deposit each month. (5) Accounts with withdrawal limitations / fees limit the maximum amount that can be withdrawn per month or comprise percentage fees for withdrawals (mostly 1% of the withdrawn amount). (6) Salary accounts are linked to a checking account at the same bank, which needs to be the income account.

[16]I recover missing volumes of individual savings accounts following the procedure used by CentERdata for total savings volumes as described in Appendix B.

[17]The availability of the exact account rate compares favorably to Honka, Hortaçsu and Vitorino (2015) who

The resulting panel data set allows observing individual-level transitions between banks and savings products for the full market over time. This presents a significant advantage over administrative data of a single bank in which individual choices are unobservable after a bank change. These properties of the dataset combined with considerable variation in the choice set and interest rates during the sample period make it well suited to analyze switching behavior of consumers.

B. *Sample Composition*

I construct the estimation sample of account users as follows. First, I focus on demand deposits held by adult household members as the data from the comparison website contains only interest rates for variable rate savings accounts, but also to avoid price variation across products simply due to maturity differences.[18] I call this the full sample. It comprises in total 8,775 savings accounts held by 2,130 individuals in the period from 2005 to 2008.

Second, I focus on the main savings account defined as the account with the largest volume share of all accounts held by an individual comparable to Barone, Felici and Pagnini (2011) and Crawford, Pavanini and Schivardi (2015) using administrative loan data on bank-firm level.[19] This main account covers on average 88.1% of the total volume held by an individual and still 72.6% for individuals with more than one account. Moreover, this approach defines a clear panel variable enabling me to consistently follow each main account over time.[20]

To construct the final estimation sample, I keep only those cases with matched interest rate, which concerns around 80% of all accounts held.[21] To be able to define a switching indicator, only individuals observed at least two consecutive periods enter the sample. Last, I follow a two-step aggregation procedure to reduce the dimension of the choice set. First, for a given bank, I aggregate accounts comprising less than 5% of the customers of that bank into one account. Second, I aggregate all small banks outside the 'top 10'-banks in terms of number of customers into an outside option comprising 2.3% of

assume that all consumers within a given bank choose the most popular account as they do not have information on account choices.

[18]This would require to incorporate maturity choice into the empirical model later, which is beyond the scope of this paper. However, only around 1.3% of accounts in the pooled sample are fixed-term deposit accounts making it unlikely that this would affect the results.

[19]This avoids modelling multiple bank relationships per decision maker. In the case of a tie (e.g., 50% on each of two accounts), I choose the first named account, as this is most likely the most important one for the respondent.

[20]Alternatively, I could treat each individual account as a separate unit of observation as mostly popular in the finance literature, e.g., Ioannidou and Ongena (2010) or Stango and Zinman (2011). This ignores the possibility of rebalancing across accounts entirely and in the current setting makes it problematic to clearly follow accounts over time as the order in which accounts are named by the respondents sometimes change, for example, if accounts are closed.

[21]Unmatched accounts include mainly accounts with missing product name but also reported savings products which were not offered by a specific bank in a particular time period.

the market. The final estimation sample contains in total 3,208 accounts held by 1,248 individuals from 2005 to 2008.

Table A1 in Appendix A compares the three samples across major demographics, market share of banks, and account volume. The descriptives show that all samples are very similar across major socio-demographics. Going from the full to the sample of main accounts, the slight change in market shares suggests that main accounts are not entirely equally distributed across banks.[22] Market shares in the final estimation sample show that there are slightly more matched accounts at ING Bank and slightly less at medium and smaller banks. Due to the focus on main accounts, account volume mechanically increases to €15,860 from €10,700 in the original sample. Nevertheless, the final estimation sample covers the market quite well in terms of representativeness.

C. Summary statistics

Table 1 shows summary statistics for all respondents in the final sample as well as for three separate subgroups of respondents: Non-switchers, switchers within bank, and switchers across bank. I define non-switchers as all respondents who did not switch their main account, while the two groups of switchers either selected a new main account at the same or at a different bank compared to the previous period.[23] The average age of all account holders is 52, 57% are male, 73% live in a couple household, and the average net income is €22,738. Moreover, 44% use online banking very often, while the average self-assessed risk aversion on a seven-point scale is 5.25. The table also shows statistics on linked choices potentially affecting the switching decision which are lagged by one year as they should favor the existing default. 59% of respondents hold only one account, 78% hold all accounts at the same bank, 74% have a checking account, and 19% a mortgage at their previous bank. With respect to account characteristics, the three largest banks share around 80% of the market followed by two medium-sized banks Fortis and SNS Bank and a set of small banks. 43% of all accounts are internet accounts, while the three most common restrictions are minimum amount (26%), lowest balance bonus (21%), and withdrawal limitations (8%). Some interesting patterns emerge when comparing across groups. Both groups of switchers are significantly more likely to have more than one account in the period before the switch and earn significantly higher interest rates after a switch compared to non-switchers. Consistent with the latter, these groups are also more likely to hold internet accounts. In terms of demographics, the groups are quite homogenous although switchers have slightly higher net income. Comparing within the group of switchers, switchers across banks are significantly more

[22]For example, ING Bank looses 4% market share, while Rabobank gains 5%.

[23]I do not count switches of products between banks that merged in the previous period as well as passive switches due to name changes of accounts or automatic defaults into newly introduced accounts.

likely to engage in multi-banking and hold checking accounts or mortgages at their main bank prior to a switch. They are also more likely to be customers of smaller banks, use online banking very often, and earn higher interest rates than switchers within banks.

An important feature for my analysis is the existence of substantial cross-sectional and time-series variation in pricing of accounts during the observed time period. Figure 1 shows the evolution of annual interest rates next to the ECB rate for each account category and bank. Due to the large number of accounts, I focus on accounts with the highest enrollment over the pooled sample in each group.[24] For all banks, restricted plain and restricted internet accounts yield the highest rates, while unrestricted plain accounts yield the lowest. Depending on the bank, unrestricted internet accounts and restricted accounts change ranking in the middle. Compared to the larger incumbent banks, small banks offer the highest rates in all account categories in most years. Notably, interest rate spreads within a given bank are quite high but vary across banks. For example, account rates at ING Bank range from 1% to 2.9% in 2006, while rates at Fortis Bank lie between 2.3% and 2.75%. In addition, there are substantial relative interest rate changes over time both within bank and across account types as well as within account types across banks. Most strikingly, the interest rate spread within ING Bank more than doubles in the observed time period due to a significant decline of interest rates for unrestricted and restricted plain accounts, while ECB rates rise from 2% to 4%. In comparison, smaller banks adjust to the ECB rate faster, in particular for restricted internet accounts.

In addition to the most popular accounts as shown in the graph, banks regularly introduce new accounts and exit old ones. For example, ABN Amro introduced three new and discontinued two accounts, while Rabobank offers a stable menu of three accounts over the sample period. These relative price changes both within and across banks are an important element for the empirical framework to identify price sensitivity and inertia separately from time-invariant unobserved account preferences.

III. Preliminary analysis of inertia

A. *Descriptive evidence*

I begin the analysis by providing some descriptive evidence consistent with inertia. Table 2 shows annual switching rates overall and separately for within and across bank switches. Bank switching is rather low between 5.7% and 7.7% per year. In addition, between 5.4% and 7.5% of individuals per year switched their main account within their existing bank. Low switching rates alone, however, do not necessarily suggest inertia

[24]This favors accounts observed over a longer time period but allows for a clearer visual inspection. All years refer to the end of the previous year, i.e. 2005 refers to the end of December 2004.

but could also indicate low benefits from switching.

To analyze this question, figure 2 shows the potential benefits from switching over the pooled sample taking into account the differential pricing and availability of accounts for different volumes. From left to right, the upper panel shows the distribution of interest rate benefits from switching to the highest rate account for three cases: within the current bank, across all banks within the same account type, and across all banks and all account types. The first graph shows that, while more than 30% of consumers select close to the highest rate account within their current bank, the remaining consumers could substantially benefit from switching resulting in an overall mean benefit of 0.89%. Intuitively, when considering switching across all accounts in the same category or all accounts in the market, the benefit distribution shifts more to the right increasing the mean benefit to 1.16% and 1.75%, respectively. The lower panel adresses the question whether the distribution of interest rate benefits differs over the volume distribution as benefits from switching are multiplicative in deposit markets. It reports the results of a locally weighted regression of interest rate benefits on invested volume for all three cases considered above. The graph shows a negative relationship between interest rate benefits and volume which nonlinearly decreases for higher volumes. These mean differences are most evident in the first part of the distribution up to €40,000 and flatten out for higher volumes.

B. *Reduced-form evidence*

Despite the substantial variation in the relative attractiveness of accounts over time and high potential benefits from switching, only few consumers actually switched as shown in the previous section. I now turn to study which of the available determinants impact switching. For this purpose, I estimate the following multinomial logit regression:

$$Pr(S_{it} = m|\mathbf{x}_{it}) = \Lambda(\mathbf{x}_{it}\beta_m) \text{ for } m = 0, 1, 2$$

where S_{it} is 0 if no switch has taken place, is 1 if an account was switched within the existing bank, and 2 if the consumer switched across banks in t compared to $t-1$. The matrix $\mathbf{x}_{it}$ contains consumer demographics including age, gender, a couple dummy, a categorical variable for different intensities of online banking usage, and a self-assessed measure of risk aversion.[25] It also includes the switching benefit defined as the distance of the default continuation rate from the highest possbile rate available

[25]Consumers are asked to rate on seven point scale how strongly they agree with the statement: 'I think it is more important to have safe investments and guaranteed returns, than to take a risk to have a chance to get the highest possible returns.'

to a consumer given his volume. This most accurately captures what consumers can gain before a switch. Moreover, the specification includes potential factors impacting account- or bank-level inertia costs including dummies for single-account and single-bank individuals as well as separate dummies for the existence of checking accounts or mortgages held by the consumer at his main bank. I enter this set of variables lagged by one period as they should favor the previous default. Last, the specification controls for the number of years observed in the panel and year fixed effects. $\Lambda(.)$ is the cumulative distribution function of the logistic distribution. Standard errors are clustered at the individual level.

Table 3 shows average marginal effects of the estimated parameters for all three outcomes.[26] In both specifications, individuals with higher benefits from switching are significantly more likely to switch. A 1 percent higher switching benefit increases the probability of switching by 2.7 percentage points within banks and 1.1 percentage points across banks representing a significant increase over the baseline probability of around 6.5 percent in both cases. Frequent online banking users are also significantly more likely to switch within and across banks. Single-account individuals are significantly less likely, while single-bank individuals are more likely to switch accounts within banks. The latter are, however, less likely to switch across banks with a negative marginal effect of 14.5 percentage points. The existence of a checking account at the default bank significantly decreases the switching probability across banks by 6.5 percentage points, while holding a mortgage at the default bank has no effect. Last, higher risk aversion slightly increases the switching within bank and decreases switching across banks. In summary, the reduced-form results show that several economic explanations are likely to contribute to inertia.

IV. Empirical Framework

A. Choice Model

In this section, I build a structural choice model allowing for inertia within and across banks, differential price sensitivities over the volume distribution and heterogeneous consumer preferences over account features. Relative to the preceding analysis, this framework allows to quantify inertia separately from persistent preference heterogeneity and study the impact of counterfactual policies. As this requires to impose more structure on the choice decision process, these additional results should be seen in light of the assumptions made in the modeling framework.

In each year $t = 1, .., T$, an individual $i = 1, ..., I$ of type $k = 1, .., K$ chooses a main

[26] Marginal effects are calculated as the derivative of the choice probability resulting from a marginal change for continuous variables and the difference in choice probabilities following a discrete change for discrete variables.

savings account $j = 1, ..., J$ from the set of available accounts at the ten largest banks or decides for the outside option to own a savings account at a small bank.[27] The individual choice set contains all accounts used in a given year available to type k.[28] A type is determined by one of five intervals in which the account volume of individual i falls ranging from €0 - €2,500 to €45,000 or more.[29] I consider the relevant market to be national in scope in accordance with statements or decisions by the Dutch and European competition authorities.[30] Let individual i's indirect utility from account j in year t be given by:

$$\begin{aligned} U_{ikjt} &= a_{ij} + \alpha(\mathbf{\Lambda}_{kt}) p_{kjt} + \eta^A y^A_{ij,t-1} + \eta^B y^B_{ij,t-1} + \epsilon_{ikjt} \\ &= V_{ikjt}(a_{ij}, p_{kjt}, \mathbf{y_{ij,t-1}}, \alpha(\mathbf{\Lambda}_{kt}), \eta) + \epsilon_{ikjt} \end{aligned}$$

Utility depends on a set of account-specific constants, a_{ij}, the interest rate p_{kjt}, a default indicator, $y^A_{ij,t-1}$, taking the value one if the savings product in t is the same as in $t-1$, , and a default indicator, $y^B_{ij,t-1}$, taking the value one if the bank is the same in t as in $t-1$. Thus, I model inertia as an implied monetary premium on the default similar to a tangible switching cost. As the default indicators measure net effects, the latter measures any additional costs a consumer might incur when switching to a new account at a different bank as compared to switching within the default bank. Note that the interest rate varies over types as some accounts have nonlinear pricing structures depending on invested volume. In line with the descriptive evidence in the previous section, I interact the price variable with a set of volume type dummies, $\mathbf{\Lambda}_{kt}$, to allow for differential price sensitivities over the volume distribution.[31] The error term ϵ_{ikjt} captures individual-account-specific attributes in each year. For each type and year, I normalize the outside option of choosing a savings account at a small bank to zero, $U_{ik0t} = \epsilon_{ik0t}$.

The account-specific constants, a_{ij}, capture unobserved preference heterogeneity varying over alternatives and decision makers but not over time. For each account, I model heterogeneity over individuals by allowing the vector $a_i = [a_{i1}, ..., a_{iJ}]$ to be multivariate normally distributed as follows:

[27] I do not model the participation decision as the overwhelming majority of Dutch consumers owns a savings account.

[28] In contrast to other work using micro data on loan decisions, e.g. Crawford, Pavanini and Schivardi (2015), I do not have to predict the prices of non-chosen alternatives in a regression framework as interest rates depend only on volume and I can observe the full pricing schedule for each account.

[29] I collapse the eleven available volume brackets into five intervals in order to be able to precisely estimate the respective price coefficients. These are: €0 - €2,500, €2,500 - €10,000, €10,000 - €25,000, €25,000 - €45,000, and, €45,000 or more

[30] Cf. Bos (2003) or European Commission (2007).

[31] Including observable preference heterogeneity such as differences in internet usage at different age levels and a time trend for increased internet account leaves the quantitative findings unchanged.

$$\begin{pmatrix} a_{i1} \\ \cdot \\ a_{iJ} \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_1 \\ \cdot \\ \mu_J \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & \cdot & 0 \\ \cdot & \cdot & \cdot \\ 0 & \cdot & \sigma_J^2 \end{pmatrix}\right)$$

where μ_j and σ_j^2 are the estimated mean and variance of the distribution of each account-specific constant which are assumed to be independent given the diagonal nature of the variance-covariance matrix. Finally, I assume that ϵ_{ikjt} is i.i.d. type 1 extreme value distributed as common in the empirical literature on demand estimation in differentiated product markets.

Some notes on the underlying assumptions of the above specification might be warranted. First, as in most of the previous literature, the model assumes that consumers are myopic and do not make dynamic decisions by, for example, forming expectations about future prices.[32] This might be justified as most retail investors should have difficulties to predict future interest rate changes in advance. Second, the model assumes that consumers have full knowledge of prices and characteristics of all accounts. Although this kind of information is readily available from regular comparison websites, consumers might not consult such websites for different reasons and instead engage in costly search.[33] Finally, I assume that volume is exogenous to the consumer's product choice. This makes sense if the two-stage choice process is sequentially ordered such that the consumer first decides about the amount to invest and then given this volume selects a product from the available alternatives.

B. Identification

Identification of the parameters relies on several unique features of the data. To identify the inertia cost parameters three important issues have to be considered: variation in the choice set over time, separation of spurious vs. structural state dependence, and the initial conditions problem.

As shown in Section II, there is substantial variation in the relative attractiveness of accounts over time both within and across banks. In addition, switching might also be induced by sudden and unexpected monetary inflows increasing the benefits from switching or making more attractive accounts with volume thresholds available to the consumer. This variation is important as otherwise consumers might just remain with a once made optimal product choice with the result that the researcher would not observe

[32] An exception is Ho (2015) who estimates switching cost in the Chinese deposit sector using a dynamic model of consumer choice based on aggregate data.

[33] I provide evidence on different sources of inertia including online banking usage as a proxy for search costs in Section VI.

any switching in the data in the most extreme case.[34]

A further challenge is to distinguish spurious from structural state dependence, a pertinent issue arising in dynamic panel models when a lagged dependent variable is included. Spurious state dependence arises if unobserved individual heterogeneity is correlated over time, while structural state dependence measures the direct impact of last period's choice on today's preferences of a consumer. In general, both of these effects will be captured by the lagged dependent variable when not properly accounted for. I follow the standard approach in the literature on state dependence and assume that the normally distributed random coefficients correctly capture the persistent unobserved heterogeneity.

The last issue regards the initial conditions problem. In the data, I cannot observe individual choices from the start of the choice process, i.e., the first time they select a savings product. This is problematic if the initial choice is correlated with unobserved heterogeneity, i.e., individual characteristics are not fully captured by the model.[35] In this case, the estimated inertia parameters will be inconsistent and upward biased. To account for this, I extend the approach by Wooldridge (2005) and model the distribution of the unobserved effect conditional on the initial choice observed for each individual and any exogenous explanatory variables. With a properly specified distribution this results in a random coefficient model where the initial condition is included as an additional covariate.[36] Precisely, the following decomposition of the individual account fixed effects applies:

$$a_{ij} = a_j + \gamma^A y^A_{ij,0} + \gamma^B y^B_{ij,0} + \nu_{ij}$$

where $\nu_{ij}|y^A_{ij,0}, y^B_{ij,0} \sim N(0, \sigma^2_{\nu_j})$ and $y^A_{ij,0}$ and $y^B_{ij,0}$ denote the first observed product and bank choice within the considered time period and a_j is an account-specific constant. Through the inclusion of the initial conditions the inertia cost parameters are only identified from individuals switching at least once during the observed time period as for those individuals remaining with their default option over the whole panel, the default indicators and the initial conditions coincide.[37] Note that the approach

[34]Dubé, Hitsch and Rossi (2010) were first to note the importance of time-varying product characteristics for the identification of state dependence.

[35]One immediate example that comes to mind would be anecdotal evidence that most consumers open their first account at the bank of their parents which is likely to depend on individual preferences of the household.

[36]While originally shown for binary probit and logit as well as ordered probit models, I extend the approach to mixed logit models. See Appendix C on initial conditions for further details. I take a slightly reduced approach compared to Wooldridge (2005), who in addition also includes the individual time averages of all exogenous covariates in the model.

[37]One could argue that such individuals should contribute to the parameter estimation as well as they reveal no preference for switching in the observed environment. However, there are several problems with this approach. First, there is no immediate other solution in the current framework to control for unobserved heterogeneity

by Wooldridge (2005) actually requires a balanced panel, while the data at stake is of unbalanced nature. This should, however, not introduce any bias if panel attrition is random and is common in the applied literature.[38] Nevertheless, in Section VI, I show that the results are robust using a balanced panel of consumers.

In addition to the identification of structural state dependence, endogeneity of interest rates is a potential concern. First, aggregate endogeneity might arise from the simultaneous determination of prices and consumer demand in equilibrium. The use of micro data should, however, alleviate these concerns as single individual choice decisions are unlikely to affect bank pricing on aggregate. Second, endogeneity in prices may be present due to omitted product characteristics correlated with interest rates. The account fixed effects included in the model mitigate this problem as long as the perceived differences in accounts are constant over time. As the observed account restrictions do rarely change over the observed time period, this seems a reasonable assumption in the current context. Nevertheless, in Section VI, I show that the results are robust using the control function approach by Petrin and Train (2010) as an additional source of identification.

C. Estimation

This section lays out the specific estimation procedure for the model described above. I estimate a random coefficient model using simulated maximum likelihood techniques as described in Train (2009). As I use panel data, I model the probability of observing a sequence of choices for each depositor. The choice probability of a depositor i of type k choosing a savings account j for the sequence $t = 1, ..., T$ is given by:

$$P_{ikj} = \int \prod_{t=1}^{T} P_{ikjt}(\mathbf{a}) d\Phi(\mathbf{a}|\theta)$$

where $\Phi(\mathbf{a}|\theta)$ denotes the multivariate normal distribution of the random coefficients and θ are the parameters of this distribution I want to estimate. The choice probability for a given year conditional on the parameter vector $\mathbf{a}$ as used above is given by:

correlated with the initial condition. Second, the estimated bounds of inertia costs for this class of individuals are potentially far off from the true inertia costs as much higher observed interest rate differences might be needed to make this group reconsider their default options.

[38] Cf., e.g., Raymond et al. (2010) analysing persistence in innovation using an unbalanced sample of Dutch manufacturers.

$$P_{ikjt} = \frac{e^{V_{ikjt}(a_{ij}, p_{kjt}, \mathbf{y_{ij,t-1}}, \alpha(\mathbf{\Lambda}_{kt}), \eta)}}{1 + \sum\limits_{j=1}^{J} e^{V_{ikjt}(a_{ij}, p_{kjt}, \mathbf{y_{ij,t-1}}, \alpha(\mathbf{\Lambda}_{kt}), \eta)}}$$

The above likelihood has no closed-form analytical solution and thus has to be approximated by simulation. Let us index a draw by $r = 1, .., R$ where R denotes the total number of draws. Then the simulation procedure works as follows. For each consumer, I first take a draw for the vector $\mathbf{a}^r$ from the distribution $\Phi(\mathbf{a}|\theta)$. For each specific draw, I calculate the logit probability for each period, and then take the product of these probabilities. This procedure is repeated for the total number of draws. The resulting choice probabilities are then averaged resulting in the simulated probability of observing a sequence of choices:

$$\hat{P}_{ikj} = \frac{1}{R} \sum_{r=1}^{R} P_{ikj}(\mathbf{a}^r)$$

which is an unbiased estimator of the true choice probability P_{ikj} summing to one over all alternatives. One can now construct the simulated log-likelihood (SLL) by inserting the simulated probabilities into the log-likelihood function:

$$SLL(\theta) = \sum_{i=1}^{I} \sum_{j=1}^{J} y_{ikj} ln \hat{P}_{ikj}$$

where y_{ikj} is an indicator function which is one for the actual sequence of choices made by individual i. Note that one only has to sum over the index i as k is a subset of the former. The maximum likelihood estimator now finds the parameter vector θ that maximizes $SSL(\theta)$. More precisely, starting from an initial parameter guess θ_0, in each iteration step the algorithm moves to a new parameter vector where $SSL(\theta)$ is higher than in the previous step until a specified convergence criterion is reached. In the results presented in the paper, I choose $R = 25$ simulation draws for each consumer. The algorithm stops when the change in $SSL(\theta)$ is lower than 0.0001 and all parameters individually change by less than 0.0001 from one iteration step to the next.

V. Results

A. Parameter Estimates

Figure 3 compares predicted and actual market shares on account level for the pooled sample to evaluate the fit of the primary choice model specification described in the previous section.[39] It shows that the model is able to fit the observed patterns in the data fairly well for all accounts as the predictions for both accounts with small and large market share are very much in line with the actual market shares. Unreported results on a year-by-year basis are highly comparable suggesting the distributional assumptions made in the previous section are not particularly restrictive.

Table 4 shows the estimates of the primary choice model. Model 1 reports the results of a simple conditional logit model including lagged indicators for the previous bank and account choice. Model 2 adds initial conditions for the first bank and account choice observed for each individual.[40] The last model shows estimates from a full mixed logit model with random account fixed effects. All results show utility parameters not marginal effects. Adding the initial conditions reduces, as expected, the parameters of the lagged indicators for previous bank and account choice as it accounts for that part of spurious state dependence correlated with initial choices. The parameter estimates further slightly decrease when allowing for random account fixed effects. The interest rate coefficients enter with the expected positive sign and significantly increase over the volume distribution. Moreover, both inertia parameters are significant at 1%-level. The inertia cost parameter for switching across banks is around one third higher compared to switching within banks.

The inclusion of an outside option allows me to assess the implied monetary costs of inertia in relation to the obtained interest rate by dividing the utility weights of inertia by the estimated interest rate coefficients in the respective volume brackets. Table 5 shows the implied average monetary costs of inertia within and across bank both in percent of volume as well as in absolute Euro terms for the population overall and separately by volume type. The implied economic magnitudes for switching across banks range from 3.4% for the highest volume type to 14.2% for the lowest. For example, for individuals in the second volume bracket including volumes from €2,500 to €10,000, inertia costs amount to 8.0% of the invested deposit volume or €436 on average, while for the fourth volume bracket between €25,000 and €45,000, they amount to 3.8% or €1,187 per year. Thus, while costs of inertia decrease in relative terms over the volume distribution consistent with the idea that benefits increase with higher invested volume,

[39] Predicted market shares are calculated in an iterative process from one year to the next as the probability of choosing a specific account as predicted by the model in a given year forms the now itself random default account probability in the next year.

[40] Data from 2004 provide the initial conditions for 2005.

the absolute magnitude in Euro terms increases with higher volumes. The latter is, for example, consistent with higher opportunity costs for wealthier individuals. While the estimates seem quite substantial, they are in line with the few earlier studies quantifying inertia based on aggregate data. Shy (2002) estimates switching costs in the range from 0% to 11% for the Finnish deposit market using aggregate data on prices and market shares. For the Norwegian loan market, Kim, Kliger and Vale (2003) estimate switching costs of 4.1% using a structural model of Bertrand pricing. Nevertheless, there are a number of potential behavioral explanations which might generate inertia and it seems unlikely that switching costs are the only driver given the estimated magnitude of inertia. I will return to this question in the last part of this section on potential sources of inertia after the robustness section.

B. *Robustness*

Table 6 reports several robustness checks to examine the sensitivity of the results to the modeling assumptions. Model 1 shows results using a balanced panel of consumers as the method by Wooldridge (2005) used in this paper, ideally relies on balanced panel data. Unfortunately, this significantly reduces the sample to 432 individuals each observed over four years. While the estimation loses some efficiency due to the smaller sample size, in particular in the estimation of price coefficients in the two lower volume categories, the results are highly comparable to the main model specification. For example, the price coefficient for volumes between €25,000 and €45,000 is 1.132 compared to 1.184 previously and the coefficient for the default account changes from an earlier 3.413 to 3.345 now.

Model 2 excludes accounts with volume above €40,000 not covered by deposit insurance during the observed time period.[41] For those consumers perceived differences in banks' riskiness might wrongly be attributed to inertia. Both the price coefficients as well as the inertia parameters are highly comparable suggesting that this does not significantly impact the estimates for the full sample. Note that due to the exclusion restriction the interaction of the interest rate with the highest volume bracket is not defined.

Model 3 addresses the issue that there could be time-varying unobserved account characteristics not captured by the account fixed effects in the main specification. As regular two-stage instrumental variable estimators do not exist for non-linear models such as the mixed logit used in this paper, I follow the control function approach as in Petrin and Train (2010). Similar to a first stage regression, I thus model the interest rate as a function of account fixed effects and a set of cost shifters exogenous to the

[41]As most volumes lie below that threshold, this concerns only 8.8% of the sample.

demand equation:

$$p_{ikjt} = a_j + \mathbf{W}_{jt}\gamma + \kappa_{ikjt}$$

where $\mathbf{W}_{jt}$ denotes the EONIA rate interacted with account fixed effects. The intuition for the use of these instruments is that the EONIA rate constitutes one of the main alternative funding sources for banks compared to deposits and can thus can be interpreted as an opportunity cost for banks. Depending on the liquidity and fee structure of an account and, as a result, differing customer flexibility, banks will differentially pass through EONIA rate changes. At the same time, the demand side is normally not affected in the short-term. The estimated residuals from the above pricing regression are then included as an additional covariate in the main specification controlling for unobserved account characteristics varying over time.[42] The results suggest that the impact of these unobserved characteristics is not very strong. The included control function is not significant in the main specification although the price coefficient in the lowest price category changes from a previous 0.315 to now 0.498. Nevertheless, the changes are relatively small suggesting that most account characteristics are constant over time and thus already controlled for by the inclusion of account fixed effects. Overall, the results found in the previous section seem to be quite stable across different specifications.

C. Sources of Inertia

This section aims to shed light on the underlying determinants of the previously estimated inertia. While often termed as a switching cost, a number of competing explanations might generate inertia. Potential sources of inertia can be roughly categorized into explicitly rational explanations such as switching, search, or learning costs as well as implicit psychological costs such as inattention, procrastination, or loss aversion. The extensive information on consumer demographics and other financial product holdings in the DNB Household Survey allows me to analyze the contribution of some of these factors. Formally, I allow the inertia parameters for previous bank and account choice to depend on consumer characteristics and linked choices as follows:[43]

$$\eta^{\psi}(X_{it}^{\psi}) = \eta_0 + \eta_1^{\psi}\mathbf{X}_{it}^{\psi} \text{ for } \psi \in \{A, B\}$$

[42]This is similar in vein to instrumental variable strategies used in previous papers for consumer goods market such as coffee, e.g., Draganska, Klapper and Villas-Boas (2010) or Bonnet et al. (2013)

[43]I implement this empirically by including a series of interactions between the inertia parameters and consumer characteristics.

$\mathbf{X}_{it}^{A}$ contains potential determinants of account-level inertia. First, it includes a set of demographic variables including a male dummy, age, a couples dummy, and net income in thousand euros. These sociodemographics might proxy for several explanations for inertia such as learning or opportunity costs of investors.[44] To proxy for a tangible switching cost, I include a dummy indicating whether the depositor held only one account in the previous year.[45] I also include two indicator variables for individuals using online banking often or very often. Such depositors are likely to have lower search costs by comparing accounts online, e.g., through price comparison websites.

$\mathbf{X}_{it}^{B}$ contains potential determinants of bank-level inertia. Comparable to above, I include a dummy which is one if the depositor held all savings accounts at a single bank in the previous year and zero otherwise to proxy for switching costs on bank level. Moreover, I include two lagged dummies indicating the existence of a salary account or mortgage at the default bank as a measure of the scope of the bank relationship.[46] The bundling of several financial products at the same bank might generate compatibility benefits for investors, e.g., easier money transfer between accounts or simultaneous accessibility of all accounts in the same online interface.[47] Last, I include a self-assessed measure of risk aversion as in Section IV. Part of the estimated inertia might arise from a subjective perception of riskiness of other banks than the default.[48]

Model (2) in Table 7 shows the results with heterogeneous inertia parameters, while Model (1) presents the results of the primary choice model for comparison. I focus on the more general Model (2) as described above. The results show that the common inertia cost component increases by around one fourth for individuals with only one account but decreases by around one sixth for frequent online banking users compared to the base category. With respect to demographics, being male significantly increases inertia, while net income is significant but of small economic magnitude.[49] Both age and the couple dummy have no effect going against the hypothesis of learning costs affecting inertia.

[44] For example, Dubé, Hitsch and Rossi (2010) cite age as a good proxy for learning costs which would imply a negative association of inertia and age conditional on all other factors correlated with age impacting inertia. However, the opposite relationship could be expected if the value of the relationship between the depositor and the house bank increases over time.

[45] This is an often used proxy for switching costs in previous reduced-form work using micro data, e.g., Brown, Guin and Morkoetter (2013) and Brunetti, Ciciretti and Djordjevic (2015). I again lag this indicator as this should favor the existing default.

[46] I do not directly observe which of the reported checking account is the salary account. In the case of several reported checking accounts, I assume that the first reported account is the salary account as respondents are likely to report their most used account first. As a mortgage is a much higher volume financial instrument, I consider the banks of all mortgages on the first and second house.

[47] While one could argue that depositors choose for checking accounts and savings accounts as a bundle simultaneously, there is an extensive literature in marketing showing that checking and savings accounts are sequentially ordered in terms of adoption patterns with the former being chosen first normally. See, e.g., Dickinson and Kirzner (1986), Stafford, Kasulis and Lusch (1982), or Li, Sun and Wilcox (2005)

[48] This might be the case even for investors covered by deposit insurance if only imperfect knowledge about the workings of the mechanism exists. See Appendix D for the exact wording of the question.

[49] Net income is measured in thousand euros.

Additional inertia costs for switching across banks are significantly larger for single-bank consumers and further increase for consumers holding a checking account at their default bank. Holding a mortgage at the default bank does not statistically significant impact inertia. The subjective risk aversion measure has a statistically significant but much smaller effect on inertia costs, while the base parameter for bank-level inertia is now insignificant. This suggests that the inertia premium for switching across banks can predominantly be explained by measures of switching costs and the scope of the bank relationship, while subjective risk aversion, e.g., via uncertainty about bank service quality of other banks than the default, plays also, albeit, a smaller role. The remaining unexplained inertia, in particular within banks, suggests that unmeasured behavioral explanations might also be important drivers of inertia in deposit markets. Quantifying their relative importance is an interesting question that I leave for future research.

VI. Implications for Bank Pricing

The previous description of a market with differentiated products and inertia on the consumer side coupled with imperfect competition creates two opposing effects from the perspective of optimal dynamic pricing of banks. As banks can rationally expect that new customers become locked in in the future, they face a trade-off between 'harvesting' and 'investing'. Harvesting describes the process of setting lower interest rates to exploit the already existing customer base, while investing is the process of pricing more aggressively to gain new customers. Under uniform pricing, as common in deposit markets, both effects work against each other. As described in Farrell and Klemperer (2007), the former effect will likely dominate for larger banks as the higher profit per existing customer (intensive margin) outweighs the profit from extending the customer base (extensive margin). This logic reverses for smaller competitors wanting to gain market share. With differentiated products and multi-product firms, predicting the equilibrium in the resulting dynamic pricing game is difficult and can only be solved numerically as, for example, in Dubé, Hitsch and Rossi (2009). While certainly worthwhile to explore, I instead provide evidence consistent with the results from the theoretical literature.

The first evidence derives from the observation that, while banks cannot price discriminate between existing and incoming customers, they can segment their pricing schedules depending on what share of these groups can be expected in different products. Following the logic in Klemperer (1995), when a products is introduced, it will first be marketed to a high share of newer customers. Then, as the product matures over time in a market with switching costs, the share of locked-in customers will gradually increase giving firms more pricing power. As a result, one would expect lower interest rates in older accounts. To test this hypothesis, I aggregate the dataset used

in the estimation to the account-year level.[50] In comparison to the estimation sample used in the choice model, I do not aggregate smaller accounts in order to be able to define account age properly and increase the sample size to improve efficiency in the estimation. As there is no data available on the age of accounts, I proxy this variable by counting the number of years an account has appeared in the DNB household survey since the year 2000.[51] I then run three separate regressions of the interest rate of an account for the volumes €1000, €10000, and €50,000 on a number of controls using the following specification:

$$p_{jt} = c_0 + l_{jt} + \mathbf{r_j}\beta + \gamma t_t + u_{jt}$$

where l_{jt} denotes account age since the year 2000, $\mathbf{r_j}$ contains account restrictions and bank fixed effects, and t_t are year fixed effects. The results are shown in Table 8. While relatively new accounts up to three years old do not pay significantly lower rates than just introduced accounts, older accounts pay significantly less with increasing life time for all volumes considered. For example, five years old accounts pay on average 0.64% and seven years old accounts 1.1% less than just introduced accounts for a volume of €10,000.[52] Interestingly, this effect of account age persists even for volumes from €50,000 upwards. I also find evidence that incumbents with larger existing customer bases price lower than smaller banks. For example, even conditional on account restrictions and account age, customers of ING Bank as one of the largest banks receive on average 0.72% to 0.95% less than customers at smaller banks over all volumes considered, while the two medium banks Fortis and SNS Bank, are on average between 0.28% and 0.69% below the rates of the set of smaller banks. The only exception is Rabobank which offers no significantly different rates compared to the smaller banks. Taken together, these findings suggest that banks might indeed incorporate inertia in their pricing decisions.

VII. Counterfactual Simulations

In this section, I evaluate the consumer welfare impact of two counterfactual policies given the model estimates of the primary specification in Section VI. All simulations are performed in a partial equilibrium framework holding interest rates fixed. Thus, counterfactual enrollment patterns do not feed back into strategic rate adjustments

[50] Anderson, Ashton and Hudson (2014) and Barone, Felici and Pagnini (2011) similarly test pricing implications of switching costs in deposit and credit markets.

[51] This is the first year of data in which I can observe account names.

[52] Anderson, Ashton and Hudson (2014) find qualitatively similar results by comparing prices of accounts less and more than 30 months old in a regression framework.

by banks. In both counterfactuals, I consider the impact of a policy reducing inertia. Precisely, I evaluate a reduction of inertia by a multiplicative factor Z so that the counterfactual inertia becomes $Z(\eta_A, \eta_B)$. The indirect utility then becomes:

$$U_{ikjt} = V_{ikjt}(a_{ij}, p_{kjt}, \widehat{\mathbf{y_{ij,t-1}}}, \alpha(\mathbf{\Lambda}_{kt}), Z\eta, \xi_{jt}) + \epsilon_{ikjt}$$

In all simulations, I take the initial condition of each consumer as predetermined. Given the deterministic initial condition, consumers choose the plan that maximizes their utility in year t subject to the estimates from the primary specification and counterfactual inertia. The simulated choice probabilities of the previous year, $\widehat{\mathbf{y_{ij,t-1}}}$, then become itself the stochastic default account and bank in the current year. This iterative process is repeated until the last observed period.[53] I then evaluate how much consumers could gain through improved choices under the counterfactual scenarios. In all simulations, I treat inertia costs as a real social cost and assume the policy to reduce inertia is costless.[54] Due to consumer-level heterogeneity in the choice model, the resulting consumer surplus has to be again approximated by simulation. Following Small and Rosen (1981), I use the compensating variation to evaluate the change in consumer surplus:

$$CV_{ikt} = \frac{1}{\alpha_{kt}} \left| \int \left[ln \sum_{j=1}^{J} e^{V_{ikjt}^{post}} - ln \sum_{j=1}^{J} e^{V_{ikjt}^{pre}} \right] d\Phi(\mathbf{a}|\theta^{pre}) \right|$$

where the superscript 'pre' defines the original scenario before the change, 'post' the alternative scenario after the policy change, and the vector a contains all account fixed effects. The coefficient α_{kt} describes as before the price coefficient for individual i of type k in time t and translates the utility changes into monetary units. The integral is again approximated by simulation using 25 simulation draws.

In the first counterfactual, I proportionally reduce both inertia parameters by four different values of $Z = [0.75, 0.50, 0.25, 0.00]$. Figure 4 presents the evolution of counterfactual market shares for the five largest banks and the set of small banks. As inertia decreases, especially ING Bank looses significant market share, while smaller banks with on average higher interest rates gain market share. In the most extreme case, in

[53] As the model cannot predict with certainty which account will be chosen, the default variables become itself random. Treating the initial condition as deterministic is in line with the primary choice specification which is modeled conditional on the initial condition. The predicted default bank is the sum of the predicted default account probabilities of all accounts offered by each bank.

[54] Thus, reductions in inertia have a direct positive welfare impact for consumers.

which inertia is fully eliminated, ING Bank and the set of smaller banks converge to the same market share at the end of the sample period. In contrast, the remaining large and medium banks remain almost unaffected in all scenarios suggesting that non-price characteristics are valued enough by consumers to prevent bank switching in the presence of lower inertia.

In the second counterfactual, I eliminate inertia costs within banks (i.e., $\eta^A_{post} = 0$) but leave costs for switching across banks at the baseline level (i.e., $\eta^B_{post} = \eta^A_{pre} + \eta^B_{pre}$). This gives an insight into the question how much consumers could gain by costlessly optimizing within their existing bank. It also shows the importance of modelling within provider switching which has not been done in previous work, presumably due to data limitations.[55]

Table 9 presents the results for both counterfactuals for the population overall, the five previously defined volume groups, as well as singles and individuals with partner. There is, in particular, lots of heterogeneity depending on the volume type. For example, as evident from column 2, reducing inertia costs by 50% results in a gain in consumer welfare of €276 each year for the average consumer but ranges from €49 for volumes up to €2,500 to €1,137 for volumes above €45,000. Intuitively, the results become stronger with increasing policy effectiveness, i.e., a higher reduction of inertia. The last column shows the results of the second counterfactual simulation. When optimizing at no cost within bank, consumer welfare increases already by €114 each year on average ranging from €11 to €512 from the lowest to the highest volume bracket. This shows that modeling provider switching alone might neglect an important aspect of inertia. Given that pure transaction costs of switching, such as costs of opening an account or establishing a relationship with a new bank, are smaller within the same bank, the results point to the relevance of information costs or psychological factors impacting inertia. Due to the partial equilibrium framework, the results should, however, be interpreted as an upper bound of the true savings from policies reducing inertia as banks are likely to adjust their pricing strategies in response.

VIII. Conclusion

This paper quantifies inertia within and across banks in retail deposit markets using a unique panel data set on individual account choices and account characteristics. In a structural choice model, I find that switching accounts across banks is around one third costlier compared to within banks consistent with descriptive patterns in the data. The estimated costs of inertia decrease in relative terms but increase in absolute monetary terms with increasing volume pointing towards higher opportunity costs of wealthier

[55] Only few papers have prices and product names within provider available. A simplifying assumption made is often that consumers choose based on average prices over all contracts offered by a specific provider.

investors. Measures of switching costs and risk aversion explain most of the inertia premium for switching across banks, while search costs as measured by online banking usage affect both inertia components. From a pricing perspective, I provide evidence that banks discriminate based on inertia as older accounts with a likely higher share of inert customers pay lower rates on average.

The identified sources of inertia are informative for the effectiveness of regulatory interventions aiming to reduce inertia. Facilitating switching across banks might have to be accompanied by efforts to increase internet literacy to improve the ability to compare prices online. Still, even in the presence of such policies a share of individuals might remain inert due to a preference for bundling financial products at a single bank. As a result, banks offering a broader range of financial services might also justifiably offer lower deposit rates compared to more specialized smaller banks.

Carefully designed regulatory measures might still result in high potential savings for consumers. In a first counterfactual, I show that reductions in inertia shift market share from larger to more competitive smaller banks. In a second counterfactual, I show that policies improving account switching within the existing bank holding inertia across banks fixed can already lead to significant gains for depositors. While such policies would foster competition, they are also likely to enhance the monetary transmission channel on a macro level as increased price sensitivity is likely to positively impact pass-through of cost changes.

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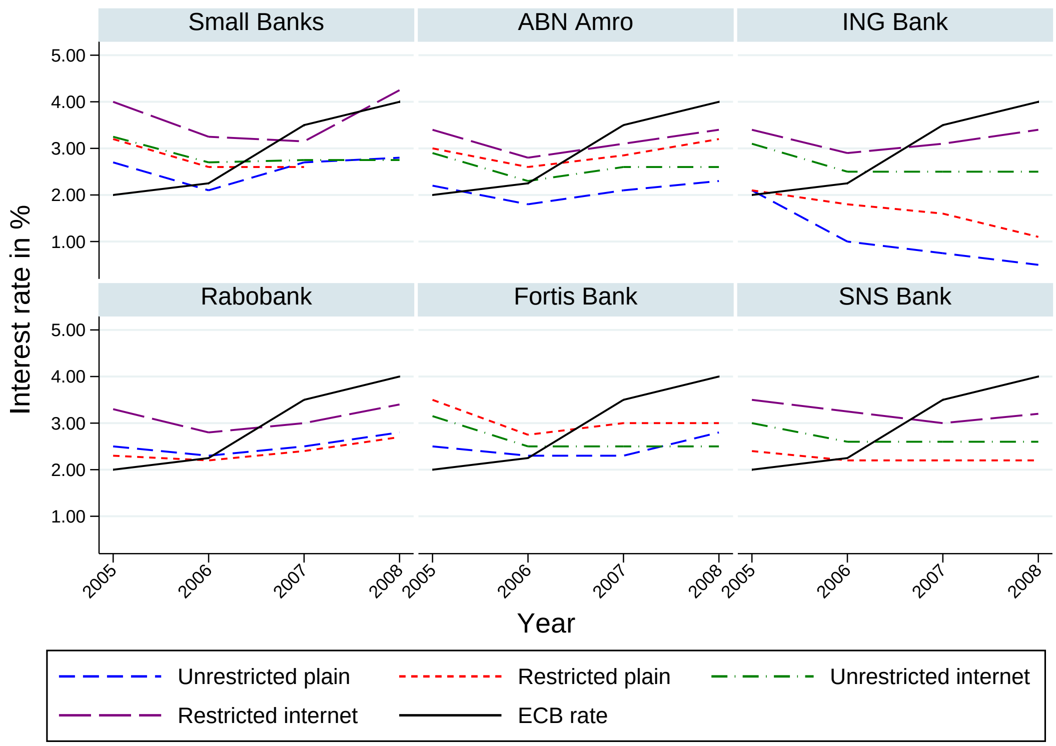

FIGURE 1. INTEREST RATES BY BANK AND ACCOUNT TYPE

Note: The figure shows annual interest rates including the ECB rate by bank and account type for accounts with the highest enrollment in each category. Small banks contains all banks outside the five largest Dutch banks. Internet accounts are fully managed online by the depositor. Restricted accounts impose additional restrictions as described in the main text. Interest rates shown assume these restrictions are fulfilled.

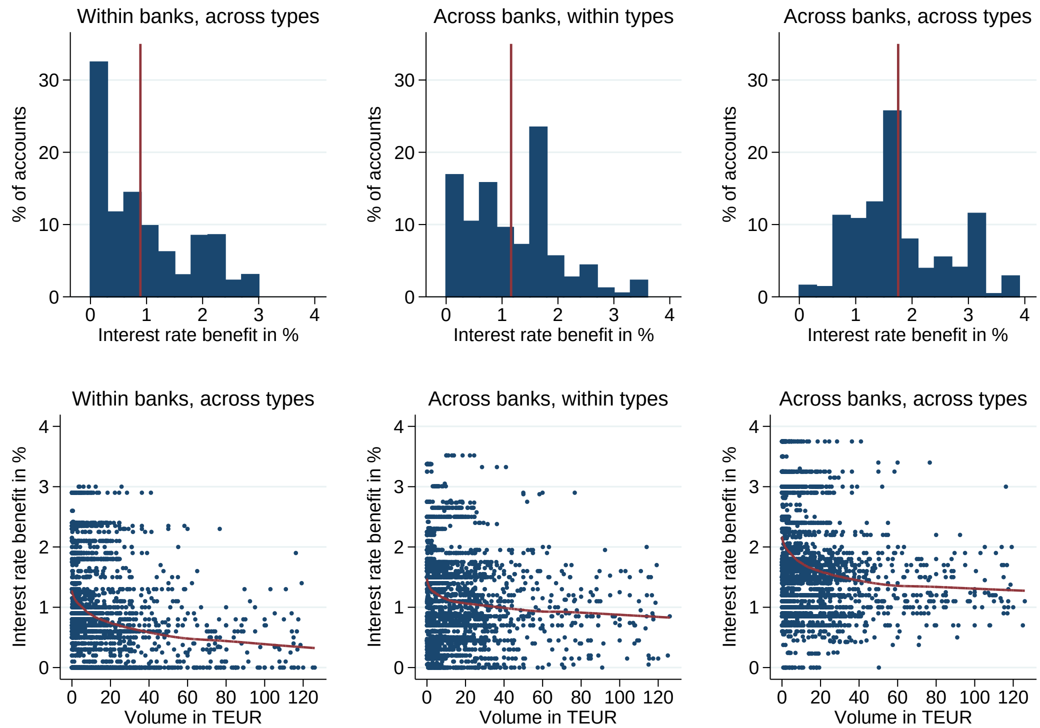

FIGURE 2. DISTRIBUTION OF INTEREST RATE BENEFITS

Note: The figure shows the potential interest rate benefits from switching within the current bank, across all banks within the same account type, and across all banks and all account types. Interest rate benefits are defined as the difference between the current rate and the highest possible rate in each case. The upper panel shows histograms for all three cases for the pooled sample. The red line indicates the mean of the distribution. The lower panel plots potential benefits for all cases against the available volume of consumers in thousand euros. The red line shows the results of a locally weighted regression of interest rate benefits on volume using a bandwidth of 0.8.

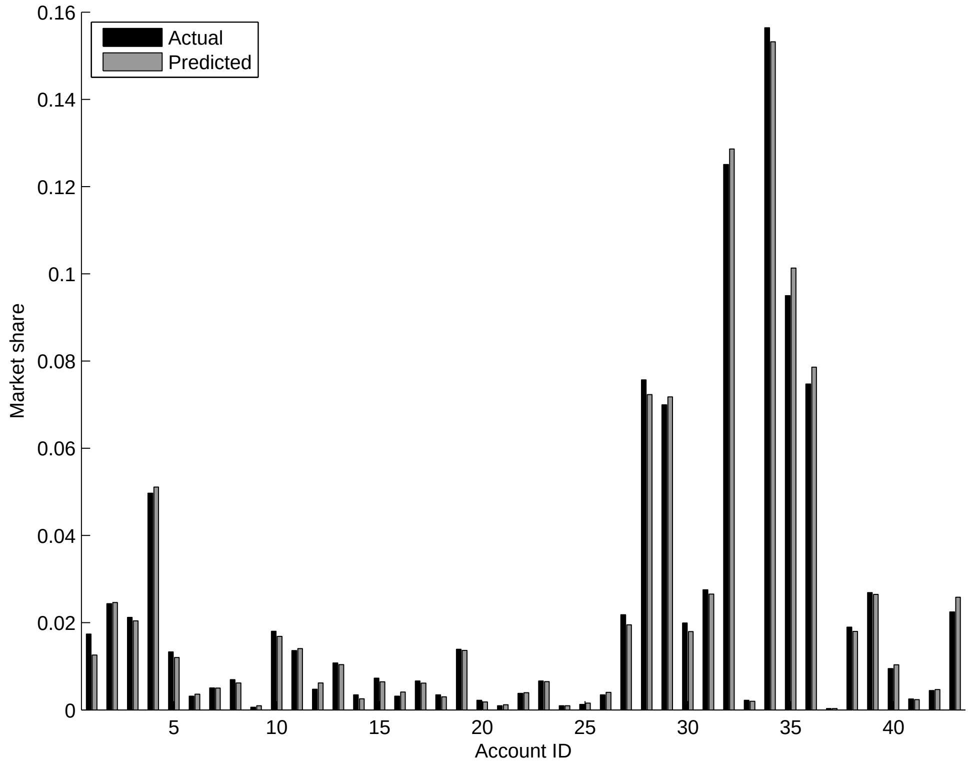

FIGURE 3. ACTUAL VS. PREDICTED ACCOUNT MARKET SHARES

Note: The figure shows the model fit by comparing actual with predicted market shares for the pooled sample on account level. Predicted market shares are calculated iteratively year by year as the default option is replaced by the predicted probability for each product in the previous year.

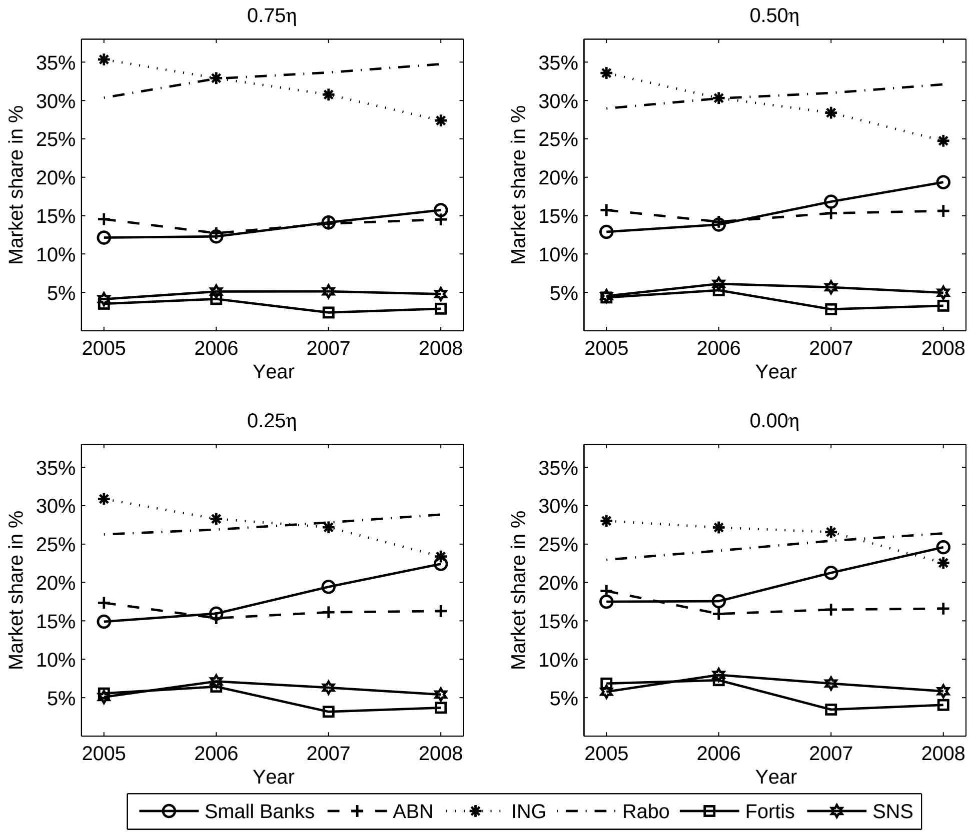

FIGURE 4. MARKET SHARES FOR DIFFERENT LEVELS OF INERTIA

Note: The figure shows annual market shares of Dutch banks based on number of customers for different counterfactual values of inertia. The category small banks contains all banks outside the five largest Dutch banks. All counterfactuals are calculated holding all other factors except inertia fixed including prices.

Table 1—Descriptive statistics

	No switch	Within bank	Across bank	Total
Observations	2,787	205	216	3,208
Age	51.87	52.56	55.03	52.13
Male	0.58	0.57	0.55	0.57
Couple	0.73	0.72	0.72	0.73
Net income in €	22,382	26,117	24,114	22,738
Online banking				
No or rarely	0.28	0.23	0.29	0.28
Often	0.28	0.33	0.20	0.28
Very often	0.43	0.44	0.52	0.44
Additional consumer info				
Risk aversion	5.24	5.53	5.09	5.25
Single account (lag)	0.63	0.45	0.19	0.59
Single bank (lag)	0.82	0.83	0.27	0.78
Checking account (lag)	0.76	0.80	0.39	0.74
Mortgages (lag)	0.20	0.20	0.11	0.19
Account characteristics				
Interest rate	2.27	2.55	2.76	2.32
Volume in €	15,541	19,366	16,645	15,860
ABN AMRO	0.13	0.15	0.14	0.13
ING Bank	0.33	0.53	0.23	0.34
Rabobank	0.35	0.18	0.20	0.33
Fortis Bank	0.03	0.04	0.04	0.03
SNS Bank	0.04	0.02	0.08	0.04
Small Banks	0.11	0.08	0.31	0.13
Internet account	0.40	0.64	0.62	0.43
Minimum amount	0.27	0.17	0.15	0.26
Lowest balance bonus	0.20	0.27	0.23	0.21
Balance growth bonus	0.02	0.10	0.02	0.02
Fixed monthly deposit	0.01	0.02	0.05	0.01
Withdrawal limitations	0.09	0.04	0.07	0.08
Salary account	0.03	0.05	0.03	0.03

Note: The table shows means of main demographics and account characteristics by switching type. Single account or bank is one for individuals holding only one account or all accounts at the same bank, respectively. Checking account indicates that the first named checking account is at the main bank, while mortgage indicates any mortgage on the first and second house if at the main bank.

Table 2—Share of Switching Accounts

	2005	2006	2007	2008
No switch	85.9	87.3	87.8	86.6
Within bank	7.5	7.0	5.4	5.8
Across bank	6.7	5.7	6.8	7.7
Total switch	14.1	12.7	12.2	13.5

Note: The table shows the share of individuals switching main accounts within bank, across bank, and not at all. A switch is defined as a change in account name compared to the previous year. Switches due to mergers or renaming of accounts are not included.

Table 3—Multinomial Logit Switching Regression

	No switch		Within bank		Across bank	
	Estimate	SE	Estimate	SE	Estimate	SE
Switching benefit	-0.038***	0.007	0.027***	0.005	0.011**	0.005
Age	-0.001	0	0	0	0	0
Male	0.019	0.013	-0.007	0.010	-0.012	0.01
Couple	0.014	0.014	-0.01	0.011	-0.004	0.011
Net income (Log)	-0.012***	0.005	0.011**	0.005	0.001	0.002
Online banking use						
Often	-0.019	0.016	0.032***	0.012	-0.013	0.011
Very often	-0.044***	0.015	0.021**	0.010	0.023**	0.012
Risk Aversion	-0.002	0.004	0.006**	0.003	-0.004*	0.002
Single account (Lag)	0.065***	0.02	-0.057***	0.013	-0.007	0.016
Single bank (Lag)	0.106***	0.031	0.039***	0.010	-0.145***	0.03
Checking acc. (Lag)	0.057***	0.016	0.008	0.011	-0.065***	0.012
Mortgage (Lag)	0.005	0.016	-0.001	0.011	-0.004	0.012
Years observed	0.008	0.006	0.001	0.004	-0.009**	0.004
Year fixed effects	Yes		Yes		Yes	
N	3141		3141		3141	
Log Likelihood	-1242.01		-1242.01		-1242.01	
Pseudo-R2	0.15		0.15		0.15	

Note: The table shows average marginal effects from a multinomial logit regression of the decision not to switch, switch within bank or switch across bank on a number of controls. The switching benefit is defined as the difference between the default continuation rate and the highest possbile rate available to a consumer given his volume. Checking account or mortgage is one if the individual holds the particular product at its default bank. Single account / bank is one if the individual holds only one account / bank in total in the previous year. Years observed counts the number of years an individual is in the sample. Standard errors are clustered at the individual level.

Table 4—Model Estimates

	Model (1)		Model (2)		Model (3)	
	Estimate	SE	Estimate	SE	Estimate	SE
Interest rate	0.308***	0.115	0.324***	0.120	0.315***	0.123
Interest rate#[2.5k-10k]	0.248**	0.118	0.252**	0.123	0.245**	0.120
Interest rate#[10k-25k]	0.397***	0.122	0.415***	0.126	0.409***	0.122
Interest rate#[25k-45k]	0.844***	0.162	0.863***	0.162	0.869***	0.160
Interest rate#[45k-more]	0.956***	0.195	0.987***	0.195	0.987***	0.202
Default product	3.893***	0.083	3.447***	0.142	3.413***	0.138
Default bank	1.915***	0.114	1.048***	0.176	1.064***	0.167
Initial product			0.589***	0.151	0.686***	0.148
Initial bank			1.035***	0.167	1.104***	0.166
N	111,347		111,347		111,347	
Log-likelihood	-2,337.90		-2,289.33		-2,269.81	
Product FE	yes		yes		yes	
Random FE	no		no		yes	

Note: The table reports estimates of utility parameters not marginal effects for the primary choice model in Section V. Model (1) shows results from a conditional logit with alternative-specific constants. Model (2) adds initial conditions for account and bank, where the initial condition is the first account or bank observed in the panel for each individual. Model (3) contains the full specification with random account fixed effects. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5—Monetary costs of inertia

	Mean amount	Rate Coef.	Within bank in %	in €	Across bank in %	in €
Population	15,860	0.651	6.6	576	8.7	756
0k-2.5k	867	0.316	10.8	94	14.2	123
2.5k-10k	5,463	0.560	6.1	333	8.0	436
10k-25k	15,948	0.725	4.7	751	6.2	985
25k-45k	31,406	1.184	2.9	905	3.8	1,187
45k-more	89,788	1.303	2.6	2,353	3.4	3,086

Note: The table shows the monetary costs of inertia within and across bank for the entire population and by volume type in percent of volume and absolute Euro terms. Calculations are based on the estimated parameters from Table 4. Mean volume is calculated within each volume type over the pooled sample.

Table 6—Robustness

	Model (1)		Model (2)		Model (3)	
	Estimate	SE	Estimate	SE	Estimate	SE
Interest rate	0.126	0.182	0.379***	0.131	0.498**	0.219
Interest rate#[2.5k-10k]	0.267	0.187	0.256**	0.121	0.245**	0.120
Interest rate#[10k-25k]	0.530***	0.178	0.437***	0.124	0.410***	0.122
Interest rate#[25k-45k]	1.132***	0.208	0.919***	0.170	0.867***	0.161
Interest rate#[45k-more]	1.166***	0.275			0.970***	0.202
Default product	3.345***	0.177	3.379***	0.144	3.416***	0.138
Default bank	1.196***	0.225	1.045***	0.178	1.066***	0.168
Initial product	0.871***	0.202	0.813***	0.153	0.683***	0.148
Initial bank	1.116***	0.228	0.997***	0.176	1.102***	0.166
Control function					-0.239	0.241
N	60,056		101,551		111,347	
Log-likelihood	-1,140.56		-2,051.38		-2,269.46	
Product FE	yes		yes		yes	
Random FE	yes		yes		yes	

Note: The table reports estimates of utility parameters not marginal effects for the primary choice model in Section V. It shows variations of the last specification in Table 4. Model 1 uses a balanced panel of consumers compared to the primary specification. In Model (2), only consumers with volume below €40T and thus covered by deposit insurance enter the sample. Model (3) adds the control function as an additional covariate using interactions of product fixed effects and the EONIA rate as instruments in the first stage pricing regression. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 7—Determinants of inertia

	Model (1)		Model (2)	
	Estimate	SE	Estimate	SE
Interest rate	0.308***	0.124	0.295**	0.128
Interest rate#[2.5k-10k]	0.209*	0.122	0.247*	0.127
Interest rate#[10k-25k]	0.438***	0.123	0.453***	0.129
Interest rate#[25k-45k]	0.891***	0.163	0.883***	0.172
Interest rate#[45k-more]	0.983***	0.207	0.957***	0.217
Default product - base	3.372***	0.139	3.237***	0.358
Default bank - base	1.030***	0.169	-0.295	0.330
Initial product	0.777***	0.151	0.709***	0.159
Initial bank	1.095***	0.168	0.580***	0.187
Default product - male			0.289**	0.138
Default product - age			0.002	0.005
Default product - couple			0.091	0.141
Default product - net income			-0.009**	0.004
Default product - single account			0.744***	0.149
Default product - online banking: often			-0.183	0.173
Default product - online banking: very often			-0.566***	0.161
Default bank - single bank			1.828***	0.207
Default bank - checking account			0.494***	0.201
Default bank - mortgages			0.307	0.257
Default bank - risk aversion			0.110**	0.050
N	109,590		109,590	
Log-likelihood	-2,225.10		-2,101.18	
Product FE	yes		yes	
Random FE	yes		yes	

Note: The table reports estimates of utility parameters not marginal effects. Model (1) shows the primary choice model as in Section V for the slightly reduced sample for comparison. Model (2) includes, in addition, a number of interactions between the inertia parameters and consumer characteristics to analyze inertia determinants. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 8—OLS of interest rate on account life

	1,000 Euro		10,000 Euro		50,000 Euro	
	Estimate	SE	Estimate	SE	Estimate	SE
Acc. age since 2000						
1	0.261	0.195	0.092	0.169	0.025	0.144
2	0.027	0.189	-0.057	0.182	-0.063	0.172
3	-0.07	0.179	-0.107	0.165	-0.129	0.161
4	-0.260*	0.151	-0.461***	0.139	-0.403***	0.126
5	-0.439**	0.172	-0.635***	0.153	-0.568***	0.139
6	-0.534***	0.192	-0.801***	0.178	-0.713***	0.161
7	-0.867***	0.24	-1.097***	0.23	-0.955***	0.216
Bank FE						
ABN AMRO	-0.137	0.152	-0.352**	0.16	-0.227*	0.117
ING Bank	-0.949***	0.205	-0.716***	0.219	-0.788***	0.204
Rabobank	-0.195	0.225	-0.166	0.223	-0.276	0.197
Fortis Bank	-0.693***	0.211	-0.409**	0.199	-0.510***	0.181
SNS Bank	-0.326**	0.133	-0.281*	0.148	-0.335**	0.158
Constant	2.882***	0.152	3.019***	0.142	2.992***	0.136
Account restrictions	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
N	242		251		253	
Adjusted R-squared	0.71		0.57		0.57	

Note: The table reports OLS estimates from a regression of account interest rate on account life, account characteristics, bank and year fixed effects for three different volumes (€1,000, €10,000, and €50,000. Account life measures the number of years an account has appeared in the DNB Household Survey since the year 2000 which is the first year account names are observed. The unit of observation in each specification is an account in a given year. Standard errors are clustered at the account level.

Table 9—Welfare impact of counterfactual inertia

	0.75η	0.50η	0.25η	0.00η	$\eta^A = 0$
Population	163	276	344	382	114
0k-2.5k	29	49	60	67	11
2.5k-10k	98	165	204	226	53
10k-25k	209	352	439	488	149
25k-45k	247	416	517	574	197
45k-more	664	1,137	1,431	1,599	512
Single	143	238	296	328	122
Family	170	290	362	403	111

Note: The table shows mean welfare changes of two counterfactuals for the average consumer and specific subgroups relative to the baseline preferences in Table 4. In counterfactual 1 in the first four columns, overall inertia is reduced by a factor z. In counterfactual 2 in the last column, inertia within bank is eliminated holding inertia across bank fixed. All simulations are performed holding prices and other factors except inertia constant.

Appendix A: Additional Descriptives

Table A1—Sample comparison

	All accounts	Main account	Final sample
Observations	8,775	5,400	3,208
Age	51.05	50.29	52.13
Male	0.56	0.55	0.57
Couple	0.75	0.74	0.73
Number of Children	0.69	0.69	0.64
Education			
Less than highschool	0.25	0.27	0.27
High school	0.31	0.32	0.31
College	0.44	0.41	0.43
Account characteristics			
ABN AMRO	0.13	0.14	0.13
ING Bank	0.34	0.30	0.34
Rabobank	0.27	0.32	0.33
Fortis Bank	0.04	0.04	0.03
SNS Bank	0.05	0.05	0.04
Small Banks	0.16	0.14	0.13
Amount in €	10,700	14,356	15,860

Note: The table shows summary statistics of main demographics and account characteristics for three different samples. All accounts contains all demand deposit accounts held by households in the DHS. Main accounts contains the sample of main account held by households, where a main account is the account with the highest volume held by each individual in the sample for a given year. Final sample includes all accounts used in the final estimation sample, i.e., accounts with matched interest rate and observed at least two periods.

Appendix B: Data Processing

Whereas the majority of survey respondents provide a bank name, the data on the names of savings accounts contain some typos, abbreviations, and few inconsistencies. I process this raw information in the DHS in the following way. Using the bank and account names from the market interest rate data as a reference for the correct spelling, I replace all incorrectly spelled names and abbreviations in the DHS by their proper name. I replace those cases in which participants report outdated names of accounts by the names of their successor accounts. Finally, I set all potential inconsistent cases to missing.[56] As I later match the DHS and market data based on volume as well, I also

[56] For example, some respondents report accounts not offered by the reported bank in 2005.

recover missing volumes of individual savings accounts following the procedure used by the official provider of the DHS (CentERdata). CentERdata first recovers volumes for individual savings accounts (details follow) and then aggregates over all accounts of each household member yielding total savings volume per household member (i.e., at the individual level). Only the recovered volume of the latter is available in the public version of the dataset. However, I am able to recover the large majority of the inserted values for individual savings accounts by following the same process that CentERdata has applied to calculate total savings account volume per household member.[57] First, if a respondent does not report the exact amount of a savings account, the respondent is asked to choose from a sequence of follow-up questions in the form of unfolding brackets. In this case, I use the mid-point of the bracketed answer or the lower bound in case of the highest open-ended category (€25,000 or more). This leaves 10.3% of accounts with missing volume. Second, for these missing cases, I use the average amount of this savings account over the last two years. This leaves 8.1% of accounts with missing volume. For the remaining individual household members with at least one account with unreported volume, an imputed value for total savings volume was used by CentERdata. This was derived from a regression of total savings volume on a large set of individual characteristics. I use this imputed value to recover the volume of individual savings accounts in the following way. If only one account of a household member is left with missing volume, I use the difference between the total savings volume and the sum of all reported account volumes of that individual to fill in the single missing volume.[58] This still leaves few individual household members with more than one account with missing volume. For those household members, I distribute this difference equally across all savings accounts with remaining missing volume.[59]

Appendix C: Initial conditions

In this appendix, I show how the logic in Wooldridge (2005) shown for binary choice model can be extended to the multinomial case with more than two products. The paper applies to cases, where the initial condition of the choice process is unknown as is the case in this work. Instead of simulating the distribution of the initial condition which is often imperfect, he suggests to control for unobserved heterogeneity correlated with the initial condition, by modelling the choice probabilities conditional on the initial

[57] Details can be found in the documentation of the DHS 2005 wave (available at: http://cdata3.uvt.nl/dhs/files/CodebookWave2005English.pdf)

[58] 60% of those household members hold only one account and thus total volume and individual account volume are equivalent.

[59] Note that in the last two cases, I only consider accounts that do not exceed the total number of accounts as originally stated by the respondent, for example, I only consider the first three reported accounts of a household that claims to have 3 accounts in total but reports four. The same approach is used in the DHS for the calculation of total savings wealth.

condition. I start by definining the general indirect utility from product j by:

$$V_{ijt} = x'_{jt}\beta + \eta y_{ij,t-1} + \alpha_{ij} + \epsilon_{ijt}$$

where x_{jt} is a set of potentially time-varying product characteristics, $y_{ij,t-1}$ is the lagged dependent variable taking the value 1 if consumer i chooses product j in $t-1$, α_{ij} is an unobserved product-specific factor, and ϵ_{ijt} is an i.i.d. type 1 extreme value distributed error term. Moreover, let $Y_{it} \in \{0, ..., J\}$ be a random variable taking the value j if product j is chosen. Then the probability that consumer i chooses product j is given by:

$$P(Y_{it} = j) = P_{ijt} = \Lambda(x'_{jt}\beta + \eta y_{ij,t-1} + \alpha_{ij}) = \frac{e^{x'_{jt}\beta + \eta y_{ij,t-1} + \alpha_{ij}}}{\sum_{j=0}^{J_t} e^{x'_{jt}\beta + \eta y_{ij,t-1} + \alpha_{ij}}}$$

Aggregation of the choice probabilities over products and time yields the probability of observing a sequence of choices for consumer i:

$$P_i = \prod_{t=1}^{T_i} \prod_{j=0}^{J} \Lambda(x'_{jt}\beta + \eta y_{ij,t-1} + \alpha_{ij})^{y_{ijt}}$$

which reduces to the simple logit formula for the case of $J = 2$. Extending the approach of Wooldridge (2005) for binary choice models to multinomial models with more than two alternatives, I model the distribution of the unobserved component conditional on the initial condition as follows:

$$\alpha_{ij} = \alpha_j + \gamma y_{ij0} + a_{ij}, \qquad \text{with } a_{ij} | y_{ij0} \sim N(0, \sigma_a^2)$$

Thus, in contrast to his paper, there is now an additional dimension of variability due to the existence of many products. The unobserved component now depends on a product-specific intercept term, the initial condition and a product-specific random effect, a_{ij}. Plugging in yields a logit model with response probability:

$$P_{ijt} = \Lambda(x'_{jt}\beta + \eta y_{ij,t-1} + \alpha_j + \gamma y_{ij0} + a_{ij})$$

Integrating over the normally distributed random effects a_{ij} from P_i and as before aggregating over products and time yields:

$$P_i = \int_{a_0,\ldots,a_J} \prod_{t=1}^{T_i} \prod_{j=0}^{J} \Lambda(x'_{jt}\beta + \eta y_{ij,t-1} + \alpha_j + \gamma y_{ij0} + a_{ij})^{y_{ijt}} d\Phi(a_0)\ldots d\Phi(a_J)$$

which has the same structure as a mixed logit of sequential choice as, for instance, described in Train (2003). Thus, the logic in Wooldridge (2005) shown for dynamic binary and ordered probit, tobit and poisson models, extends to models of unordered choice, in particular the conditional logit model with the difference that now there is no closed form solution for the likelihood so the model needs to be estimated by simulation.

Appendix D: Questions used

Account Characteristics
1 Minimum amount: Minimum amount required to earn full interest rate
2 Lowest balance bonus: Balance may not fall below specified amount threshold during calendar year/quarter to earn full rate
3 Balance growth bonus: Balance needs to grow by specified amount per calendar year/quarter
4 Limited withdrawal: Maximum withdrawal per month
5 Additional fees: withdrawal / account fees
6 Salary account: Salary account required at the same bank
7 Internet account: Account is fully managed online

Account Name
Can you describe what kind of account it is (e.g. a 'GroeiGemak Spaarrekening', a 'Bonus Spaarrekening' with ABN AMRO, a 'Plusrekening' or a 'Kapitaalrekening' with the Postbank, or a 'Rabo Rendement Rekening')?
any answer ...

Bank information
Savings accounts
With which bank or financial institution is your [1st thru 7th] account registered?
1 ABN AMRO
2 Postbank
3 Rabobank
4 ING Bank

5 Fortis Bank
6 SNS Bank
7 other

Checking accounts
With which bank or financial institution is your [1st thru 5th] account registered?
1 ABN AMRO
2 Postbank
3 Rabobank
4 ING Bank
5 Fortis Bank
6 SNS Bank
7 other

Mortgages
With which financial institution have you taken out the [1st thru 5th] mortgage? 1 ABN AMRO
2 Postbank
3 Rabobank
4 ING Bank
5 Fortis bank
6 SNS Bank
7 Nationale Nederlanden
8 AEGON
9 AMEV
10 Bouwfonds Nederlandse Gemeenten
11 ABP
12 Other financial institution
Note: I group ING and Postbank together as the former mainly operates through the latter in the market for savings accounts. In case of 'other', respondents are asked to name the exact name of the bank. Bank information for mortgages is asked for the first and second residential house.

Online banking use
Nowadays, a number of banks offer the possibility to arrange banking affairs through Internet, without the mediation of a person. Examples of such a facility are: HomeNet, Internetbanking or Girotel. Do you use such a facility?
1 no

2 yes, very rarely
3 yes, every now and then
4 yes, often
5 yes, very often
6 I don't know
Note: I group the first three categories together due to few observations in category 2 and 3 and no significant differences across these categories in the estimation specification.

Net Income
Equal to the derived net income on individual level as provided by CentER in the aggregated data on income.
Note: In contrast to the DHS which counts net income as missing if one of the sub components is missing, I count net income as missing only if all asset subcomponents are missing. I also use information from previous years within the same individual to reduce the number of missings. Both variables are highly similar in terms of distributional aspects, since often only small subcomponents are not reported.

Risk aversion
Please indicate on a scale from 1 to 7 to what extent you agree with the following statements, where 1 indicates 'totally disagree' and 7 indicates 'totally agree':
'I think it is more important to have safe investments and guaranteed returns, than to take a risk to have a chance to get the highest possible returns.'

Savings Volume
What was the total balance of your SAVINGS OR DEPOSIT ACCOUNTS on 31 December 2004?
1 amount: ...
2 don't know