Agony of Choice – Trading off Stability and Competition in the Banking Markets

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Michael Hellwig* Falk Hendrik Laser†

March 15, 2019

Abstract: We investigate the trade-off between financial stability and competition policy by focusing on the merger of ABN AMRO and Fortis Bank NL in the Dutch retail banking market. The merger was affected by the financial crisis in which the Dutch state nationalized the banks and completed the merger intending to stabilize the financial markets. Based on a structural model we simulate the merger to predict changes in the interest rates for savings accounts. Our analysis builds on representative data on Dutch consumer choice for savings accounts conditional on individual choice sets and product characteristics covering the time period from 2007 to 2010. We model the demand for savings accounts as discrete choice for differentiated products using a random-coefficients logit model. On the supply side we assume Bertrand Nash competition in a multiproduct oligopoly. Our results indicate anti-competitive effects in terms of too low interest rates. To the best of our knowledge we are the first to apply merger simulation methods in the context of banking using disaggregated data.

JEL: D22, G21, G34, L11, L25, L40, L41

Keywords: Antitrust, competition policy, merger analysis, state aid, retail banking, random-coefficients logit models, differentiated products.

*ZEW – Leibniz Centre for European Economic Research and MaCCI Mannheim Centre for Competition and Innovation, Address: P.O. Box 10 34 43, D-68034 Mannheim, Germany, E-Mail: hellwig@zew.de

†Goethe University Graduate School of Economics, Finance and Management (GSEFM) and Technische Universität Darmstadt, Department of Law and Economics, Address: Hochschulstraße 1, D-64289 Darmstadt, Germany, E-Mail: laser@vwl.tu-darmstadt.de

1 Introduction

In practice competition policy often involves a trade-off between different policy goals. While policy makers often put forward the protection of jobs,[1] in banking the stabilization of financial markets is a main policy goal and especially was during the recent financial crisis. Allowing market consolidation through mergers served as a measure to mitigate the adverse effects of the financial crisis in several cases (e.g. JPMorgan Chase and Bear Stearns, or Bank of America and Merril Lynch in the U.S.; Lloyds and HBOS in the U.K.; and mergers among Landesbanken in Germany). Yet, such measures were highly controversial. For instance, the Office of Fair Trading objected to the merger of HBOS and Lloyds voicing concerns about the greater than 30 % market share of the new entity and the elimination of HBOS as a challenger to the four larger established banks. The Secretary of State, however, overruled the objection, which was in line with the Bank of England, the Financial Services Authority and the Treasury stressing the necessity to maintain financial stability (Vives, 2016). This example illustrates the dilemma policy makers can find themselves in. While mergers might be instrumented to mitigate the effects of financial crises, interventions could result in harmful increases of market power.

In this paper, we investigate the trade-off between financial stability and competition policy by focusing on the merger of ABN AMRO and Fortis Bank NL in the Dutch financial sector. This is a particularly interesting case. Being one of the largest bank takeovers in recent years financial stability concerns prompted policy makers to engage in substantial market interventions involving state aid and allowing a merger in an already concentrated market.

Initially, a consortium of Royal Bank of Scotland, Fortis (referring to the mother company), and Banco Santander purchased ABN AMRO for 71.1 billion euro in October 2007. Fortis was supposed to take over the business unit Netherlands amongst others. Yet, when the financial crisis hit the international financial markets in 2008, Fortis

[1] See, e.g., the *EDEKA/Kaiser's Tengelmann* merger in the German supermarket sector in 2015. Although the merger had been prohibited by the German Federal Cartel Office, the German Minister of Economic Affairs issued a ministerial authorization conditionally clearing the merger arguing that job security prevails over the expected restraints on competition.

faced serious difficulties raising capital and, eventually, needed to be nationalized by the Netherlands, Belgium and Luxembourg. The Dutch state purchased the Dutch business of Fortis in October 2008 including the Dutch activities of ABN AMRO. Willing to finalize the intended merger regarding the Dutch activities, the Dutch state provided liquidity facilities so that ABN AMRO and Fortis Bank NL (referring to the Dutch business unit of Fortis) finally merged under ABN AMRO in July 2010. The European Commission (EC) concluded in April 2011 that the capitalization measures constitute state aid but approved them subject to a set of conditions involving restrictions on price leadership for standardized savings and mortgage products.

In our analysis, we focus on the Dutch market for savings accounts and investigate whether ABN AMRO and Fortis Bank NL might have resulted in negative effects for consumers. We build a model to simulate counterfactual scenarios of the merger. Specifically, we use our model to predict the counterfactual situation that ABN AMRO and Fortis Bank NL already merged in the beginning of 2010 and compare it to the outcomes for the case that no merger has taken place.

We model demand for savings accounts as discrete choice for a differentiated goods by identifying the consumers' main savings decision on the market for savings accounts. Employing a disaggregated approach taking into account the characteristics of both products and consumers helps to mitigate the endogeneity problem between prices and unobserved product characteristics. The supply side is modeled assuming Bertrand Nash competition in a multiproduct oligopoly. Calibrating the model with demand-side estimates derived from a random-coefficients logit model allows us to simulate bank behavior in counterfactual scenarios. By making adjustments to the ownership structure in the model we are able to predict the pricing behavior of banks in the what-if scenario in which the two banks operated under complete separate ownership.

Our empirical analysis draws on the representative DNB Household Survey (DHS) containing detailed yearly information on the saving behavior of more than 2,000 Dutch households. We merge the survey data with product information on savings accounts including interest rates and account restrictions retrieved from price comparison websites

specialized on Dutch saving products.[2] Our data covers the time period from 2007 to 2010 and enables us to observe consumer choice conditional on relevant product characteristics and the corresponding individual choice sets over time.

We predict that the merger had a significant effect on interest rates in the market. In the merger case ABN AMRO and Fortis Bank NL would have had interest rates 6% and 8.76% lower than in the case without a merger. Our results suggest that the *ABN AMRO/Fortis Bank NL* merger could have created anti-competitive effects on the Dutch retail banking market. This raises the notion of taking into account these additional social costs when trading off competition policy against financial stability.

Our paper aligns with both the empirical banking literature and the applied industrial organization literature using structural models to conduct counterfactual analyzes. Berry et al. (1995) and Goldberg (1995) provide comprehensive work on the US car market where the latter investigates the effects of tariffs on the market. More recently an increasing number of studies is dedicated to the banking market. Dick (2008), for example, uses a structural model to estimate demand for deposit services of U.S. commercial banks and measures the effects of US branching deregulation. Molnar et al. (2013) estimate demand for deposit services in order to test supply models in the Italian retail banking market. Egan et al. (2017) analyze the feedback loop between financial distress and the ability to access (uninsured) deposits in the US. Honka et al. (2017) investigate how advertising influences choice in the US retail banking market. Finally, Crawford et al. (2018) build a comprehensive model to analyze the interactions between asymmetric information and imperfect competition in the Italian lending markets.

Examples for the implementation of merger simulations are Ivaldi and Verboven (2005), Björnerstedt and Verboven (2016) and Molnar (2008). Ivaldi and Verboven (2005) analyse a merger in the European truck market and compare the prediction of the merger simulation to other market power tests. Björnerstedt and Verboven (2016) conduct a merger simulation and ex-post evaluation in the Swedish market for analgesics to test merger simulation as a prediction tool. Molnar (2008) applies merger simulation

[2]We obtain most data from 'SpaarInformatie'. See http://www.spaarinformatie.nl.

to the Finish banking market using aggregated data.

While many studies analyzing consumer choice in a discrete choice setting use aggregated data we employ detailed consumer-level data. The use of disaggregated data promises more efficient estimates and is better suited to describe demand choices driven by heterogeneous preferences and general substitution patterns. To the best of our knowledge we are the first to apply merger simulation methods in the context of banking using disaggregated data. We aim to contribute to the understanding of the banking markets given its importance for national economies.

The paper is structured as follows. In the next section we provide background information on the merger between ABN AMRO and Fortis Bank NL and the Dutch banking market. Section 3 introduces the model and the steps we undertake for simulation. In section 4 we describe in detail the compilation of our dataset. Sections 5 and 6 present the estimation and our results respectively. The last section 7 summarizes and concludes.

2 The merger of ABN AMRO and Fortis Bank NL

The sale of ABN AMRO was initiated by a publicly disclosed letter of the British hedge funds TCI complaining to ABN AMRO about poor share price returns and urging to "actively pursue the potential break up, spin-off, sale or merger."[3] The letter from February 2007 echoed in the media and reinforced discussions and negotiations about a sale of ABN AMRO. After a bidding battle between the British bank Barclays and a consortium of Royal Bank of Scotland, Fortis, and Banco Santander, the majority of ABN AMRO's shareholders accepted the consortium's offer worth 71.1 billion euro in October 2007, making it one of the largest bank takeover until today.

The consortium's plan to split the assets of ABN AMRO assets mentioned Royal Bank of Scotland obtaining the business units Private and Business Clients in Asia, Europe, and North America while Banco Santander received Banco Real and Antonveneta. Fortis obtained the business units Asset Management, Private Banking, and Netherlands which

[3]See http://www.telegraph.co.uk/finance/2804714/Letter-from-TCI-to-ABN-Amro.html, last accessed on March 15, 2019.

it intended to merge with its own Dutch arm Fortis Bank NL. All cases were subject to merger control by the European Commission (EC).

Regarding the Dutch assets, the EC conditionally cleared the merger between ABN AMRO and Fortis in October 2007. The EC had concerns regarding the Dutch commercial banking market, in which the combination of the first (ABN AMRO) and fourth largest bank (Fortis Bank NL) would significantly increase the already high concentration level (European Commission, 2007). The EC required the sale of several components of the Dutch business unit before the merger could become legal in order to protect corporate customers from reduced competition. The EC, however, did not raise concerns about anti-competitive effects in the similarly concentrated retail banking market due to a modest market share of Fortis Bank NL (being a distant fourth player in terms of market position after ING, Rabobank and ABN AMRO).

During the time of preparing the merger and in the advent of the global financial crisis in 2008, Fortis faced liquidity issues also caused by the high acquisition price for ABN AMRO (share of Fortis: 24 billion euro) and needed to be rescued in a combined effort of the three governments of the Netherlands, Belgium and Luxembourg. The Dutch state purchased the Dutch business of Fortis for 16.8 billion euro in October 2008. This also included the stake in the holding of the consortium comprising the Dutch activities of ABN AMRO.

Willing to finalize the intended merger, the Dutch state provided liquidity facilities to implement the separation of the Dutch activities of ABN AMRO from the holding of the consortium and to cover the costs of the EC divestiture-remedy realized as the sale of several components to Deutsche Bank in April 2010. While this resulted in the finalization of the initial merger of Fortis Bank NL and ABN AMRO in July 2010, the capital injections of the Dutch state were subject to state aid investigations by the EC. The EC concluded in April 2011 that the recapitalization measures, which amounted to between 4.2 and 5.45 billion euro (excluding the takeover price),[4] constitute state aid (European Commission, 2011). Yet, the EC acknowledged that the need for supporting

[4]The purchase price was not considered as representing state aid to the two entities as they did not receive the corresponding money.

the banks rather stemmed from undercapitalization than from excessive risk taking or unsustainable business models thus approving the support package.

The approval, however, was subject to a set of conditions. The conditions included (amongst others) a ban on acquisitions and on advertising state ownership as well as restrictions on price leadership for standardized savings and mortgage products. That is, ABN AMRO is not allowed to offer price conditions which cannot be matched by non-aided competitors. These conditions were set for a duration of three years and would be prolonged to a maximum of five years if the Dutch state continues to hold more than 50% of the ordinary shares after three years. During the state aid investigations, the Dutch state expressed its commitment to a complete exit aiming to recover its initial investment plus funding costs. Despite a successful IPO in November 2015, it still held a 56.3% stake in ABN AMRO by the beginning of 2019.[5] The bans thus only expired in April 2016.

Years after the merger, the Dutch central bank concludes that high concentration is persistent in the market and calls for less dominance of large banks and the necessity to promote the position of small banks and niche players. The central bank mentions the recent mergers in the market (*ABN AMRO/Fortis Bank NL* and *Rabobank/Friesland Bank*) as one source of high concentration (DNB, 2015). Furthermore, the Dutch competition authority finds that the retail banking sector has become less competitive after the financial crisis and identifies the consumers' limited propensity to switch banks (consumer inertia) as another reason for low competitiveness (ACM, 2014).

3 Model

Our structural model builds on demand and supply as two building blocks. We use estimated demand-side parameters to calibrate the model. Making assumptions on joint bank behavior closes the model. With our model we are able to simulate a new equilibrium representing counterfactual conditions. Among retail banking markets, we choose the market for savings accounts to be the relevant market as we can more easily com-

[5] See https://www.abnamro.com/en/about-abnamro/our-company/corporate-governance/shareholder-structure/index.html, last accessed on March 15, 2019.

pare between products contrary to other banking products. For instance, term deposits might exhibit different maturities and are thus not easily comparable. Another argument for comparability is that no fees are applied to savings accounts. Furthermore, for savings accounts we can be more confident that consumer choice is driven by a saving motive contrary to checking accounts which also serve to cater transactional purposes (e.g. payments, reference account to receive salary etc.).

3.1 Demand

We use a mixed multinomial logit model (mixed logit model) for the demand side. Assuming a random utility model (RUM) we can interpret the mixed logit model as a random-coefficients model in which the coefficients vary between individuals.

The indirect utility of consumer i for the savings account product j of bank b at time t can be expressed as

$$\begin{aligned} U_{jt}^i &= V_{jt}^i + \epsilon_{jt}^i \\ &= x_{jt}\beta^i + y_{jt}\gamma + \epsilon_{jt}^i, \\ i &= 1, ..., I, j = 1, ..., J, b = 1, ..., B, t = 1, ..., T. \end{aligned} \tag{1}$$

The term V_{jt}^i reflects the deterministic part of consumer utility and ϵ_{jt}^i is a random term which is iid extreme value. In our discrete choice setting each consumer chooses one product out of a set of alternatives. RUM consistency implies that a consumer chooses the alternative yielding the highest utility. Furthermore, in the random-coefficients model we can differentiate between variables for which the coefficients differ across individuals (i.e. x_{jt}) and variables for which the coefficients are constant (i.e. y_{jt}). Note that the corresponding vector of coefficients for x_{jt} is superindexed with i in equation (1).[6]

The mixed multinomial logit is a generalized form of the the standard conditional logit model introduced by McFadden (1973). The probability of individual i choosing alterna-

[6]Note that the random coefficients model as presented above can be rewritten to $U_{jt}^i = x_{jt}\beta + z_{jt}\mu^i + \epsilon_{jt}^i$, where $\eta_{jt}^i = z_{jt}\mu^i + \epsilon_{jt}^i$ represents the random part of utility. In this error component representation correlation between alternatives is introduced by the random component $z_{jt}\mu^i$ contrary to the standard logit where the error component consists solely of the iid component ϵ_{jt}^i.

tive j conditional on the vector of random coefficients β^i of individual i is represented by (for expository purposes we will omit the time index t from here on):[7]

$$L_j^i(\beta_i) = \frac{exp\left(V_j^i(\beta^i)\right)}{\sum_k exp\left(V_k^i(\beta^i)\right)}. \tag{2}$$

The individual vector β^i, however, is not observable. The (unconditional) mixed logit probability for individual i to choose alternative j is derived as an integral of the standard logit probabilities by integrating out the vector of random parameters β^i and represented by

$$P_j^i = \int \left(\frac{exp\left(V_j^i(\beta^i)\right)}{\sum_k exp\left(V_k^i(\beta^i)\right)} \right) f(\beta) d\beta, \tag{3}$$

where $f(\beta)$ is the mixing distribution of the vector of random coefficients, usually specified to be normal or lognormal.[8]

One of the advantages of the mixed logit model vis-à-vis the conditional logit model or the nested logit model is that it does not exhibit the independence of irrelevant alternatives (IIA) property at any stage. In the conditional logit model the ratio of probabilities of two alternatives is independent of the attributes or the existence of all other alternatives yielding rigid substitution patterns. The nested logit model mitigates this problem as the IIA property does not hold for alternatives in different nests. However, it still holds within each nest and the nesting structure requires further assumptions on potential product groupings. In contrast, in the mixed logit model the ratio of probabilities of alternative j and alternative j' is dependent on all attributes and the existence of other alternatives than j or j'. Equation (4) for the cross-price elasticity of a change in the interest rate d of alternative j illustrates the flexibility in the substitution patterns:

$$\eta_{j'j}^i = -\frac{d_j}{P_{j'}^i} \int \beta_d^i L_j^i(\beta) L_{j'}^i(\beta) f(\beta) d\beta, \tag{4}$$

[7] The subsequent paragraphs introducing the mechanics of the mixed logit follow Train (2009).

[8] Note that the mixed logit probabilities collapse to the standard logit probabilities when all coefficients are identical across individuals.

where β_d^i is the individual coefficient on the interest rate d. The elasticity differs for each alternative j'. That is, an increase in the interest rate for alternative j will lead to different decreases in the probabilities for each alternative j' unlike in the standard logit model where the probability of choosing alternative j' is canceled out in the formula for the cross-price elasticity. Further, the change in the probability to choose alternative j' depends on the correlation between the conditional likelihoods of choosing alternative j' and j. Alternatives with similar attributes exhibit more switching between each other. To conclude, in the mixed logit model the substitution patterns are determined by the mixing distribution and thus determined empirically by the available data. No a-priori assumptions on product groupings is required.

The disaggregated approach helps us to mitigate the endogeneity problem between prices and unobserved product characteristics. Analyzing demand behavior on the individual level allows us to rule out the possibility that the demand units have an impact on prices and product characteristics (Goldberg, 1995). Based on the individual-level choices we derive market-level demand to be used in our simulation exercises through aggregation. As a consequence of the disaggregated approach we do not require any a-priori assumptions about the shape of the aggregate demand curve. We define the price derivatives of aggregated demand as the weighted sum of individual price derivatives. For aggregation we construct population weights based on the distribution of bank choice in our untreated sample, the representative DNB Household Survey.[9]

3.2 Supply

In a simplified banking model banks generate profits by lending money to firms below their own borrowing costs. As a common approach in the separate analysis of deposit or loan markets we allow for separate modeling of pricing decisions in the credit and the deposit markets (see for example Canhoto (2004) or Pita Barros (1999)). Focusing on

[9]For our estimation analysis on the product level, we only use observations with consistent answers for product choice as described in the data section. The question for the main bank for savings accounts is answered more frequently as some respondents do not report the exact account product but the corresponding bank. By weighting according to bank choice we aim to obtain representative weights for the aggregation procedure.

the latter we assume banks to maximize profits in the market for savings accounts with the deposit rates as their choice variables. Untypical of maximization problems, in our case the choice variables (i.e. the deposit rates) have a negative direct effect on profits. In order not to formulate a degenerated problem, we add $\bar{r_b}$ which is the expected loan rate for bank b. This set-up acknowledges that banks raise deposits to finance lending.[10] Offering savings accounts to consumers involves both variable and fixed operating costs which differ across the account products. Variable costs are for example additional needs for IT capacity and employees for administration and the provision of customer services. The difference in variable costs across products can result from reduced costs for services as for example for internet managed accounts or from differences in cost efficiencies across banks. We introduce product-specific costs c_j denoting the per unit of demand costs for account product j. We assume c_j for each product to be constant. The maximization problem of bank b owning a subset of products F_b can therefore be written as:

$$\max_{\{d_j \forall j \in F_b\}} \pi_b(\mathbf{d}) = \sum_{j \in F_b} (\bar{r_b} - c_j - d_j) q_j(\mathbf{d}) \tag{5}$$

where $q_j(\mathbf{d})$ depicts demand for savings account j and $\mathbf{d}$ is a $J \times 1$ vector of deposit rates. We can think of the term $\bar{r_b} - c_j$ $(= r_{j,net})$ as the expected loan rate (net of marginal costs) specific to product j. Setting d_j allows the bank to set the profit margin, $r_{j,net} - d_j$ for product j. This is analogous to the formulation of the problem when prices enter positively into the firms' profit functions and profit margins are equal to $p_j - mc_j$. Taking into account the optimal pricing decision rules for all banks and assuming Bertrand competition the Nash equilibrium is defined by the following system of first-order conditions:

$$q_j(\mathbf{d}) + \sum_{k \in F_b} (\bar{r_b} - c_k - d_k) \frac{\partial q_k(\mathbf{d})}{\partial d_j} = 0, \qquad j = 1, ...J. \tag{6}$$

[10] Banks can also use savings accounts as instruments meant to acquire client information, or to cross sell (Džmuráňová & Teplý, 2016).

Equation (6) can be rewritten in vector notation:

$$\mathbf{q}(\mathbf{d}) + \{\boldsymbol{\theta} \odot \boldsymbol{\Delta}(\mathbf{d})\}(\mathbf{r_{net}} - \mathbf{d}) = 0 \tag{7}$$

where $\mathbf{q}(\mathbf{d})$ is the $J \times 1$ demand vector, $\mathbf{r_{net}}$ is the $J \times 1$ net expected loan rate vector and $\boldsymbol{\Delta}(\mathbf{d}) \equiv \partial \mathbf{q}(\mathbf{d})/\partial \mathbf{d}'$ is the $J \times J$ Jacobian of first derivatives. $\boldsymbol{\theta}$ is the $J \times J$ product-ownership matrix, with $\theta(j,k) = 1$ if savings accounts j and k are offered by the same bank and $\theta(j,k) = 0$ otherwise. $\odot$ depicts element-by-element multiplication. Equation (7) can be used to back out the term $\mathbf{r_{net}}$ which is needed for the subsequent merger simulation.

3.3 Merger Simulation

We simulate merger conditions in 2010 as the counterfactual event as in the original situation reflected in the data ABN AMRO and Fortis Bank NL only merged in the second half of the year. We fit equation (7) with pre-event actual data from 2009 to back out the net expected loan rate vector r_{net}^{2009}. Before simulating 2010 conditions, we have to adjust the estimates for the expected loan rate for the changing environment on the banking markets. We use the change of the 3 month Euribor interbank lending rate between 2009 and 2010 ($\Delta Euribor_{2010,3months}$) to account for less profitable investment possibilities mainly due to changing monetary policy. We add the (negative) difference in the interbank lending rate from r_{net}^{2009} to obtain a proxy for 2010 expected net loan rate conditions $\hat{r}_{net}^{2010}$ (i.e. $\hat{r}_{net}^{2010}$=r_{net}^{2009}+Δ $Euribor_{2010,3months}$).[11]

In order to simulate merger deposit rates we rewrite equation (7) and solve for 2010 deposit rates d^{2010} using estimated demand parameters, bank first-order conditions, expected net loan return rates $\hat{r}_{net}^{2010}$ and the demerger-adjusted product-ownership matrix:

$$\mathbf{d}^{2010} = \hat{\mathbf{r}}_{net}^{2010} - \{\boldsymbol{\theta}^{2010} \odot \boldsymbol{\Delta}(\mathbf{d}^{2010})\}^{-1}\mathbf{q}(\mathbf{d}^{2010}). \tag{8}$$

We can solve for merger deposit rates using the system of linear demand functions

[11] The difference in the 3 month Euribor between 2010 and 2009 was approximately -0.4%.

$\mathbf{q}(\mathbf{d}^{post}) = \mathbf{a} + \mathbf{\Delta}(\mathbf{d}^{pre})'\mathbf{d}^{post}$ with $\mathbf{a}$ being the vector of intercepts (Björnerstedt & Verboven, 2014).

4 Data

We construct our dataset by merging data from two sources. We use data from the DNB Household Survey (DHS)[12], a representative Dutch panel survey, to obtain detailed household information including information on debt and asset holdings. Most importantly, this comprises individual product choices for savings accounts. We retrieve data from Dutch online comparison platforms for banking products, most notably 'SpaarInformatie', to obtain product-level information on savings accounts products. This includes the interest rate paid on the accounts and several forms of restrictions[13] applying to the account products. We observe all changes in the interest rate and calculate the annual average. Furthermore, we identify the introduction date for each account product and calculate how many years a product already is in the market.

Around 2,000 households participate in the DHS each year. While all members of the household answer questions on general information, only members of the household older than 16 are confronted with questions related to income and wealth. After identifying the account product by the entered account name we match account product information to each observation.[14] Respondents can enter information for up to seven savings accounts

[12]The data are collected through the 'CentERpanel' at CentERdata, handled by Tilburg University. The DHS consists of several questionnaires to collect information about household finances and individual financial decisions. The panel of households which is used for the survey is designed to constitute a representative sample of the Dutch population. Recruitment for the panel is based on a random national sample drawn from private postal addresses. Upon commitment for participation in the panel, households are included in a database. If a household already in the panel drops out of it, another household from the database with similar characteristics is included into the panel. Despite previous agreement to participate in the panel, response rates are typically around 80% and vary across the different questionnaires. In order to achieve full representativeness sample weights can be used. Participation in the panel is awarded with a financial compensation (Teppa & Vis, 2012).

[13]This comprises: i) online usage only ii) minimum amount requirements to open and maintain account, iii) bonus on minimum amount on account within a quarter and base rate on remainder, iv) fixed deposits, v) withdrawal limitations and vi) group eligibility constraints (e.g. account can only be opened by students).

[14]Survey participants have to report both the name of the bank and the product name for each of their accounts. Not all respondents report the exact product name which requires a hand matching procedure. During hand matching we rely on a comprehensive list of account products retrieved from 'SpaarInformatie'. Deviations in reporting from actual account names include abbreviations, typos or alternative naming. During hand matching we compare, on a bank-by-bank basis, the reported answers

in the survey. If a person reports several accounts we assign the one containing the highest amount of savings as a person's main account. If the information on the savings amount is not available we assign the account yielding the highest interest rate.[15] We drop observations for which we could not establish a match.[16] Further we disregard observations for individuals reporting that they do not have any savings account which corresponds to having chosen the outside option.[17] Thus we focus on modeling the choice between different account products conditional on using this savings vehicle and estimating price effects for customers staying in the market. Modeling the decision for alternative savings vehicles is beyond the scope of our paper.

In essence, our dataset includes one observation per person per year corresponding to the savings account a person has chosen. For every year and every individual we expand the dataset by all available accounts an individual is able to chose to obtain the conditional choice sets.

Table 1 lists the number of savings account products in our dataset by bank and year from 2007 to 2010. The first panel lists the amount of products offered by bank. The three large banks offer a wide array of products including five or more products. The smaller banks seem to specialize and often only offer one product. Roughly speaking we observe around 60 products in the market per year, two thirds of which are products exhibiting at least one of the above mentioned conditions. Approximately one third of total products are for online usage only.

Table 2 shows the market shares derived from our sample for 2007 to 2010. For each

with all available account products of the respective bank and choose the account which is closest in terms of name similarity. If a survey participant specifies a bank name but no concrete account name as the respondents have either entered '99' (equivalent to 'I don't know') or reported a generic word for savings account (e.g. rekening) we assign the basic respectively most often used account of that bank. We do not include these observations in our main dataset but use them for robustness checks.

[15] Ideally, we would use the savings account with the highest deposits in all cases but this information is only reported in relatively few cases. Still, there is a positive correlation between accounts with the highest interest rate and highest deposits for individuals reporting the savings amount.

[16] We drop observations for which the reported account name corresponds to another bank than actually reported by the survey participant. We drop observations for which no account identification is possible as given answers are too remote to the actual account names to constitute a reliable match. We also drop observations which could be matched but exhibit inconsistent timing. These are observations for which respondents refer to account products which are not in the market at that time.

[17] This concerns individuals reporting a bank but no account name or reporting actively that they do not have one.

year our sample consists only of individuals who were observed in the previous period in order to identify whether a person has opened a new account or (re)chosen the account from the previous period. In line with the market description of the Dutch competition authority (ACM, 2014) we observe a highly concentrated market. The three large banks account for almost 80% of the market. Following the three large banks the market sustains a few mid-sized banks (SNS Bank, ASN Bank, Fortis Bank NL and Aegon) and a larger group of small fringe banks.

Figure 1 shows that there is considerable variance in the offered interest rates both across and within banks. We illustrate this by comparing the interest rates on accounts in 2008. Accounts are grouped by bank and according to whether account restrictions apply or not. For all banks displayed restricted accounts offer on average higher interest rates than unrestricted accounts. Note that Fortis Bank NL only offered restricted savings accounts. The group of other banks offers on average the highest interest rates. Presumably, smaller fringe banks have to raise awareness in the market by higher interest rates to compensate for lower marketing expenses or presence through bank branches. The interest rate spread between and within restricted and unrestricted accounts indicates at banks applying product differentiation. Note further that banks offer several unrestricted accounts at different interest rates which seems to be implausible at first sight. These were often introduced in different years. Anderson et al. (2014) find that banks use product age for price discrimination. New products with higher deposit rates are used to attract new customers while existing customers stick to old products with lower deposit rates.

The effect of loosening monetary policy after the financial crisis in 2008 is depicted in Figure 2. It displays the average interest rate across account products for the three large banks and Fortis Bank NL between 2007 and 2014. Since 2008 there is a steady decline in the interest rate for all banks with the exception of a short relief for some banks in 2011. The last products of Fortis Bank NL are withdrawn from the market in 2011.[18]

The changing macroeconomic and monetary conditions do not only affect the average

[18]While ABN AMRO continues these products under its name for some while, customers are successively switched to ABN AMRO products.

interest rates but also the dispersion of interest rates offered in the market. In Figure 3 we demonstrate this trend. The spread between the highest and lowest priced account product and more generally the variance in interest rates was reduced substantially between 2006 and 2014. With loosened monetary conditions banks reduce differentiating prices within their own set of products and vis-à-vis competitors.

5 Estimation

We estimate the following main specification of the demand-side of our model for the calibration period from 2007 to 2009:

$$\begin{aligned} U^i_{jt} = \alpha_b &+ \beta^i_1(interest\ rate_{jt}|opened{=}0\ ^i_t) \\ &+ \beta^i_2(interest\ rate_{jt}|holding{=}1\ ^i_t) + \beta^i_3 internet_{jt} \\ &+ \gamma_1 minimum\ amount_{jt} + \gamma_2 bonus\ rate_{jt} + \gamma_3 other_{jt} + \gamma_4 product\ age_{jt} \\ i = 1,...,I, j = 1,...,J, b = 1,...,B, t = 1,...,T. \end{aligned} \tag{9}$$

In our main specification our model includes bank intercepts, α_b for large and mid-sized banks[19], in order to account for bank specific characteristics such as brand reputation and marketing expenses potentially driving consumer choice on the product-level. Bank fixed effects capture potential correlations between unobserved factors and the interest rate on the bank level. We believe that in the retail banking market unobserved factors potentially influencing consumer decision can be aggregated on the bank level for several reasons. Firstly, concerns about financial stability for instance apply on the bank level and not on the product level. Secondly, differences in service quality other than reflected by our product differentiation variables as for example *internet* should arise only across banks as banks potentially use the same hotlines, online platforms etc. for all their products. Thus, past experience for products can be captured on the bank level. Lastly, unlike in the market for consumer goods such as for example cars, differences in style and

[19]Including bank fixed effects for a total of 7 banks subsumes a common fixed effect for the remaining fringe banks. This common effect captures the effect of unobserved factors for choosing the product of a potentially less known player in the market.

reputation should not play a role for banking products. The coefficients for *interest rate* interacted with *opened* and *holding* are random and vary across individuals. We employ the interactions with *opened* a dummy for whether a person has opened the account in period t, and *holding* a dummy for whether a person (re)chose the same account product as in the previous period $t-1$, in order to account for different sensitivities for the interest rate among customers. We consider individuals having chosen a new account (shoppers) to be more aware of market conditions and investment possibilities than individuals sticking to their previously made choice and potentially being affected by consumer inertia. The random coefficients β_1^i and β_2^i capture additional potential heterogeneity regarding the relevance of the interest rate for product choice across individuals.

The following dummy variables are product characteristics serving product differentiation. The dummy *internet* indicates whether an account is for online usage only. We model this restriction having heterogeneous effects across individuals. For instance, younger customers might be more willing to accept self administration of their accounts online due to a higher exposure to digital processes. The remaining product characteristics enter non-randomly into our model as we assume that the taste for conditions is the same for all customers. The variable *minimum amount* indicates whether account opening requires a certain minimum amount. *bonus rate* depicts whether customers are rewarded for not withdrawing savings by offering a bonus on the minimum amount within a quarter and a base rate on the remainder. *other* subsumes the restrictions that an account features one or more of the following: fixed deposit plan, withdrawal limitations or group eligibility constraints (e.g. only for youth). The variable *product age* measures the time a product has already been available in the market in years. As mentioned, banks can use the age of a product as a price discrimination tool. We estimate our model in a panel to account for correlations in repeated decision making by the same individuals. Further, in order to account for correlated decision making within households we cluster standard errors at the household level. Table 3 depicts the respective summary statistics for the chosen savings accounts.

6 Results

Table 4 reports our regression results. Equation (9) is estimated with data from the calibration period from 2007 to 2009. The three reported specifications differ with regards to the set of bank fixed effects included. In our main specification containing fixed effects for large and mid-sized banks all our estimated parameters are statistically significant at conventional confidence levels.

Regarding the group interest rate variables for individuals having opened a new account or (re)chosen their previous account, we obtain two moments for the distribution of the coefficients as we specified them as random. The average effect for customers opening a new account is substantially larger than for customers sticking with their previously made decision. We interpret this as a first sign of consumer heterogeneity. Consumers opening a new account can be considered as shoppers who are more aware of favorable pricing conditions. Consumers who already made a choice in one of the previous periods react less sensitively to the interest rate as they might be affected by consumer inertia. A second indication for consumer heterogeneity is that the standard deviations for the three variables specified as random are both large and statistically significant.

Account restrictions affect product choice differently. The product restrictions *minimum amount*, *internet* and the account restrictions subsumed under *other* affect choice probabilities negatively. This seems reasonable as conditions such as withdrawal limitations or a required minimum amount impose true costs or obstacles to open an account. The standard deviation estimated for the random coefficient on *internet* is surprisingly large which could reflect heterogeneity in the preference to self administer an account. While some customers might have difficulties in not being able to rely on counter services at bank branches and for example commissioning transfers in online portals, others might well cope with doing so and even appreciate products with well developed online platforms. The coefficient on *bonus rate* is not significant in any of our specifications. We take from this that the restriction does not negatively affect consumer choice. Bonus interest payments on the highest balance within a quarter do not constitute a hard restriction in the sense that consumers are always worse off in comparison to unrestricted accounts.

Patient consumers might be rewarded while consumers in need of liquidity might lose out when withdrawing funds and receiving on average a lower interest rate. Product age has the expected positive effect on consumer choice indicating potential lock-in situations for customers.

Across our three chosen specification results are quite similar concerning the sign of the most coefficients and statistical significance. However, the level of the two group coefficients for the interest rate increases in the amount of fixed effects included. As previously discussed, including bank fixed effects is important in order to account for unobserved factors as for example service quality which are potentially correlated with the interested rate and affecting consumer choice. In light of the differences between the estimates for the interest rate on which we base the demand side calibration of the model we prefer the specification including bank fixed effects for large and mid-sized banks in our sample. Including neither only fixed effects for the large banks nor for all banks constitutes a compromise between controlling for unobserved factors and not overfitting the model.

Table 5 reports derived own-price elasticities averaged on the bank level for 2007 to 2009. Note that the signs are positive in our application as an increase in the interest rate usually triggers an increase in demand. With only a few exceptions demand reactions are elastic. The three large banks have among the lowest elasticities while some of the smaller fringe banks have quite large estimates for the own-price elasticity. The range of own price elasticities reflects different degrees of market power across banks. Larger banks seem to be able to price less aggressively as a result. Over time elasticities seem to increase on average. This might be a result of lower interest rates in general leading to a movement on the aggregated demand curve to a higher elasticity area. Columns (2) and (3) of table 6 report the results of OLS regressions of cross-price elasticities on product characteristics. The results presented in column (2) indicate that interest rates are positively correlated with own-price elasticities suggesting profit-maximizing behavior of the banks applying favorable prices to consumers where elasticities are high and vice versa. Column (3) reiterates this statement reporting regression results including bank

fixed effects.

Illustrating cross-price elasticities and correspondingly substitution patterns is more challenging. Each year the choice set consists of 60 products on average leading to roughly 60 times 60 cross-price elasticities. To gain insight into the substitution patterns on the product level we regress cross-price elasticities on similarity measures for the account restrictions employed in the demand side estimation. The dummy variable takes the value one if both account products have the same outcome in the respective account restriction and takes the value zero otherwise (e.g. if both accounts are online only account products (or both are not) the similarity dummy for online usage is one). Column (1) in table 6 presents the results of an OLS regression on the similarity measures and a constant. The average for cross-price elasticities (not in the table) is -0.043. The coefficients for the similarity measures for the restrictions *other*, *minimum amount* and *internet* are statistically significant and negative. Our intuition is that similar alternatives have increased switching activities between them (i.e. more negative cross-price elasticities). Product age has a positive sign potentially indicating that consumers tend to switch to newer products once they switch. We take from these results that our model is capable of capturing heterogeneous reactions to changes in the interest rates.

Table 7 reports the simulation results for 2010 applying the simulation procedure introduced in section 5 by solving for the vector of deposit rates as defined in equation 8. Column 1 displays simulated weighted interest rate averages for 2010 for the case of joint ownership of ABN Amro and Fortis Bank NL (merger). Column 2 displays analogously the results for the case of separate ownership of ABN Amro and Fortis Bank NL (no merger). In both cases we use the backed-out expected net loan vector using data from 2009 adjusted by the change in the 3 month Euribor rate for the simulation. Column 3 reports realized weighted interest rates for comparison. In order to obtain weighted averages we aggregate product-level interest rates on the bank level using the market shares of the products as weights. We use weighted interest rates in order to obtain a more realistic measure for the final effect on consumers and not let our predictions be driven by account products with marginally small market shares. Results in column

4 finally present predicted merger effects in percentage points reporting the difference in predictions from columns 1 and 2. For all banks we predict negative merger effects with the highest effects for the two merging banks ABN Amro and Fortis Bank NL. In terms of percent change, ABN Amro on average reduces interest rates by $\left(\frac{-0.112}{1.879} \approx\right) -6\%$ and Fortis Bank NL by $\left(\frac{-0.212}{2.419} \approx\right) -8.76\%$. A striking result is that the model predicts substantial price effects also for banks not directly involved in the merger suggesting increased detrimental effects for consumers.

We note that our model is not able to predict well the general level of interest rates which can be seen in the comparison of predicted interest rates under the no-merger situation (column 2) and realized values (column 3). Average interest rates decreased on average by 0.9 percentage points between 2009 and 2010 (cf table 3) which is a stronger decline than the change in the 3 month Euribor between 2009 and 2010. It seems that retail interest rates reacted relatively sluggishly to the changing monetary environment as a large drop in the interbank loan rate occurred earlier than 2009. If we adjust the expected loan rate by 0.9 instead of 0.4 as performed in the current set-up we obtain an improved fit in terms of predicting the levels of realized interest rates (results not reported). This points at the challenge when using our model as a forecasting tool to calibrate the model with accurate forecasts about monetary conditions. However, the main goal of our model is to predict mutually dependent price changes of banks in the market given underlying substitution patterns of consumers.

7 Conclusions

In this paper we estimate a structural model with an application to the Dutch retail banking market. We use our model to simulate merger effects on interest rates on savings accounts of the *ABN AMRO/Fortis Bank NL* merger. The merger was initiated in late 2007 and completed in July 2010. For 2010 we simulate prices for the merger and the no merger case. Using detailed consumer-level data we are able to model demand choices driven by heterogeneous preferences.

We predict that the merger had significant effects on interest rates in the market. ABN AMRO would have priced interest 6% lower and Fortis Bank NL would have priced interest 8.76% lower on average in the merger case. Our model also predicts significant interest declines for the other market participants in the merger case.

Our findings suggest that the merger between ABN AMRO and Fortis Bank NL exhibits social costs prior to completion. It harmed consumers through lower interest rates on their savings accounts. Regarding the trade-off between financial stability and competition policy in the banking markets, our results suggest that the costs of stabilizing financial markets do not only include the capitalization measures but also costs due to lessened competition. Avenues for future research comprise incorporating financial markets in the supply side in order to simulate effects had the state aid not been granted.

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Appendix

Table 1: Number of products by bank and year

	2007	2008	2009	2010
rabobank	4	7	7	7
ingbank	8	8	10	8
abnamro	9	10	9	9
snsbank	2	2	2	2
fortisbank	5	6	6	7
aegon	3	4	4	4
argenta	1	2	2	2
asn	4	4	4	4
atb	2	2	2	2
crediteurope	1	1	1	1
dsb	2	2	2	-
friesland bank	1	1	1	1
garantibank	2	2	2	2
nationalenederlanden	1	1	1	1
ohra	2	2	2	2
regiobank	4	4	4	4
robeco	1	1	1	1
triodos	1	1	2	2
centraalbeheer	-	1	1	1
moneyou	-	1	1	1
nibc	-	1	1	1
leaseplanbank	-	-	-	1
total	53	63	65	63
restricted	35	44	45	43
internet only	15	21	22	22

Notes: The table displays the amount of account products offered by bank. The lower panel depicts the total amount of account products, the amount of account products with any kind of restriction and the amount of account products which are internet managed only.

Table 2: Bank chosen for main account

	2007	2008	2009	2010
rabobank	37.06	38.02	35.45	34.84
ingbank	28.96	27.38	26.74	28.44
abnamro	12.77	12.30	11.15	11.11
snsbank	4.22	4.53	4.97	6.21
fortisbank	3.31	3.15	4.01	4.24
aegon	3.76	3.79	3.14	3.01
argenta	0.34	0.56	0.87	0.85
asn	3.99	4.63	5.49	6.12
atb	0.46	1.02	0.87	0
dsb	1.48	1.11	2.00	-
friesland bank	0.68	0.46	0.61	0.38
garantibank	0.23	0.09	0.26	0
ohra	0.34	0.46	1.31	0.94
regiobank	0.46	0.37	0	0.09
robeco	1.94	1.57	0.70	1.13
centraalbeheer	-	0.28	0.17	0.19
crediteurope	0	0.19	0.70	0.09
triodos	0	0.09	0.26	0.28
moneyou	-	0	0.35	0.85
nibc	-	0	0.96	1.13
nationalenederlanden	0	0	0	0.09
Observations	877	1081	1148	1062

Notes: This table displays the distribution of banks chosen by year in our sample. If a person reports several accounts, we assign the one containing the highest amount of savings as a person's main account. If the information on the savings amount is not available we assign the account yielding the highest interest rate. We include only individuals who were observed in the previous period in order to identify whether a person has opened a new account or (re)chosen the account from the previous period. We exclude all observations for which we cannot assign a product choice and individuals who have chosen the outside option. The figures on bank choice are displayed in percentage points.

Table 3: Summary statistics

	mean	sd	min	max
2007				
Interest average	2.9	.81	.51	4.5
Minimum amount	.3	.46	0	1
Bonus rate	.16	.37	0	1
Other	.1	.3	0	1
Internet	.3	.46	0	1
Product age	3.3	1.6	0	5
Opened	.093	.29	0	1
Holding	.91	.29	0	1
2008				
Interest average	3.4	1.1	.5	5.4
Minimum amount	.31	.46	0	1
Bonus rate	.17	.38	0	1
Other	.12	.33	0	1
Internet	.35	.48	0	1
Product age	3.6	2.2	0	6
Opened	.17	.38	0	1
Holding	.83	.38	0	1
2009				
Interest average	2.8	.81	1	4.8
Minimum amount	.32	.47	0	1
Bonus rate	.19	.39	0	1
Other	.12	.32	0	1
Internet	.35	.48	0	1
Product age	4.2	2.4	0	7
Opened	.5	.5	0	1
Holding	.5	.5	0	1
2010				
Interest average	1.9	.45	.46	3.2
Minimum amount	.29	.45	0	1
Bonus rate	.19	.39	0	1
Other	.1	.3	0	1
Internet	.36	.48	0	1
Product age	4.9	2.5	0	8
Opened	.51	.5	0	1
Holding	.49	.5	0	1

Notes: This table reports summary statistics of variables used in the regression analysis separately by year.

Table 4: Demand side estimates

	(1)	(2)	(3)
Minimum amount	-0.720***	-0.756***	-0.971***
	(0.089)	(0.098)	(0.082)
Bonus rate	0.045	0.040	0.194**
	(0.077)	(0.079)	(0.078)
Other	-0.672***	-0.720***	-0.634***
	(0.114)	(0.116)	(0.116)
Product age	0.508***	0.593***	0.441***
	(0.027)	(0.031)	(0.020)
Interest average|Opened=1	1.047***	1.339***	0.739***
	(0.086)	(0.093)	(0.067)
Interest average|Holding=1	0.196***	0.371***	-0.011
	(0.061)	(0.066)	(0.045)
Internet	-0.515**	-0.516**	-0.730***
	(0.206)	(0.203)	(0.212)
SD			
Interest average|Opened=1	0.940***	1.241***	0.692***
	(0.097)	(0.113)	(0.095)
Interest average|Holding=1	0.997***	1.186***	0.765***
	(0.074)	(0.078)	(0.060)
Internet	4.947***	4.867***	5.114***
	(0.405)	(0.395)	(0.422)
Observations	172896	172896	172896
Bank fixed effects	large and mid-sized banks	all banks	large banks

* p<0.1, ** p<0.05, *** p<0.01

Notes: This table displays the results of different demand side specifications using the mixed logit estimator for the calibration period 2007-2009. Reported coefficient estimates represent effects on marginal utilities and not on choice probabilities. Standard errors are clustered at the household level and displayed in parentheses. The interactions with the interest average are mutually exclusive. A person either has opened a new account or (re)chosen the previous alternative. Hence, the coefficients can be interpreted as group averages. The first panel reports point estimates for the included coefficients. The second panel lists the second moment of the distribution of the covariates specified as random. All estimations include a different set of bank fixed effects which are not reported in the table. Our main specification reported in column (1) contains fixed effects for each of the three large banks (Rabobank, ING and ABN AMRO) and the four mid-sized banks (Aegon, ASN, SNS Bank and Fortis Bank NL). The specifications in column (2) and (3) include fixed effects for all banks and for large banks only respectively. The mixing distribution for the random coefficients is the normal distribution. The size of the individual choice set determines how many observations enter the estimation for each person.

Table 5: Own-price elasticities averaged by bank

	2007	2008	2009
rabobank	0.998	1.595	1.373
ingbank	1.582	1.130	1.485
abnamro	1.056	1.615	2.365
regiobank	1.119	0.794	2.392
triodos	1.549	1.093	2.742
aegon	2.384	3.806	3.556
argenta	3.780	5.112	3.889
asn	2.514	2.467	2.215
garantibank	3.023	5.365	4.268
snsbank	3.281	3.110	3.412
atb	5.541	5.259	3.299
crediteurope	4.944	6.515	3.928
nationalenederlanden	1.822	1.589	3.303
ohra	4.195	5.380	6.204
robeco	1.202	0.879	1.062
fortisbank	1.202	2.513	3.876
dsb	2.151	2.803	3.670
friesland bank	2.364	1.852	2.198
moneyou		8.600	6.396
nibc		9.143	6.359
centraalbeheer		9.384	8.526

Notes: This table displays the unweighted average of own-price elasticities by bank.

Table 6: Correlations of elasticities

	cross-price	own-price	own-price
Other (same)	-0.009***		
	(0.003)		
Minimum amount (same)	-0.011***		
	(0.002)		
Bonus rate (same)	0.029***		
	(0.003)		
Product age (same)	0.010***		
	(0.003)		
Internet (same)	-0.053***		
	(0.002)		
Other		0.655**	0.860***
		(0.272)	(0.286)
Minimum amount		0.062	0.215
		(0.175)	(0.223)
Bonus rate		-0.363*	0.191
		(0.217)	(0.228)
Product age		-0.058	-0.098*
		(0.045)	(0.051)
Internet		-0.026	-0.068
		(0.179)	(0.222)
Interest Average		2.108***	1.710***
		(0.100)	(0.125)
Constant	-0.023***	-3.593***	-3.205***
	(0.004)	(0.433)	(0.517)
Observations	9296	168	168
Bank fixed effects	no	no	yes

* p<0.1, ** p<0.05, *** p<0.01

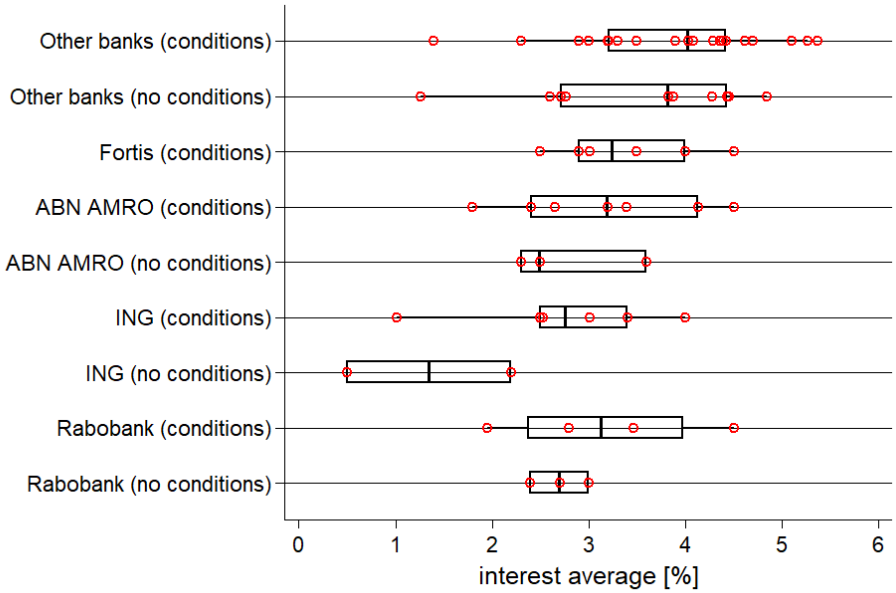
Notes: This table displays the results of different regressions of cross- and own-price elasticities on product characteristics similarity measures and product characteristics respectively using OLS.

Table 7: Predicted effects of the merger (2010)

	predicted merger interest rate	predicted no-merger interest rate	realized interest rate	predicted merger effect
rabobank	1.870	1.940	1.679	-0.0696
ingbank	1.482	1.527	1.606	-0.0440
abnamro	1.724	1.836	1.631	-0.112
triodos	1.879	1.963	1.523	-0.0841
aegon	2.448	2.504	1.684	-0.0568
argenta	2.759	2.841	2.308	-0.0817
asn	3.070	3.101	2.323	-0.0311
garantibank	2.965	2.994	2.107	-0.0295
moneyou	3.370	3.452	2.302	-0.0825
nibc	3.361	3.444	2.316	-0.0825
snsbank	2.364	2.394	2.139	-0.0306
atb	2.647	2.722	1.493	-0.0756
centraalbeheer	4.119	4.209	2.353	-0.0897
crediteurope	2.799	2.828	1.600	-0.0293
ohra	3.190	3.258	2.147	-0.0684
robeco	1.716	1.746	1.610	-0.0301
fortisbank	2.206	2.419	1.868	-0.212
frieslandbank	2.224	2.305	1.847	-0.0809

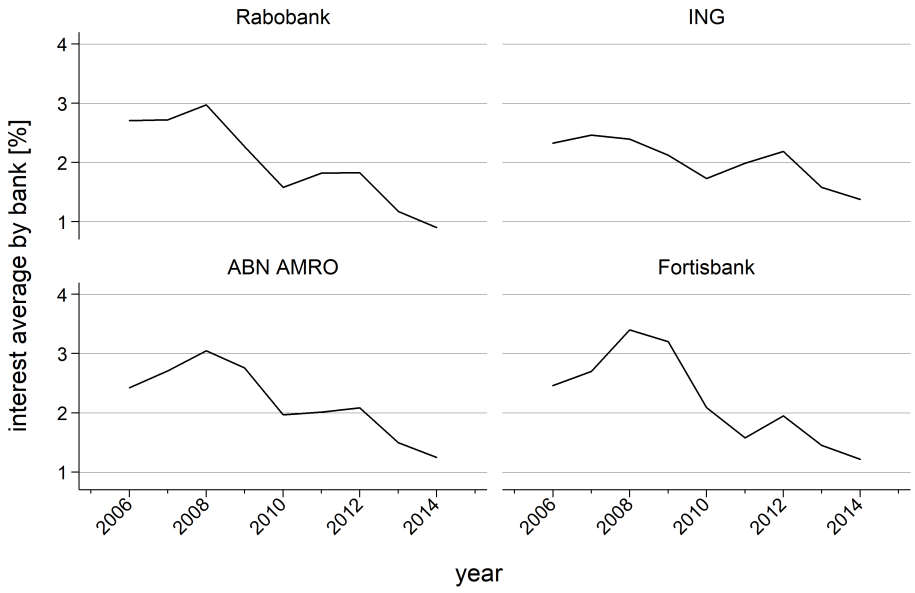
Notes: This table displays simulated weighted interest rate averages on the bank level for 2010 for the case of joint ownership of ABN Amro and Fortis Bank NL (merger) in column 1 and for the case of separate ownership of the two banks (no merger) in column 2. Column 3 reports realized weighted interest rate averages by bank. In order to obtain weighted averages we aggregate product-level interest rates using market shares as weights. Column 4 presents predicted merger effects on the bank level reporting the difference of predicted interest rates in the merger case in column 1 and predicted interest-rates in the no-merger case in column 2. All numbers are reported in percentage points.

Figure 1: Interest rate dispersion by bank (2008)



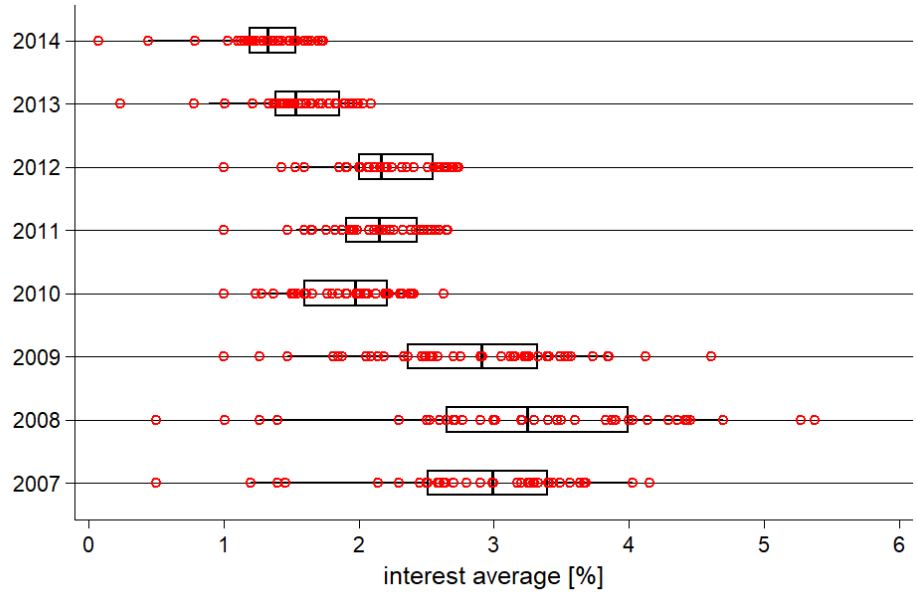
Notes: This figure illustrates interest rates paid on restricted and unrestricted accounts by banks in 2008. Fortis Bank NL only offered restricted account products.
Source: 'SpaarInformatie' and own calculations.

Figure 2: Development of average interest rates by banks



Notes: This figure illustrates the development of the average interest rate across account products by bank between 2007 and 2014.
Source: 'SpaarInformatie' and own calculations.

Figure 3: Interest rate dispersion by year



Notes: This figure compares interest rates of all available account products between 2007 and 2014.
Source: 'SpaarInformatie' and own calculations.