History-based price discrimination and welfare: Evidence from the Dutch mortgage market

Jurre H. Thiel†

Preliminary — please do not cite without permission

January 19, 2018

Abstract

This paper studies whether history-based price discrimination, charging different prices to existing and new consumers, increases or decreases consumer surplus, profits and welfare in markets with switching costs. Exploiting a ban on history-based price discrimination in the Dutch mortgage market, I estimate a structural model of demand and supply on micro-level data. The supply model consists of a dynamic game, which I estimate using a new solution concept: Sparse Markov Perfect Equilibrium (SMPE). In an SMPE, agents optimally pay attention to a subset of state variables instead of the full state. Contrary to existing methods, this allows estimation of games with large state spaces. My results indicate that, for an average mortgage, banning history-based price discrimination increases consumer surplus with €303 and total welfare with €596.

1 Introduction

History-based (or behavior-based) price discrimination, the practice of charging different prices to consumers with different purchasing histories, is a common practice: in markets such energy, telecommunications and finance new customers often get charged a different (lower) price than customers that stay with their previous supplier. Despite the widespread occurrence of such price differences, whether history-based

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* I thank Victor Aguirregabiria, Mauro Mastrogiacomo, José-Luis Moraga-Gonzalez and Matthijs Wildenbeest for their many comments and suggestions. This paper has benefited from presentations at 2017 EARIE in Maastricht and the University of Toronto. Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank. In this paper use is made of data of the DNB Household Survey.

† Vrije Universiteit Amsterdam and Tinbergen Institute. E-mail: J.h.thiel@vu.nl
price discrimination increases or decreases consumer surplus, profits and welfare is theoretically ambiguous. While a large literature documents the existence of history-based price discrimination, no paper has to the best of my knowledge empirically studied this question. In this paper, I study whether a ban on history-based price discrimination in the Dutch mortgage market increased or decreased consumer surplus, bank profits and welfare.

In the Dutch mortgage market, most households fix their interest rate for a certain period, most commonly ten years. When this period ends, they can either renew their mortgage at their current bank or switch to a different one. However, switching is costly: for the average household, switching costs are around €3000 in addition to the opportunity cost of time. Compared to uniform pricing, firms then have an incentive to charge higher prices to existing customers who find it costly to switch, and lower prices to new customers who they need to entice to switch. It is not obvious which of those two effects dominates consumer welfare. Indeed, the theoretical literature on history-based price discrimination in the presence of switching costs (Chen 1997; Taylor 2003; Gehrig, Shy, and Stenbacka 2012; Rhodes 2012) generally finds that, compared to uniform pricing, history-based price discrimination can be both increase and decrease consumer welfare, and is divided on the predicted effect on firm profits and total welfare.

Consistent with this theory, before 2013, Dutch banks would offer higher interest rates to customers that would prolong their mortgage than to customers that did not previously have a mortgage at that bank. Regulators were concerned that such history-based price discrimination was harmful to consumers. As a result, regulations were introduced stipulating that from 2013 onwards banks have to offer the same interest rate to new and to prolonging customers if those customers have a similar risk profile. I study whether this ban increased or decreased consumer surplus, bank profits and total welfare. I do so using administrative data from the Dutch central bank, which include the universe of mortgages from institutions under its supervision.

I find that before the 2013 ban there were indeed significant interest rate differences between prolonging and new customers. On average, a prolonging household paid an interest rate that was between .254 (in 2010) and .450 (in 2009) percentage points higher than a new customer. Since the average mortgage in my sample is about €150,000 this means that prolonging households paid between €183 and €324 per year more in interest (after tax).

To assess the effects of the ban on history-based price discrimination, I estimate a structural model of demand and supply. Because higher sales today imply more locked-in consumers in the future, banks play

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1. Typical costs include advice, taxation, notary and insurance fees. A calculation by the country’s largest mortgage broker suggests total costs of about €6000 for an average household. Since these costs are tax deductible and the top marginal income rate is 52%, the average household will incur monetary costs of about €3000. (https://www.hypotheker.nl/jouw-woonsituatie/hypotheekoversluiten/, Accessed March 8, 2017.)
2. These institutions have a combined market share of 75% - 80% (Mastrogiacomo and Van der Molen 2015).
a dynamic game. The state space of this game is infinite-dimensional. The reason for this is that when demand is heterogeneous today’s demand depends on the full joint density of previous market shares and household demographics. Traditional methods for estimation of dynamic games cannot deal with games with large state spaces. I solve this problem by introducing a new solution concept that is more amenable to estimation: Sparse Markov Perfect Equilibrium (SMPE). An SMPE is a Markov Perfect Equilibrium (MPE) in which firms perform sparse maximization (Gabaix 2014): they optimally condition their policy functions only on a subset of the payoff-relevant state variables. This can be motivated by relaxing the usual implicit assumption that information on the state is free. When firms have to perform costly market research, they will only pay for information on those state variables of which knowledge has the largest impact on their profits. This intuition is formalized in an SMPE. The relevant state in an SMPE is smaller than in an MPE so that SMPE’s can be estimated where estimating an MPE is impossible. Which state variables banks pay attention to can be estimated using standard variable selection techniques. My approach differs from the typical approach taken in the literature on the estimation of dynamic games, which tends to make ad hoc assumptions to deal with the curse of dimensionality.

SMPE gives a data-driven way to reduce the dimension of the relevant state space, while at the same time providing a micro-foundation for this procedure.

While it is possible, after determining which variables banks pay attention to, to estimate an SMPE in the same way as an MPE, I further introduce a new method to estimate Euler equations when a firm has more controls than state variables. This is the case in my model since banks set interest rates for many different types of loans while they pay attention to a few state variables. The method exploits the fact that when the number of controls is larger than the dimension of the (sparse) state, multiple values of the controls lead to the same future state. It must then be the case that the current period’s profits are maximal amongst those values. This intuition generates a set equations that can be estimated without making assumptions on the discount factor or banks’ expectations about the future.

My results indicate that banning history-based price discrimination leads to economically significant increases in consumer surplus, bank profits and welfare of .397 cents per euro loaned, or about €55 million per year in total, split almost equally between consumer surplus and bank profits. This is mainly due to a reallocation effect: the ban causes the market share of more efficient banks to increase.

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3. Most methods, most prominently Bajari, Benkard, and Levin (2007), contain a first stage in which firms’ actions are regressed on state variables. If the number of state variables is larger than the number of periods, this is impossible. So-called nested fixed point methods, in which an equilibrium is calculated for every candidate parameter vector, take too much time when the state space is large. The nested fixed point method of Abbring et al. (2017) is fast, but only applicable to models of firm entry and exit.

4. For example, many papers group states together. A prominent example is Collard-Wexler (2013), who groups plants of different sizes together and ignores markets with too many firms to reduce the state space. Another common strategy is to assume that firms’ behavior only depends on some average or total value of the state instead of the full distribution. For example, Kalouptsidi (2014), assumes that ship manufacturers’ value functions depend only on the total backlog in the market and Barwick and Pathak (2015) assume that real estate agent’s commissions depend only on average housing market conditions.
2 Related literature

This paper is broadly related to two strands of literature: one on history-based price discrimination and empirical models of state-dependent demand and one on simplifying solution concepts for dynamic games.

While there is a relatively large literature documenting the existence of history-based discrimination (Asplund, Eriksson, and Strand 2008; Ioannidou and Ongena 2010; Barone, Felici, and Pagnini 2011; Alé 2013), there work is not much work estimating its effects. Cosguner, Chan, and Seetharaman (2017) use simulations to study the effect of history-based price discrimination on cola manufacturers’ profits.

I exploit a ban on history-based price discrimination to study its effects on profits also look at consumer surplus and total welfare.

My paper is related to various other papers that estimate dynamic models of firm pricing in the presence of state-dependent demand. Che, Sudhir, and Seetharaman (2007) and Cosguner, Chan, and Seetharaman (2016) develop empirical models of supply in the presence of switching costs of the cereal and cola markets respectively. These markets do not feature history-based price discrimination. Rickert (2016) studies the effect of switching costs on supply estimates in the context of antitrust analysis. More broadly, my paper contributes to a growing literature documenting and estimating switching costs (Viard 2007; Dubé, Hitsch, and Rossi 2009; Cullen and Shcherbakov 2010; Miller and Yeo 2012; Nosal 2012; Cullen, Schutz, and Shcherbakov 2015; Ho 2015; Shcherbakov 2016; Weiergräber 2017). This literature estimates the effects of (different levels of) switching costs on market outcomes. I take the level of switching costs as given and focus on price discrimination.

Secondly, my paper contributes to a literature on simplifying solution concepts for dynamic games. In recent years, various solution concepts have been introduced, such as oblivious equilibrium (Weintraub, Benkard, and Van Roy 2008), experience based equilibrium (Fershtman and Pakes 2012) and moment-based Markov equilibrium (Ifrach and Weintraub 2016). These approaches make computation of equilibria of dynamic games easier. SMPE makes estimation easier. SMPE is closest to the moment-based Markov equilibrium of Ifrach and Weintraub 2016. In both approaches, firms pay attention only to a subset or summary of state variables. In Ifrach and Weintraub 2016 the assumption is that firms pay attention to the full state of dominant firms and some moments of the state of fringe firms. In an SMPE, no such assumptions are made. Instead, firms choose which variables they pay attention to based on a cost-benefit analysis. This means that SMPE can also be used when the dimension of a common state or of the states of dominant firms is large.

Another study on the profitability of history-based price discrimination on firm profits is Dubé et al. (2016). However, contrary to the Dutch mortgage market the movie market they study does not switching costs and the effects of history-based price discrimination thus follow from very different mechanisms.
3 The Dutch Mortgage Market

In the Netherlands, mortgages are primarily sold by banks. Three banks (ABN Amro, ING and Rabobank) dominate the market, with a competitive fringe consisting of smaller banks and pension funds. Approximately 55% of households own their house.\(^6\)

Mortgages in the Netherlands are, contrary to what is typical in the United States, with recourse so that consumers are personally liable for any outstanding mortgage debt in case of default. However, mortgages smaller than the average national house price are typically insured by the government through the so-called national mortgage guarantee (Nationale Hypotheek Garantie, or NHG in Dutch). The NHG pays off the remaining balance if a household defaults on its mortgage because of divorce, disability or unemployment.\(^7\) Enrollment in the NHG costs 1% of the loan sum. Banks view mortgages with NHG as low risk and offer significant interest rate discounts if consumers choose to enroll.\(^8\)

Consumer behavior is shaped by the generous deductibility of mortgage interest payments. Prior to 2013, mortgage interest was deductible from income taxes almost without preconditions. As a result, non-amortizing mortgages were extremely popular because they maximized tax savings. Since 2013, mortgage interest is only deductible for mortgages that amortize in at most 30 years, except for households who already purchased a non-amortizing mortgage prior to 2013.\(^9\) As a result, non-amortizing mortgages are no longer fiscally attractive and banks offer only annuity or linear mortgages to households without an existing non-amortizing mortgage. Banks are allowed to extend loans with a balance larger than the value of the underlying collateral. Up to 2012, mortgages were allowed to have a loan-to-value ratio of up to 106%. From 2013 onwards, the maximal loan-to-value ratio has gradually been lowered to 101% in 2016. The deductibility of mortgage interest, combined with the fact that household savings are locked in the pension system, makes it very attractive to take out large loans. As a result, down payments are rare.\(^10\)

3.1 Ban on history-based price discrimination

The origin of the Dutch ban on history-based price discrimination lies in the observation that after a large initial drop during the the 2008 financial crisis, mortgages interest rates in the Netherlands quickly increased again from 2009 onwards, while they stayed low in other European countries (Dijkstra, Randag, and Schinkel).\(^6\)

8. The average interest rate difference is between .4 and .7 percentage points (Fransman, 2017).
10. For example, in 2016, the average loan-to-value ratio of mortgages with NHG protection was 95%. See “WEW jaarcijfers 2016: Bouwen aan vernieuwing”. \url{https://www.nhg.nl/Over-NHG/Nieuws/Actueel-detail/ArtMID/833/ArticleID/129/WEW-jaarcijfers-2016-Bouwen-aan-vernieuwing} Accessed January 14, 2018.
Various possible reasons have been given for this, from collusion to the large reliance of Dutch banks on external funding, the cost of which increased sharply after the financial crisis. After an investigation, the Dutch competition authorities saw no reason to intervene, but they did provide some recommendations to make the Dutch mortgage market more competitive (Nederlandse Mededingingsautoriteit 2011). One recommendation, which the government followed, was to ban history-based price discrimination, as they believed the differences in interest rates between prolonging and first-time customers to be anti-competitive. As a result, the ban on history-based price discrimination came into effect on January 1, 2013.

The text of the law states that institutions are legally obliged to offer the same interest rate to households who renew their fixed interest rate period as to households who are first-time customers at that institution, if those two households have a similar risk profile. As the responsible regulator AFM later clarified, this does not mean that banks are barred from all types of price discrimination (Autoriteit Financiële Markten 2015). For example, institutions are allowed to (and in practice do) offer a discount if a household also has a deposit account at the same institution. The only requirement is that such discounts are equally available to existing and first-time clients.

4 Data

4.1 Data sources

I employ two data sources. My main data source is the Loan-Level Data (LLD) from the Dutch Central Bank (DNB). The LLD are a database of all outstanding mortgage loans of most of the institutions under DNB supervision. For every year between 2013 and 2015 inclusive, I observe a yearly sample of the full portfolio of the reporting institutions.

In addition, I use the DNB Household Survey (DHS). The DHS is a yearly survey of a random sample of approximately 2000 Dutch households on their household finances. I use the DHS because the LLD are a choice-based sample: it does not provide any information on households that purchase the outside option, i.e. no mortgage. I add the demographic information on those households from the DHS. I also use the DHS to infer switching behavior pre-2013, as detailed below. Since the LLD are a choice-based and the DHS is a random sample, I will adjust for different sampling probabilities in the demand estimation.

11. See Dijkstra, Randag, and Schinkel (2014a) and the other articles in the same issue of the Journal of Competition Law and Economics for an overview of the arguments.
12. The missing institutions are foreign institutions, which are not under DNB supervision, and some very small institutions for whom it would be an excessive administrative burden to provide the data. All in all, the LLD contain between 75% and 80% all outstanding mortgages in the Netherlands (Mastrogiacomo and Van der Molen 2015).
4.2 Inferring switching

From 2013 onwards, I observe a yearly sample of the full mortgage market. This means that I can follow households over time and observe their switching behavior. However, different banks use different schemes to encode household id’s. This means that when a household switches to a different bank, I cannot observe to which bank exactly. Therefore I probabilistically match switching households as detailed in Appendix B.1. Since the first wave of the LLD is 2013, I cannot follow households over time in the pre-ban period based on this data. I do observe which households could have switched and when but did not. That means that the LLD misses data on households that did switch. Therefore, I add data on switching households from the DHS for the period 2009-2012.

4.3 Sample selection

My empirical strategy depends on comparing the interest rate that new and prolonging households pay for the same mortgage. One reason other than purchasing history for such interest rate differentials may be differences in risk. To rule out as much as possible that interest rate differences are caused by differences in risk, I focus on mortgages with NHG insurance. As explained in Section 3, such mortgages are insured by the government so that from the perspective of mortgage underwriters they are more or less risk free. However, mortgages are only eligible for NHG insurance when the purchase amount is at most €245,000. As a result, households that have a mortgage with NHG differ systematically from those that do not. Table 1 shows that on average, households with NHG are 11.5 years younger, their household income is €20,000 lower and they own properties valued €120,000 less than households without NHG. My results should thus be understood to be local to this subsample.

I further restrict my sample by only considering mortgages with a fixed interest rate period of around five, ten, fifteen or twenty years. If a mortgage has a fixed interest rate period within six months of any of these periods, I round off the duration to that length, i.e. I round a fixed interest rate period of 57 months to

<table>
<thead>
<tr>
<th>NHG</th>
<th>No NHG</th>
</tr>
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<tbody>
<tr>
<td>Age household head (years)</td>
<td>37.5</td>
</tr>
<tr>
<td>Household income (€)</td>
<td>50536</td>
</tr>
<tr>
<td>Initial loan (€)</td>
<td>96939</td>
</tr>
<tr>
<td>Property valuation (€)</td>
<td>196943</td>
</tr>
<tr>
<td>Observations</td>
<td>766093</td>
</tr>
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</table>

Table 1: Comparison of households with mortgages with and without government insurance (NHG), for household who start a new fixed interest rate period in the years 2009-2015.

13. In 2015. The maximum purchase amount was somewhat higher in previous years, up to €276,190 in 2012.
Table 2: Proportion (%) of fixed interest period durations by start year of the fixed interest rate period.

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</thead>
<tbody>
<tr>
<td>5 years</td>
<td>12.71</td>
<td>12.42</td>
<td>24.94</td>
<td>25.80</td>
<td>31.36</td>
<td>26.29</td>
<td>10.55</td>
</tr>
<tr>
<td>10 years</td>
<td>79.28</td>
<td>80.28</td>
<td>66.19</td>
<td>63.98</td>
<td>64.30</td>
<td>64.50</td>
<td>63.98</td>
</tr>
<tr>
<td>15 years</td>
<td>2.56</td>
<td>1.91</td>
<td>3.12</td>
<td>3.59</td>
<td>2.32</td>
<td>2.98</td>
<td>8.08</td>
</tr>
<tr>
<td>20 years</td>
<td>5.46</td>
<td>5.40</td>
<td>5.74</td>
<td>6.63</td>
<td>2.02</td>
<td>6.23</td>
<td>17.39</td>
</tr>
<tr>
<td>Observations</td>
<td>85021</td>
<td>158751</td>
<td>150219</td>
<td>139623</td>
<td>102618</td>
<td>140686</td>
<td>178052</td>
</tr>
</tbody>
</table>

six years. The reason for not considering other fixed interest rate periods is that they all have very small market shares. Although for consistency I also exclude these fixed interest rate periods in the reduced form portion of this paper, the results derived therein are virtually unchanged would they have been left in.

In my data there remain interest rate differences between households purchasing the same type of loan in the same month even after controlling for history-based price discrimination. These differences are caused by the fact that I observe the date on which the loan deed was signed, which is different from the date the interest rate was offered: e.g. one household who signed their mortgage in March might have received their interest rate offer in January and another their (different) offer in February. A second cause of these differences is other types of price discrimination which I do not observe. Most banks for example offer a small discount on the interest rate if a household opens a deposit account at the same bank. Therefore, I take as the interest rate the modal interest rate of the same product in the same month. Some products have zero sales in certain months. For those loans I impute the interest rate based on a simple linear regression.14

4.4 Sample statistics

Table 2 describes the relative market shares of the remaining fixed interest rate durations. A fixed interest rate period of ten years is by far the most common, with a market share between 64% and 80%. A five year period is the second most common, with relatively small market shares for fifteen and twenty years. In 2015 the market share of ten and twenty year fixed interest periods increases dramatically. I attribute this to consumers wanting to “lock in” the historically low interest rates in 2015.

Table 3 describes the remaining loans in my sample. The average interest rate decreases from 2009 (5.26%) until 2015 (2.81%). The average fixed interest rate period is approximately ten years, comparable with the mode. The proportion of loans that is prolonged rather than a new purchase increases dramatically after the history based price discrimination ban in 2013, from around 10% before to between 22% and 44% after. This means that household switch less often to a different bank after their fixed interest rate period ends. This is consistent with the theoretical prediction that markets with history based price discrimination

14 I run separate regressions for the interest rates for new and old customers. I include bank, loan type, fixed interest rate period and month fixed effects. The regressions have an $R^2$ of .827 (new customer interest rate) and .886 (old customer interest rate).
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<tbody>
<tr>
<td>Interest rate (%)</td>
<td>5.26</td>
<td>4.65</td>
<td>4.65</td>
<td>4.49</td>
<td>4.09</td>
<td>3.56</td>
<td>2.81</td>
</tr>
<tr>
<td></td>
<td>(0.47)</td>
<td>(0.44)</td>
<td>(0.51)</td>
<td>(0.53)</td>
<td>(0.55)</td>
<td>(0.59)</td>
<td>(0.49)</td>
</tr>
<tr>
<td>Current balance (€)</td>
<td>84008</td>
<td>89310</td>
<td>90774</td>
<td>90584</td>
<td>86857</td>
<td>87828</td>
<td>86350</td>
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<tr>
<td></td>
<td>(54220)</td>
<td>(53672)</td>
<td>(55667)</td>
<td>(53232)</td>
<td>(56394)</td>
<td>(57420)</td>
<td>(55165)</td>
</tr>
<tr>
<td>Fixed interest rate period (months)</td>
<td>120</td>
<td>120</td>
<td>114</td>
<td>115</td>
<td>105</td>
<td>113</td>
<td>139</td>
</tr>
<tr>
<td></td>
<td>37</td>
<td>36</td>
<td>42</td>
<td>45</td>
<td>36</td>
<td>44</td>
<td>53</td>
</tr>
<tr>
<td>Proportion prolonged mortgages (%)</td>
<td>11.0</td>
<td>9.8</td>
<td>12.7</td>
<td>11.0</td>
<td>21.9</td>
<td>30.2</td>
<td>44.0</td>
</tr>
<tr>
<td></td>
<td>(31.3)</td>
<td>(29.7)</td>
<td>(33.3)</td>
<td>(31.3)</td>
<td>(41.4)</td>
<td>(45.9)</td>
<td>(49.6)</td>
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<td>140686</td>
<td>178052</td>
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Table 3: Loans with NHG by start year of the fixed interest rate period. Standard errors in parentheses.

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</thead>
<tbody>
<tr>
<td>Annuity</td>
<td>4.05</td>
<td>3.78</td>
<td>4.77</td>
<td>7.53</td>
<td>34.88</td>
<td>43.53</td>
<td>36.37</td>
</tr>
<tr>
<td>Linear</td>
<td>0.35</td>
<td>0.44</td>
<td>0.56</td>
<td>0.81</td>
<td>2.50</td>
<td>4.47</td>
<td>4.37</td>
</tr>
<tr>
<td>Bullet</td>
<td>41.01</td>
<td>40.23</td>
<td>40.12</td>
<td>39.33</td>
<td>30.69</td>
<td>30.99</td>
<td>37.60</td>
</tr>
<tr>
<td>Savings mortgage</td>
<td>43.52</td>
<td>48.32</td>
<td>47.44</td>
<td>47.31</td>
<td>22.91</td>
<td>10.92</td>
<td>10.48</td>
</tr>
<tr>
<td>Life mortgage</td>
<td>7.76</td>
<td>4.89</td>
<td>5.12</td>
<td>3.47</td>
<td>6.20</td>
<td>7.41</td>
<td>7.88</td>
</tr>
<tr>
<td>Investment mortgage</td>
<td>1.35</td>
<td>1.35</td>
<td>1.27</td>
<td>0.99</td>
<td>1.24</td>
<td>1.42</td>
<td>2.04</td>
</tr>
<tr>
<td>Other</td>
<td>1.96</td>
<td>0.99</td>
<td>0.71</td>
<td>0.55</td>
<td>1.58</td>
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Table 4: Payment types of loans with NHG by start year of the fixed interest rate period.
Table 5: Average interest rate difference between prolonging and new customers.

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</tr>
</thead>
<tbody>
<tr>
<td>Prolonged mortgage</td>
<td>0.450***</td>
<td>0.254***</td>
<td>0.408***</td>
<td>0.293***</td>
<td>0.113***</td>
<td>0.0879***</td>
<td>0.200***</td>
</tr>
<tr>
<td></td>
<td>(0.0232)</td>
<td>(0.0170)</td>
<td>(0.0200)</td>
<td>(0.0143)</td>
<td>(0.00798)</td>
<td>(0.00684)</td>
<td>(0.0133)</td>
</tr>
<tr>
<td></td>
<td>(0.00256)</td>
<td>(0.00166)</td>
<td>(0.00253)</td>
<td>(0.00157)</td>
<td>(0.00175)</td>
<td>(0.00207)</td>
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</tr>
</tbody>
</table>

Standard errors in parentheses
Average interest rate difference between prolonged and new NHG mortgages
The independent variable is the interest rate. All regressions include product x month fixed effects.

∗ p < 0.05, † p < 0.01, ‡ p < 0.001

feature more switching than markets without (Chen 1997). Table 4 shows that before 2013, non-amortizing loans such as bullets and savings mortgages were by far the most popular. Because from 2013 onwards such new non-amortizing mortgages no longer qualify for interest rate deductibility, the proportion of non-amortizing loans that start a new fixed interest rate period is much smaller after 2013.

4.5 Evidence of history-based price discrimination

In this section, I present reduced-form evidence on the extent of interest rate differences between new and existing customers and the effect that the 2013 ban on history-based price discrimination had on these differences. To get an idea of these quantities, Figure 1 plots the difference in average interest rates between new and prolonging consumers for bullet loans with a fixed interest rate period of ten years, the most popular loan in the Dutch market. The figure shows that prolonging consumers on average paid higher interest rates than new consumers. After the 2013 ban on history-based price discrimination, this difference becomes noticeably smaller. However, the figure suggests that even after the ban interest rate differences persist.

The same trends appear in Figure 2, which graphs the average difference between the interest rate a consumer actually pays and the average interest rate agreed for that the same type of loan in the same month. Two loans are determined to be the of the same type if they are originated by the same institution, have the same repayment method (i.e. annuity or savings) and have the same fixed interest rate period duration. Before the 2013 ban, there was an average interest rate difference between new and prolonging customers of between .1 and .3 percentage points. After the ban, there is a dramatic drop in this difference. However, prolonging consumers still pay interest rates that are approximately .05 percentage points higher than new consumers, which suggests some non-compliance.

In Table 5, I regress the interest rate consumers pay on month × product fixed effects and whether the loan is prolonged or not. Thus, I compare the interest paid by prolonging and new customers for the
<table>
<thead>
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<th>Start date fixed interest rate period</th>
<th>New</th>
<th>Prolonged</th>
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<tbody>
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</tr>
<tr>
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<tr>
<td>2016</td>
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</table>

Figure 1: Average interest rate for bullet loans with a fixed interest rate period of ten years, by start date of the fixed interest rate period.
Figure 2: Average difference between agreed interest rate and average interest rate for the same product and fixed interest rate period.
same loan in the same month. Before the 2013 ban, prolonging consumers paid statistically higher interest rates than new consumers. This difference is also economically significant. Since the average household in my sample has a mortgage of around €150,000, the differences in interest rates imply that prolonging consumers paid between €183 (in 2010) and €324 (in 2009) after tax in yearly interest payments more for the same type of loan as new consumers. These estimates conform to previous estimates made by the regulatory agency in the run-up to the 2013 ban on history-based price discrimination.\(^{15}\)

After the 2013 ban on history-based price discrimination, the interest rate difference between prolonging and new consumers dropped but remains statistically significant (Table 5). In economic terms, a prolonging household with an average mortgage of €150,000 pays between €64 (in 2014) and €144 (in 2015) more for the same type of loan than a household who is a new consumer at the same bank. Thus, the ban on history-based price discrimination significantly reduced the interest rate difference between prolonging and new households, but did not eliminate it completely. This finding is consistent with statements made by the AFM, the regulatory agency charged with upholding the ban on history-based price discrimination, that there are some loopholes banks use to partially get around the ban.\(^{16}\) For simplicity, I will however assume that banks charge a single interest rate after the ban.

### 4.6 Empirical strategy

To estimate the causal effect of the ban on history-based price discrimination, I use the following empirical strategy. I estimate structural models of demand and supply. Since, as explained above, I am better able to follow switching households over time after 2013, I estimate both models on the post-ban period (2013-2015). Given estimates of banks’ policy functions after the ban, I can predict what interest rates they would have counterfactually set pre-ban had history-based price discrimination already been banned then. Comparing these counterfactual interest rates with observed interest rates gives an estimate of the effect of the ban on history-based price discrimination on interest rates. The estimated demand model then gives estimates of the effect of the ban on consumer surplus and estimates of marginal costs allow me to calculate the effect on bank profits. This strategy estimates a causal effect if I am able to control for all relevant changes in the mortgage market around the time of the ban. I discuss the assumption further in Section 7.

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15. See for example the newspaper article “Straf voor verlengen hypotheek moet van tafel”, Het Financieele Dagblad, 25 september 2010.

16. For example, many banks offer a discount if the mortgage contract is certified by a notary within a certain time frame. Since prolonging a mortgage does not require certification by a notary, such discounts are automatically not available to prolonging households (Autoriteit Financiële Markten 2015). Such discounts are now banned, but will still sometimes offered during my sample.
5 The demand for mortgages

5.1 Specification

I estimate a standard discrete-choice model of demand. The relevant market in month $t$ consists of households whose mortgages’ fixed interest rate periods end and households who move in that period and may purchase a mortgage if they buy rather than rent. Denote all households that make a purchasing decision at time $t$ by $H_t$. A household chooses from up to $J$ possible mortgages: from 2013 onwards, a household can only purchase a non-amortizing mortgage if it previously owned a non-amortizing mortgage. Denote all mortgages in household $i$’s choice set by $J_i$. Banks sell multiple mortgages. Denote by $J_b$ the set of mortgages sold by bank $b$. I denote by $j = 0$ the outside option, which is sold by “bank” $b = 0$.

In the remainder of this paper, I will often refer to households who have previously purchased a mortgage from some bank $b$. Such statements should always be understood to be valid for $b = 0$ as well, i.e. such statements also apply to households who previously purchased the outside option.

The utility household $i$ derives from mortgage $j$ depends on the mortgage’s characteristics $X_{jt}$, its interest rate $r_{jts}$, household characteristics $D_{it}$ and potentially switching costs $s_{it}$. I subscript the interest rate with $s \in \{0, 1\}$ to indicate the interest rates banks charge pre-ban to old and new customers, respectively.

Consumers face two frictions: switching costs and inattention. A household pays switching costs if it purchases a mortgage from a different bank—switching to a different type of mortgage by the same bank is free. This is a simplification since switching to a different type of mortgage will typically involve some costs. However, the main costs of switching to a different a bank—taxation, notary and insurance fees—do not need to be paid when staying at the same bank. Let $\Delta_{ijt}$ be a dummy denoting whether household $i$ needs to pay switching costs to purchase mortgage $j$. The second friction is inattention: many households do not even consider switching to a different bank when they receive an offer to renew their interest rate from their current bank. A recent survey indicates that only 40% of renewing households consider other options, the remaining 60% simply accept the offer from their current bank. Ignoring this inattention significantly biases the estimates of switching costs upwards. Therefore, I assume that a household that already has a mortgage only considers switching with probability $p^a = 0.4$.

---

17. It is possible that a household ends its fixed interest rate period prematurely. This is costly, but it can sometimes be worthwhile if interest rates have dropped sufficiently since the start of the fixed interest rate period. However, ending a fixed interest rate period prematurely does not imply the need to switch: most households end up renewing the loan at their current bank. Therefore, I take the choice to end a fixed interest rate period as exogenous and model the mortgage choice of households that do so the same as of households whose fixed interest rate period ends contractually.

18. The outside option includes not having a mortgage, as well as having a mortgage by an institution which is not in my sample.


20. See Kiss (2017) for more on disentangling attention and switching costs.

21. I’m looking into getting the access to the underlying data of the aforementioned survey so that this probability can change with household demographics.
interest rate with probability 1.

The utility household $i$ derives from purchasing mortgage $j$ is

$$u_{ijt} = X_{jt} \Pi_D D_{it} - (\alpha_{it} r_{jt1} + s_{it}) \Delta_{ijt} - \alpha_{it} r_{jt0}(1 - \Delta_{ijt}) + \varepsilon_{ijt}.$$ 

$\Pi_D$ and $\alpha_{it}$ are coefficients and $\varepsilon_{ijt}$ is an error term. The outside option gives utility

$$u_{i0t} = -s_{it} \Delta_{i0t} + \varepsilon_{i0t}.$$ 

In this specification, switching to and from the outside option is costly. The assumption that switching from the outside option is costly reflects that the same fees need to be paid when purchasing a new mortgage as when switching. Switching to the outside option is also costly as paying off a mortgage before its end date typically triggers a fine.

The model includes random coefficients on the interest rates $\alpha_{it}$ and switching cost $s_{it}$. I specify these random coefficients for household $i$ as follows:

$$\begin{pmatrix} \log \alpha_{it} \\ \log s_{it} \end{pmatrix} = \Pi_{ac} D_{it} + \Sigma \eta_{it},$$

$$\eta_{it} \sim \text{i.i.d. } N(0, I).$$

To keep the model tractable, I do not include full random coefficients on the product characteristics $X_{jt}$ but I do interact them with household demographics. I also restrict the off-diagonal elements of $\Sigma$ to be 0, i.e. there is no correlation between the random coefficients for interest rates and switching costs except through household demographics. I assume that $\varepsilon_{ijt}$ follow an i.i.d type 1 extreme value distribution, so that household $i$’s conditional choice probabilities $p_{ijt}$ have the usual mixed logit formulation:

$$p_{ijt} \equiv P(i \text{ purchases } j | X_{jt}, D_{it}, i \text{ pays attention}) = \int \frac{\exp\{u_{ijt}\}}{\sum_{k \in J} \exp\{u_{ikt}\}} d\Phi(\alpha_{it}, s_{it}),$$

where $\Phi(\cdot)$ is the joint distribution of household $i$’s random coefficients.

### 5.2 Discussion

The model makes some simplifying assumptions. Firstly, in reality the decision where to live and which mortgage (if any) to purchase is a joint one. For simplicity, I abstract from the housing decision and take households’ desired loan sum as given. I thus only model which mortgage household purchase and not for what amount. Loan-to-value ratios for NHG loans are on average around 95%, which indicates that most
households borrow close to as much as they can. Thus, conditional on a households’ decision to borrow or purchase a home, I do not expect that banks’ interest rates have an effect on the amount they borrow.

A second simplification I make is that households purchase a single loan. I do so despite the fact that many households combine different loans, for example a savings mortgage with an annuity, into a single mortgage. The reason for this is that the second mortgage almost always either has the same repayment method (but has for example a different maturity) or is an annuity. Modeling the choice of the second (and potentially third) loan would impose significant difficulties, since it would require a model for the decision how much of the total loan sum to allocate to what type of loan in additional to a model on which products to buy. However, there is little variation in the type of second loan so that the gains do not outweigh the benefits.

Thirdly, I assume that demand is static, despite the fact that households in this market face an inherently dynamic problem: when fixing their interest rate, they have to form expectations about the interest rates they face when they have to renew their interest rate. One reason I estimate a static model is precisely because I believe it is too complicated for most households to think ahead ten years and realize they might have to pay more then, let alone form correct expectations about the strategic behavior of banks in the future. Indeed, given that 60% of households do not even pay attention at the moment they have to make a decision, it seems unreasonable to assume a significant fraction pays attention to dynamic considerations. A second reason for estimating a static demand function is that virtually all households in my sample make only a single decision during my sample period, so that any dynamic model would be identified only by functional form.

5.3 Estimation

I estimate the model derived above by simulated maximum simulated likelihood. The only household characteristic I include is household income. For the product characteristics \( X_{jt} \) I use originating bank, repayment type (e.g. annuity, linear, bullet, savings, investment, life) and interest rate reset period dummies (5, 10, 15, 20 years).

To control for the endogeneity of interest rates I use the control function approach (Petrin and Train 2010). As instruments, I use banks’ cost of funding and previous market shares. The cost of funding is a valid instrument since it shifts banks’ supply curves but does not directly affect demand. Previous market shares are a valid instrument if they are uncorrelated with current unobserved product qualities. This is the case if shocks to unobserved product qualities in previous product qualities are uncorrelated with current shocks to unobserved product qualities\(^{22}\). Previous market shares are determined relatively long in the

\(^{22}\) Note that I do not require that market shares are uncorrelated with the level of unobserved product characteristics. The reason is that I estimate the first stage separately for every product. For a given product, its long-run unobserved product quality is given.
past: most households that have to renew their loans today fixed their interests ten years ago. Therefore I do not view this assumption as particularly restrictive.

To simulate the likelihood of a single household I draw $R = 100$ samples from the log-normal distribution. To reduce the number of required draws, I use Halton sequences instead of pseudo-random draws. A household that switches or purchases the outside option by definition has considered other options. The likelihood contribution of such a household given its draws $\{a_{itr}, c_{itr}\}_{r=1,...,R}$ is therefore

$$L_{it}(\Pi_D, \Pi_{ac}, \Sigma, \text{switches}) = \frac{1}{R} \sum_{r=1}^{R} \frac{\exp\{u_{ijt}(a_{itr}, c_{itr})\}}{\sum_{k=0}^{J} \exp\{u_{ikt}(a_{itr}, c_{itr})\}}.$$  

A household that didn’t switch might have done so because it didn’t pay attention or because it decided not to switch. If it didn’t pay attention, it simply renewed its existing mortgage so that its likelihood contribution is 1. Therefore, the likelihood contribution for a non-switching household is

$$L_{it}(\Pi_D, \Pi_{ac}, \Sigma, \text{renews}) = \frac{p^{|r|}}{R} \sum_{r=1}^{R} \frac{\exp\{u_{ijt}(a_{itr}, c_{itr})\}}{\sum_{k=0}^{J} \exp\{u_{ikt}(a_{itr}, c_{itr})\}} + (1 - p^{|r|}),$$

where $p^{|r|} = \frac{p^{|r|}}{1 - p^{|r|}}$ is the probability that a household paid attention conditional on renewing and $p^{|}$ is the marginal probability that a household switches.

As explained in Section 4, I have a choice-based sample in which households that purchase the outside option have a smaller probability of being in my sample than households that purchase an inside good. Manski and Lerman (1977) show that reweighing the simulated likelihood gives consistent estimates based on a choice-based sample. Let $q_i$ be the sampling probability of household $i$. The log-likelihood is then

$$\log L(\Pi_D, \Pi_{ac}, \Sigma) = \sum_i \frac{\log L_i(\Pi_D, \Pi_{ac}, \Sigma)}{q_i}.$$

### 5.4 Results

Estimation proceeds in two steps. In the first stage I regress banks’ policy functions on previous market shares and the cost of funding. I run separate regressions for every product, for both the interest rate paid by new and existing customers. As Figure 3 shows the instruments are highly relevant. The lowest partial $F$-statistic across all first stage regressions is 70. Most regressions also have a high $R^2$.

Estimates of the demand model are in Table 6. There is very little difference between the specification with and without random coefficients. Indeed, the estimated standard errors of the random coefficient disturbances are not significantly different from zero. Therefore, I use specification without random coefficients for the remainder of this paper.
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<tr>
<td>Observations</td>
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</table>

\(^1\) Standardized household income
\(^2\) Standard deviation of errors in random coefficient
\(^3\) Bank dummy values cannot be reported due to confidentiality
\(^4\) Mean coefficients implied by the estimated models for log α\(_{it}\) and s\(_{it}\)

Table 6: Demand estimates. Standard errors, in parentheses, account for first stage estimation error (Karaka-Mandic and Train [2003]). The baseline product is a 5 year annuity in the market for amortizing mortgages and a 5 bullet in the market for non-amortizing mortgages.
The estimates imply that the average own-interest rate elasticity is \(-1.37\). Demand amongst consumers that pay attention is much more elastic however with an average elasticity of \(-3.42\). This suggests that inattention causes interest rates to be significantly higher. The model implies average switching costs of \(0.774 / 0.912 = 0.849\) percentage points, i.e. households switch to an otherwise equivalent mortgage if its interest rate is at least \(0.849\) percentage points lower. However, there is significant heterogeneity in both switching cost and households’ sensitivity to interest rate so that for some household the cut-off will be much lower or higher.

6 A dynamic model of interest rates

6.1 Model

Because the interest rate a bank sets today affects the number of captive consumers it has tomorrow, the interest rate decisions of a bank are dynamic. I use a non-standard equilibrium concept, Sparse Markov Perfect Equilibrium, to model the resulting dynamic game. Before I introduce it below, I describe the constituent parts of the model: the state, how it evolves and banks’ flow profit functions.

The state consists of two parts: cost shocks and previous sales. There is no private information: the complete state is known to all banks at the beginning of every month. At the beginning of every month, there is a shock to the common cost of funding \(i_t\). In the Netherlands, mortgage funding comes from many different sources, including short-term and long-term deposits, money market funds and securitization. I use the average funding costs of new mortgage loans as compiled by The European Central Bank Statistical Data Warehouse.\(^{23}\)

\(^{23}\) To be precise, I subtract the margins on mortgage loans (series RALM.NL.LMGLHH.EUR.MIR.Z) from average interest rates on mortgage loans (series MIR.NL.B.A2C.AM.R.A.2250.EUR.N) to calculate the cost of funding.
The second state variable consists of previous market shares, which banks need to take into account because households face switching costs. However, because of the heterogeneity in the demand function, banks not only need to take into account the amount of mortgages they sold in the past, but also the type of consumers they sold them to. Thus, the payoff relevant state variable is the joint density of previous sales and demographics of households that are in the market at time $t$, $\mathcal{H}_t$. Denote this density by $f_t(b, D)$, where $b$ is a random variable denoting which banks households in $\mathcal{H}_t$ purchased from previously. Denote the set of all state variables at time $t$ by $\sigma_t = \{f_t(\cdot, i_t)\}$.

Let $r_b$ and $r_{-b}$ be the interest rates set by bank $b$ and its competitors, respectively, and $r$ be the vector of all interest rates. The demand for mortgage $j$ from consumers who previously bought from bank $b$ is

$$D_j(b, r) = \int p_j(b, r, D) f(b, D) dD.$$ 

Denote by $c_j$ the marginal cost of supplying a loan of €1. I let

$$c_{jt} = \gamma_{j0} + \gamma_{j1} r - \gamma_{j2} r_{-b}.$$ 

$\gamma_{j0}$ measures any marginal cost in addition to the cost of funding of supplying loan $j$, for example the implied costs of pre-payment risk (which differ across loan types). Some loan types, such as savings or investment mortgages, are commonly sold together with other high-margins products such as life insurance. $\gamma_{j0}$ also measures this implicit cross-subsidy. I restrict $\gamma_{j0}$ to be the same for all loans with the same repayment method sold by the same bank, e.g. all annuities sold by bank $b$ have the same $\gamma_{j0}$. $\gamma_{j1}$ and $\gamma_{j2}$ measure the cost of funding. Similarly, I restrict $\gamma_{j1}$ and $\gamma_{j2}$ to be the same for all loans with the same fixed interest rate duration sold by the same bank, e.g. all 10-year loans sold by bank $b$ have the same $\gamma_{j1}$. Thus $\gamma_{j1}$ and $\gamma_{j2}$ measure the differences in cost of funding of loans with different fixed interest periods as a function of the average cost of funding.

The flow profits of bank $b$ in state $\sigma$ are

$$\pi_b(\sigma) = \sum_{j \in J_b} \left\{ (r_{j0} - c_j) D_j(b, r_b, r_{-b}) + \sum_{b' \neq b} (r_{j1} - c_j) D_j(b', r_b, r_{-b}) \right\}.$$ 

The first term consists of the profits from customers who do not switch, the second term from customers who do.

Given the state and all banks’ interest rates, the future state can be calculated as follows. At time $t$, the proportion of households with mortgage $j$ whose mortgage will expire in $\tau$ months is equal to the weighed sum of the proportion at time $t - 1$ of households with that mortgage expiring in $\tau + 1$ months and the market share at time $t - 1$ of mortgage $j$ among mortgages with a duration of $\tau$ months. The weights are
the number of mortgages expiring in $\tau + 1$ months and the number of expired mortgages at time $t - 1$, respectively. The evolution of the joint density of previous purchases and household characteristics, evaluated at a point $(j, D)$, can be written as

$$f_{t+\tau}(b, D) = \frac{|H_t|}{|H_t| + |H_{t+\tau}|} f_{t+\tau}(b, D) + \frac{|H_t|}{|H_t| + |H_{t+\tau}|} \sum_{j \in J} \sum_{b' \in \Phi} \phi_j(\tau) p_j(b', r, D) f_t(b, D),$$

where $\phi_j(\tau)$ is an indicator function that equals 1 if and only if product $j$ has a fixed interest duration of $\tau$ months. $|H|$ denotes the number of elements in $H$, i.e. $|H_t|$ is the number of households that make a purchasing decision at time $t$. Combining this transition function for all points $(j, D)$ and all $\tau = 1, \ldots$, gives the full transition function for $f$:

$$f_{t+\tau} = \Gamma_t(s, r).$$

### 6.2 Sparse maximization: theory

In the supply model derived above, the payoff-relevant state is infinite-dimensional: banks have to keep track of the joint density of previous market shares and household demographics. This creates a challenge when estimating the model as existing methods (e.g. Bajari, Benkard, and Levin (2007)) require a first stage in which policy functions are regressed on state variables—this is impossible if the dimension of the state is too large.

To solve this challenge, I introduce a new solution concept that allows easier estimation of games with large state spaces: Sparse Markov Perfect Equilibrium (SMPE). In an SMPE, agents optimally pay attention to a subset of the state. As a result, the domains of their policy functions have a smaller dimension, making estimation and calculation much simpler. This concept is not only computationally attractive, but also behaviorally. Banks do not just know the state they are in, they need to perform some kind of market research. Such research is costly. Therefore, they will only try to figure out those state variables of which knowledge has a sufficiently large impact on their profits. For example, the MPE of the supply model implies that banks’ policies are a function not just of past market shares, but also of market shares across households with an income of €30,000, of €31,000, and so on, as the full density of household demographics and past market shares is payoff-relevant. Most likely, it does not pay off for banks to invest in such detailed knowledge. SMPE formalizes this intuition.

Sparse maximization was introduced by Gabaix (2014) for static settings and Gabaix (2016) for dynamic settings. I extend this work to dynamic games. The procedure banks follow is as follows:

1. Ex ante, banks choose which state variables they pay attention to. Banks incur a fixed cost to pay...
attention to a variable.

2. It is optimal to pay attention only to state variables
   (a) of which knowledge sufficiently changes a bank’s optimal action, and,
   (b) which show sufficient variation over time.

3. Every period, banks form a sparse state: they substitute some default value for state variables they
don’t pay attention to.

4. A bank maximizes its profits given its competitors’ actions as in a normal MPE way except it believes
it is in the sparse state instead of the true state.

I will now briefly explain this procedure formally, first for static problems (for ease of exposition) and then
for dynamic problems. Please see the aforementioned articles for a more in-depth treatment. Finally, I
extend the dynamic single-player problems from Gabaix (2016) to dynamic games.

In the simplest setting, sparse maximization works as follows. Assume an agent needs to maximize an
objective function $u(a, x)$, where $a$ is some action and $x$ some $n$-dimensional vector of parameters on which
his payoff depends.  

However, there is a cost to paying attention to parameter $x_i$ equal to $g(m_i) = \kappa m_i^\alpha$
for $\alpha, \kappa > 0$, where $m_i \in [0, 1]$ denotes the level of attention the agent pays to parameter $x_i$. $m_i = 1$ denotes
full attention and $m_i = 0$ indicates that the agent completely disregards parameter $x_i$. Define the agent’s
perceived representation of $x_i$ as $x^s_i = m_i x_i$. For a given attention vector, the agent then maximizes his
objective function using the perceived representation of $x$, i.e. he solves $\max_a u(a, x^s_i)$. When choosing
how much attention to pay to a certain parameter, the agent weighs the benefits of paying attention versus
the cost. The benefits of paying attention can be measured by the extent to which the agent’s optimal
action would change if he would pay more attention. To formalize this, I first need to introduce some more
notation. Denote by $a_d = \arg\max_a u(a, 0)$ the default action, that is the action when the agent doesn’t pay
any attention to any parameter. Further assume that the agent thinks that $x$ is drawn from a distribution
with $c_{ij} = \mathbb{E}[x_i x_j]$ and $\mathbb{E}[x_i] = 0$. Finally define by $a_{x_i} = \frac{\partial a(x)}{\partial x_i}|_{x=0}$ the derivative of the optimal action with
respect to $x_i$ of a rational agent (i.e. an agent that doesn’t use sparsity) at the default action. The sparse max
operator is then defined as follows.

**Definition 1 (Sparse max operator without budget constraint (Gabaix 2014))**  The sparse max, $\text{smax}_{a|x,\sigma, \kappa} u(a, x)$
is defined by the following procedure.

1. Choose the attention vector $m^*$:

\[
m^* = \arg\min_{m \in [0, 1]^n} \frac{1}{2} \sum_{i=1}^{n} m_i \sum_{j=1}^{n} (1 - m_i) \Lambda_{ij} (1 - m_j) + \kappa \sum_{i=1}^{n} m_i^\alpha \]

25. I borrow the notation in this section from Gabaix (2016).
with the cost-of-inattention factors $\Lambda_{ij} = -\sigma_{ij}a_xu_{ax}a_xj$ and $u_{aa} = \frac{\partial^2 u(a,0)}{\partial a^2}$. Define $x^s_i = m^*_ix_i$, the sparse representation of $x$.

2. Choose the action

$$a^s = \arg\max_a u(a, x^s).$$

An SMPE is an MPE, except using sparse maximization. Thus, their policy functions depend only on their sparse states. Since banks do not pay attention to the full state, they cannot precisely predict their competitors’ actions. Instead, a bank believes its competitors behave as if they were in the bank’s sparse state as well. Denote by $\check{\sigma}_b$ bank $b$’s sparse state and by $\rho_b(\check{\sigma}_b)$ its policy function.

Equilibrium then requires that for every possible state $\sigma$, banks’ policy functions are sparse maximizers of their discounted expected profits. Thus, in equilibrium bank $b$’s Bellman equation is

$$V_b(\check{\sigma}_b) = \arg\max_{\pi_b} \pi_b (r, \rho_{-b}(\check{\sigma}_b), \check{\sigma}_b) + \beta E_{i'} [V_b (\check{\Gamma}_b(\check{\sigma}_b, r, \rho_{-b}(\check{\sigma}_b), i'))], \quad (1)$$

where $\rho_{-b}$ are the policy functions of $b$’s competitors and $\beta$ is the discount rate. Let $\check{\Sigma}_b$ be the set of bank $b$’s possible sparse states. An SPME is then defined as follows.

**Definition 2 (Sparse Markov Perfect Equilibrium)** A Sparse Markov Perfect Equilibrium consists of policy functions $\rho_b : \check{\Sigma}_b \rightarrow \mathbb{R}^{2|J_b|}$, such that

$$\rho_b(\check{\sigma}_b) = \arg\max_{\pi_b} \pi_b (r, \rho_{-b}(\check{\sigma}_b), \check{\sigma}_b) + \beta E_{i'} [V_b (\check{\Gamma}_b(\check{\sigma}_b, r, \rho_{-b}(\check{\sigma}_b), i'))],$$

for all banks $b \in B$ and all states $\check{\sigma}_b \in \check{\Sigma}_b$, where $V_b(\cdot)$ is given by (1).

I leave the theoretical properties of SMPE’s for further research. It seems however likely that just as for ordinary MPE’s, many SPME’s of a single game can exist.

### 6.3 Sparse maximization: identification and estimation

I estimate the supply side game to uncover the deep parameters of the model: marginal costs $\gamma_j$ for all $j$. The estimation of the supply side game proceeds in two stages. In the first stage, I simultaneously estimate banks’ sparse state representations and their policy functions using Lasso. The first stage estimates are then used to estimate the deep parameters of the model.
6.3.1 Identification of sparse state representations

The intuition behind the identification of sparse state representations is simple: a bank pays attention to a state variable if and only if its policy function is a function of that state variable. This is true since the sparse max operator picks precisely those state variables to pay attention to that have the largest impact on a bank's optimal action. Conversely, if a state variable is not related to a bank's optimal action, i.e. policy function, it must be the case that it is not optimal to pay attention to this variable. Since policy functions are observed by the econometrician, it is possible to use standard variable selection techniques to identify a bank's sparse state representation.

To formalize this intuition, I need to make one assumption. The sparse max operator can generate partial attention. That is, when banks perform sparse maximization it is possible that they set \( m_i \in (0, 1) \) for some \( i \), so that the banks pay some but not full attention to the associated state variable. However, I am not able to identify partial attention. Therefore, I have to assume that banks' attention vectors are sparse, by which I mean that either \( m_i = 0 \) or \( m_i = 1 \) for all \( i \). Gabaix (2014) shows that the following assumption on the cost of attention function is sufficient to generate sparsity.

Assumption 1 (No partial attention) The cost of attention function \( g(m_i) = \kappa m_i^\alpha \) satisfies \( \alpha < 1 \).

This assumption is partially testable. Gabaix (2014) shows that when \( \alpha > 1 \) there is no sparsity at all, i.e. that attention vectors will satisfy \( m_i \in (0, 1) \) for all \( i \). This lack of sparsity implies that banks' policy functions are functions of all state variables, which is testable. Only the knife-edge case \( \alpha = 1 \) has to be ruled out by assumption, since for \( \alpha = 1 \) both sparsity and partial attention can occur.

6.3.2 Estimation of sparse state representations and policy functions

Since the variables in a bank's policy functions are equal to its sparse representation of the state, estimating the former simultaneously reveals the latter. I use Lasso to estimate the sparsity of banks' policy functions, then OLS to estimate their coefficients as in Belloni and Chernozhukov (2013). Using post-Lasso OLS is important, since the Lasso alone shrinks coefficients towards zero too much, leading to implausible counterfactual interest rates.

Banks sell multiple products with different interest rates. An SMPE implies that the policy functions of all the products of the same bank should depend on the same sparse state representation. This is because paying attention has a fixed cost per state variable per firm: thus, it never pays for a bank to ignore a state variable for some products but not for others. In other words, it is required to select the same variables for

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26. For legibility, I write paying attention to a state variable. It should be understood that by this I also mean any function of state variables, such as particular moments of the previous market share distribution \( f \).

27. I have also tried using the fitness-based threshold Lasso combined with post-Lasso OLS, which according to Belloni and Chernozhukov (2013) is superior to just post-Lasso OLS. However, the thresholding did not induce any additional sparsity in my case so that the fitness-based threshold Lasso is equivalent to ordinary Lasso.
all policy functions of the same bank. To accomplish this, I use what the machine-learning literature calls a multi-task Lasso \((Zhang\,2006)\). The multi-task Lasso simultaneously estimates the coefficients of multiple models, imposing the same sparsity structure on all of them.

The multi-task Lasso works as follows. Group all observed interest rates by bank \(b\) in a \(T \times 2|J_b|\) matrix \(R_b\), where the \((t, j + s|J_b|)\)-element of \(R_b\) is \(r_{jt}\), the interest rate charged for product \(j\) at time \(t\) for old \((s = 0)\) and new \((s = 1)\) customers. Let \(X\) be a \(T \times K\) matrix of possible regressors, where \(K\) can be larger than the number of observations \(T\). The multi-task Lasso is defined as

\[
\hat{B} = \arg \min_B \frac{1}{2T} \|R - XB\|_{\text{Fro}}^2 + \lambda \|B\|_{21},
\]

where \(\|A\|_{\text{Fro}} = \sqrt{\sum_{ij} a_{ij}^2}\) is the Frobenius norm and \(\|A\|_{21} = \sum_i \sqrt{\sum_j a_{ij}^2}\) is the \(\ell_1\ell_2\) norm. \(\lambda > 0\) is the typical regularization parameter that generates sparsity. I use the optimal \(\lambda\) as suggested by Belloni and Chernozhukov \((2013)\). The \(j^{th}\) column of the estimated coefficients \(\hat{B}\), call it \(\hat{\beta}_j\), contains the estimated parameters for \(r_j\). The multi-task Lasso constrains these estimates such that all \(\hat{\beta}_j\)’s of the same bank have the same sparsity structure. In other words, \(\hat{B}\) will contain a zero row for every covariate that is not included\(^{28}\).

In \(X\) I include (functions) of the relevant state variables \(i_t\) and \(f_t(b, D)\). One problem is that the latter is a density and thus infinite-dimensional. I solve this as follows. I include the marginal market shares of deciding households, \(\int f_t(b, D) dD\), as variables. I run the multitask post-Lasso OLS as described above using a second-degree polynomial of these variables. Then, I split the sample into two groups (rich and poor), and add the conditional market shares \(\int_{d > E[D]} f_t(b, D) dD\) and \(\int_{d \leq E[D]} f_t(b, D) dD\). Invoking the Frisch-Waugh-Lovell theorem, I regress the residuals of the first regression on the residuals of a regression of the split market shares on the non-split market shares to see whether they offer additional explaining power. If they do, I split every group again—so you get the market shares for the four income quantiles—and use the same procedure until no variables are added.

Since it is possible to estimate sparsity directly from the data, this empirical procedure is consistent with any model that generates sparsity. Step 1 of Definition\(^1\) the procedure banks follow to choose which variables they pay attention to, is not required to estimate marginal costs. Since this step puts testable restrictions on which variables banks pay attention to—paying attention to these variables must lead to a larger increase in profits than paying attention to the ignored variables—my model has empirical content\(^{29}\).
Table 7: Structure of banks’ policy functions. A checkmark indicates that the policy function of a bank (column) depends (possibly non-linearly) on the variable (row).

<table>
<thead>
<tr>
<th></th>
<th>Bank A</th>
<th>Bank B</th>
<th>Bank C</th>
<th>Bank D</th>
<th>Bank E</th>
<th>Bank F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Funding cost</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Market share A</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Market share B</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Market share C</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Market share D</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Market share E</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Market share F</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

$R^2$ 0.99 0.993 0.992 0.991 0.994 0.991

6.3.3 Policy function estimates

Table 7 contains the estimated structure of banks’ policy functions, and therefore also the variables in their sparse state. As a condition for obtaining the LLD, I am not allowed to identify the competitive conduct of individual banks. Therefore, I anonymize bank names and do not report coefficients.

The multitask Lasso leads to a significant reduction of the size of the relevant state space: the actual state is infinite-dimensional, the estimated sparse states have at most five variables in their domain. Yet, the fit is excellent, with $R^2$’s very close to one for all banks. Every bank’s policy function depends on the cost of funding, as expected. In addition, their policy functions depend on the marginal (with respect to household demographics) market shares of three or four other banks. No bank’s policy function depends on market shares conditional on households falling into a certain income bracket. Banks typically pay attention to their own market share and/or the market share of their closest competitors in terms of size: i.e. large banks pay attention to other large banks, and smaller banks more to other small banks.

6.4 Estimation of model

To estimate the primitives of the supply model, I use banks’ stochastic Euler equations. It turns out that banks’ number of controls (interest rates) banks is larger than the dimension of their states. As a result, I can generate “moments” using only data from the current period. To see why, consider an example of a single agent that has two controls $r_1, r_2$ and one (perceived) state variable $\sigma$. Its Bellman equation is

$$V(\sigma) = \max_{r_1, r_2} \pi(\sigma, r_1, r_2) + \beta \mathbb{E} V(\Gamma(\sigma, r_1, r_2)),$$

28. One downside of this approach is that the multi-task Lasso also chooses the same functional form for every policy function when higher-order polynomials and interactions of variables are included. I have experimented with running a separate Lasso for every policy function to estimate its functional form after using the multi-task Lasso to pick which variables are in its domain, but this did not lead to significantly different results.

29. I plan to develop this idea further in future versions, e.g. by using moment inequalities to test the model’s assumptions.
where $\Gamma(\cdot)$ is the evolution law. This model can equivalently be written as

\[ V(\sigma) = \max_{\sigma'} \tilde{\pi}(\sigma, \sigma') + \beta \mathbb{E} V(\sigma'), \quad (2) \]

\[ \tilde{\pi}(\sigma, \sigma') = \max_{r_1, r_2 \text{ s.t. } \Gamma(\sigma, r_1, r_2) = \sigma'} \pi(\sigma, r_1, r_2). \quad (3) \]

The first order conditions of the latter maximization problem are

\[ \frac{\partial \pi}{\partial r} - \lambda \frac{\partial \Gamma}{\partial r} = 0, \quad (4) \]

where $\lambda$ is the Lagrange multiplier. Except for $\lambda$ and any unknown parameters of the model, all quantities are observed or can be calculated. Since there are two first order conditions and one multiplier, one parameter of the model can be estimated without using the first order conditions implied by the Bellman equation (2).

The intuition for this result is as follows. Say that $\frac{\partial \Gamma}{\partial r_1} = \frac{\partial \Gamma}{\partial r_2}$. If $\frac{\partial \pi}{\partial r_1} > \frac{\partial \pi}{\partial r_2}$, the bank has the following profitable deviation. It can increase $r_1$ and simultaneously decrease $r_2$ by $\epsilon$. This leaves next period’s state unaltered but strictly increases today’s profits. Therefore, if $\frac{\partial \pi}{\partial r_1} = \frac{\partial \pi}{\partial r_2}$, it is required that $\frac{\partial \pi}{\partial r_1} = \frac{\partial \pi}{\partial r_2}$.

Generalizing this logic, optimality requires that in every month and for every interest rate a bank sets, the derivative of its profit function with respect to that interest rate is proportional to the derivative of the evolution law.

The same result can be derived for the full model. Let $S_b$ be the number of variables in bank $b$’s sparse state $\hat{\sigma}_b$. The equivalent of (4) is

\[ g_{bt}(\pi, \lambda) \equiv \frac{\partial \pi_b}{\partial r_b} - \lambda \frac{\partial \hat{\Gamma}_b}{\partial r_b} \lambda_{bt} = 0, \quad (5) \]

where $\lambda_{bt}$ contains the $S_b$ multipliers of bank $b$ in month $t$. Post-ban, there are $|J_b|$ first order conditions: one for every interest rate. If $S_b < |J_b|$, as is the case, these first order conditions contain additional information that can be used to estimate banks’ marginal costs.\footnote{I derive the functional forms of these first order conditions in Appendix B.2. It is important to note that, following the definition of an SMPE, a bank maximizes its profits conditional on the policy functions of its competitors in its own sparse state. Thus, when calculating the first order conditions of bank $b$, one must use the estimated policy functions of its competitors evaluated in $b$’s sparse state. Using only the first order conditions implied by (3) and not those implied by (2) has various benefits. Firstly, it does not require the direct calculation of expectations, nor their estimation by substitution of future observed values. This is especially important in my application as in an SMPE banks have non-rational behavior.}

I stress that there is nothing in the definition of an SMPE that requires this to be the case; it is what I find empirically. For example, one could also estimate the SMPE of a model with one control, so that there are never any additional degrees of freedom whatever the sparsity structure of banks’ policy functions.
Table 8: Average marginal costs (over banks) when the cost of funding equals \( i_t = .57 \), by repayment method and fixed interest rate duration.

<table>
<thead>
<tr>
<th></th>
<th>Dynamic, sparse states</th>
<th>Dynamic, all market shares</th>
<th>Static</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5 yr.</td>
<td>10 yr.</td>
<td>15 yr.</td>
</tr>
<tr>
<td>Annuity</td>
<td>2.14</td>
<td>2.28</td>
<td>2.30</td>
</tr>
<tr>
<td>Linear</td>
<td>1.44</td>
<td>1.58</td>
<td>1.60</td>
</tr>
<tr>
<td>Bullet</td>
<td>1.27</td>
<td>1.41</td>
<td>1.43</td>
</tr>
<tr>
<td>Savings</td>
<td>1.75</td>
<td>1.89</td>
<td>1.91</td>
</tr>
<tr>
<td>Life</td>
<td>0.62</td>
<td>0.76</td>
<td>0.78</td>
</tr>
<tr>
<td>Investment</td>
<td>0.81</td>
<td>0.95</td>
<td>0.97</td>
</tr>
</tbody>
</table>

expectations and using this method allows estimation without specifying how banks do form expectations.\(^{31}\)

Finally, it is possible to estimate marginal costs without specifying banks’ discount factor \( \beta \), which is typically not identified without further exclusion restrictions. Of course, these benefits come at the cost of a loss of efficiency if the model is specified correctly and the discount factor is identified or known.

I estimate marginal costs as follows. For every candidate parameter vector \( \gamma_b \) and period \( t \), I find the Lagrange multipliers \( \lambda_{bt}(\gamma_b) \) —subscripted to indicate their dependence on the trial parameters—that solve bank \( b \)’s first order conditions \(^5\). Since this an overdetermined system of equations, it will not be possible to find \( \lambda_{bt} \) that solve \(^5\) for all (or any) \( \gamma_b \). Therefore, I find \( \lambda_{bt}(\gamma_b) \) by OLS. I then search over parameters \( \gamma_b \) to minimize the average (over months) first order conditions, i.e. I solve pseudo-GMM objective \(^{32}\).

\[
\min_{\gamma_b} \left( \frac{1}{T} \sum_{t=1}^{T} g_{bt}(\gamma_b, \lambda_{bt}(\gamma_b)) \right)^T \left( \frac{1}{T} \sum_{t=1}^{T} g_{bt}(\gamma_b, \lambda_{bt}(\gamma_b)) \right).
\]

6.4.1 Marginal cost estimates

Table 8 contains the average (over banks) marginal costs for the different type of loans when the cost of funding \( i_t \) equals its average value in my sample. For comparison, I also estimate the supply model under two additional sets of assumptions. First, that banks pay attention to the market shares of all banks. Second, that banks are not forward-looking and optimize their flow profits.

Under sparse maximization, the marginal costs estimates follow expected patterns: amortizing mortgages (annuity and linear) are more expensive than non-amortizing mortgages. This reflects that non-amortizing mortgages, in particular life and investment mortgages, cross-subsidize other (often mandatory) products sold by the same bank, such as life insurance or investment products. For a given repayment type, marginal costs are increasing in the duration of the fixed interest rate period.

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31. For example, it is possible that banks are “naive” and expect to obtain the rational value function (without sparse maximization) or that they are fully sophisticated and expect the value function induced by \(^1\) (Gabaix 2016).

32. The first order conditions do not contain any structural errors—any error is caused by the substitution of estimated for actual demand. Therefore this procedure cannot be interpreted as GMM.
Table 9: Effects of the ban on history-based price discrimination on consumer surplus, profits and welfare in cents per euro loaned.

<table>
<thead>
<tr>
<th></th>
<th>Potential first-time buyers</th>
<th>Renewing households</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Attentive</td>
<td>Inattentive</td>
</tr>
<tr>
<td>$P$(Switch) (%)</td>
<td>-4.866</td>
<td>0.077</td>
<td></td>
</tr>
<tr>
<td>Consumer surplus conditional on switching</td>
<td></td>
<td>0.471</td>
<td></td>
</tr>
<tr>
<td>Total consumer surplus</td>
<td>0.067</td>
<td>0.176</td>
<td>0.336</td>
</tr>
<tr>
<td>Profits</td>
<td></td>
<td></td>
<td>0.196</td>
</tr>
<tr>
<td>– Reallocation effect</td>
<td></td>
<td></td>
<td>0.427</td>
</tr>
<tr>
<td>– Price effect</td>
<td></td>
<td></td>
<td>-0.231</td>
</tr>
<tr>
<td>Welfare</td>
<td></td>
<td></td>
<td>0.397</td>
</tr>
</tbody>
</table>

This pattern does not obtain for the specifications where banks pay attention to the market shares of all banks or optimize their static profits. Here, it is sometimes the case that 15-year mortgages have higher marginal costs than 20-year mortgages. This pattern is counterintuitive and suggests that the sparse model is the correct one. Overall marginal costs are lower in the sparse model than in the static model but higher than in the dynamic model where banks pay attention to all market shares.

7 Results

7.1 The effect of history-based price discrimination on consumer surplus and welfare

My strategy for estimating the effects of the ban on history-based price discrimination is as follows. First, I use the policy function estimates from the post-ban period to predict what interest rates would have been pre-2013 had history-based price discrimination already been banned then. Since I observe the interest rates when history-based price discrimination is legal in the data, I can combine these predictions with my demand and marginal cost estimates to estimate the causal effect of the ban on consumer surplus, bank profits and welfare. My estimates control for changes in the cost of funding and previous market shares. This method therefore identifies a causal effect if there are no other relevant changes in the mortgage market except for the ban on history-based price discrimination. Below I discuss some other changes to the mortgage market and how they might impact my estimates.

Table 9 shows the estimated effects of the ban on history-based price discrimination. Consumer welfare increases with .202 cents per euro loaned. This means that a household with an average mortgage of
\( \varepsilon 150,000 \) gains \( \varepsilon 303 \) in consumer surplus per year. The largest benefit accrues to renewing households that do not pay attention, who gain .336 cents per euro loaned or \( \varepsilon 504 \) for an average mortgage in consumer surplus. This conforms to the reduced form evidence on the average difference in interest paid by renewing and new households (Table 5). Since the estimates do not depend on these pre-ban interest rate differences, this helps to validate the model.

Attentive renewing households gain .176 cents per euro loaned (or \( \varepsilon 264 \) for an average mortgage) in consumer surplus. This is mainly because their consumer surplus conditional on renewing increases significantly, owing to the disappearance of the interest rate difference for new and renewing customers. They also gain because they save on switching costs: the ban causes attentive renewing households to be 4.866 percentage points less likely to switch. Switching and new households also gain slightly: .077 and 0.067 cents per euro loaned respectively.

Bank profits also increase. Table 9 shows that the ban on history-based price discrimination causes an increase in profits of .196 cents per euro loaned, or \( \varepsilon 294 \) per year for an average mortgage of \( \varepsilon 150,000 \). This difference can be decomposed into two parts. The first is the reallocation effect, which is the difference in bank profits under counterfactual market shares but observed interest rates. The reallocation effect is .427 cents per euro loaned. This means that the ban increases the market shares of more efficient banks. The second effect is the price effect, which measures the change in bank profits going from observed to counterfactual interest rates. The price effect is negative: -.231 cents per euro loaned. This loss in profits is because banks can no longer “harvest” their locked-in customers.

Adding up, the ban on history-based price discrimination causes an increase of total welfare of .397 cents per euro loaned, or \( \varepsilon 596 \) per year for an average mortgage. This increase is almost completely due to the reallocation effect: the increase in consumer surplus due to the disappearance of interest rate differences between new and renewing customers is completely canceled out by the profit loss banks incur because of this very disappearance.

7.2 Discussion

The estimates of the effects of the ban on history-based price discrimination are causal if there are no exogenous changes to the mortgage market that cause interest rate to differ before and after the ban. My estimates control for changes in the cost of funding and previous market shares. However, various other changes happened in the Dutch mortgage market around the ban on history-based price discrimination. I now discuss some of these changes and how they might impact my results.

The most important change that occurred around this period is that after 2013 the Dutch mortgage market became more competitive: the market share of smaller banks grew and margins decreased (Fransman...
As a result, the counterfactual interest rates I predict for the pre-ban period are potentially biased downwards. This would imply that my estimates of consumer surplus and the reallocation effect are biased upwards and my estimate of the price effect is biased downwards. However, it should be noted that the increase in competitiveness might itself (partially) have been a result of the ban on history-based price discrimination. Indeed, this was the main aim of the regulator.

A second change is the ban on non-amortizing mortgages for new home purchases in 2013. This leads to a change in households’ choice sets, which as I describe in Section 5, I control for. This change in choice sets could as a secondary effect also change mortgage pricing. If banks change interest rates as a result of this change in choice sets, one would expect interest rates for new customers of bullet loans—which can only be purchased by those who previously had a bullet at a different bank—to differ from those for new customers of annuities—which can also be purchased by first-time buyers. As Figure 4 in the Appendix shows, there is no change between the interest rates of those loans after the ban.

8 Conclusion

This paper studied the effects of a ban on history-based price discrimination in the Dutch mortgage market. In this market, households that renew their mortgage paid on average between €183 and €324 in interest more than new customers for the same loan. Such interest rates differences are possible because of inattention of renewing households and switching costs. The latter are significant: on average, a household switches to an otherwise equivalent loan by a different bank only if its interest rate is at least .849 percentage points lower.

I estimate the effect of the ban by developing a structural model of demand and supply of the Dutch mortgage market. The supply side is a dynamic game with an infinite-dimensional state space. To deal with this, I introduce a new solution concept, Sparse Markov Perfect Equilibrium (SMPE). In an SMPE, banks only pay attention to the most important state variables. I show that these state variables can be identified using Lasso. My results imply that banks pay attention to four or five variables: thus, SMPE reduces the dimension of the problem from infinite to four or five.

Estimates of the demand function and marginal costs then allow me to calculate the effect of history-based price discrimination on consumer surplus, bank profits and welfare. Consumer surplus increases with €303 for an average mortgage. This is mainly because inattentive renewing households no longer pay higher interest rates than new customers. Bank profits increase by €294 for an average mortgage, because of a reallocation effect: after the ban on history-based price discrimination, households purchase from more efficient banks.
References


A Additional figures

B Estimation details

B.1 Matching households over time

To match switching households over time, I employ the following algorithm. First, I discard all households that do not switch between the LLD in year \(t\) and year \(t + 1\). I can exactly identify these households because every bank uses a unique scheme to identify households over time.\footnote{The only exception is ABN Amro, which switches its identifying scheme one. I match those mortgages using the same algorithm.} For the remaining loans, I calculate the distance between all loans in the old and the new LLD. The distance between loan \(i\) in year \(t\) and loan \(s\) in year \(t + 1\) is the norm between its loan and household characteristics, i.e.

\[
d(i, j) = | | X_i - X_j | |,
\]
Figure 4: Average interest rate for annuity and bullet loans
where $X_i$ are the standardized characteristics of loan $i$. As characteristics I take the birth year of the household head, the payment type of the loan, the outstanding balance at the moment of switching and the maturity year of the loan. I then assign loan $i$ as being loan $j$’s previous loan with probability

$$\frac{\exp\{d(i, j)\}}{\sum_k \exp\{d(k, j)\}},$$

where the sum in the denominator is over all loans in year $t$ that I cannot match based on loan id in year $t + 1$. I further adjust the matching probabilities such that the aggregate probability of switching equals the switching probability I observe in the DHS and such that the correct proportion of loans in year $t + 1$ is not assigned any previous loan, i.e. is a new mortgage.

### B.2 Supply side first order conditions

The derivatives of bank $b$’s profitis for a product $k$ with respect to its interest rate for old and new customers are

$$\frac{\partial \pi_b}{\partial r_k} (r_b, s) = \sum_{j \in J_b} \left( (r_{k0} - i_t - \gamma_j) \frac{\partial D_j}{\partial r_k} (b, \psi, r_b, \hat{\rho}_b^b (s)) + D_k (b, \psi, r_b, \hat{\rho}_b^b (s)) \frac{\partial \pi_b}{\partial r_k} (r_b, s) = \sum_{j \in J_b} \sum_{d \neq b} \left( (r_{j1} - i_t - \gamma_j) \frac{\partial D_j}{\partial r_k} (d, \psi, r_b, \hat{\rho}_b^b (s)) \right) \right) \right)$$

The market share of bank $d \neq b$, if it is in bank $b$’s sparse state representation, evolves as follows

$$\frac{\partial \Gamma_d}{\partial r_k} (r_b, s) \propto \sum_{j \in J_b} \frac{\partial D_j}{\partial r_k} (d', \psi, r_b, \hat{\rho}_b^b (s))$$

$$\frac{\partial \Gamma_d}{\partial r_k} (r_b, s) \propto \sum_{j \in J_b} \sum_{d' \neq b} \frac{\partial D_j}{\partial r_k} (d', \psi, r_b, \hat{\rho}_b^b (s)).$$

I ignore a constant that measures the size of tomorrow’s market versus today’s market since it will be subsumed by the Lagrange multipliers $\lambda$.

Substituting these expressions into (5) gives that bank $b$’s first order conditions in month $t$ can be written as

$$\sum_{j \in J_b} \left((r_{k0} - i_t) \frac{\partial D_j}{\partial r_k} (b, \psi, r_b, \hat{\rho}_b^b (s)) \right) + D_k (b, \psi, r_b, \hat{\rho}_b^b (s)) = \sum_{j \in J_b} \gamma_j \frac{\partial D_j}{\partial r_k} (b, \psi, r_b, \hat{\rho}_b^b (s)) + \lambda_b \frac{\partial \Gamma_j}{\partial r_k} \sum_{j \in J_b} \sum_{d' \neq b} \left((r_{j1} - i_t) \frac{\partial D_j}{\partial r_k} (d, \psi, r_b, \hat{\rho}_b^b (s)) \right)$$

The left side of these equations can be calculated given the estimated demand model and bank $b$’s policy functions. The right side is composed of quantities that can similarly be calculated and unknown parameters $\gamma_j$, $\lambda_b$, $\kappa$. The right hand side is linear in these parameters, therefore the supply side first order conditions give rise to a linear system of equations.