THE LONDON SCHOOL OF ECONOMICS AND
POLITICAL SCIENCE

# Essays in Household Finance

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A thesis submitted to the Department of Economics of
the London School of Economics for the degree of
Doctor of Philosophy.

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*To my inspiring parents,*

*for giving me the courage and strength to find myself.*

## Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).



I declare that my thesis consists of approximately 35,000 words.

## Statement of Conjoint Work

I certify that Chapter 3 of this thesis is co-authored with Nikos Artavanis, Daniel Paravisini, Amit Seru and Margarita Tsoutsoura. I contributed 20% of the work in Chapter 3.

## Acknowledgements

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# Abstract

This thesis consists of three essays on household finance and banking.

The first chapter examines the role of brokers in the UK mortgage market. Mortgage brokers operate as intermediaries between households and lenders, acting as expert advisors for consumers and as distributors for mortgage providers. Using loan-level data from the universe of UK mortgage originations, I study the interactions between households, brokers and lenders. I find that, in this market, brokers often charge fees to households, while at the same time receiving commission payments from lenders for the sale of their products. The data suggest that these commissions can distort brokers' advice, potentially generating an agency problem between households and brokers. However, I also find evidence that brokers can benefit consumers by increasing upstream competition. By facilitating the entry of new, lower-cost mortgage providers, brokers increase competition among lenders, which can result in lower interest rates for households. It is important to understand both the positive and negative effects of having brokers when considering regulation in this market.

The second chapter empirically analyzes the effects on welfare and market structure of regulations restricting broker compensation in the UK mortgage market. To study the net effect of these regulations in equilibrium, I estimate a structural model that features households' demand for mortgage products and broker services, lenders' optimal pricing decisions, and broker-lender bilateral bargaining over commission rates. I use the estimates to evaluate the impact of policies restricting brokers' commission payments. I find that a ban on commissions leads to a 25% decrease in consumer welfare, whereas a cap equal to the median commission increases consumer surplus by 10%. The intuition behind this finding is that by introducing

a more restrictive cap, we are decreasing broker market power at the expense of increasing lender market power. A tighter cap will increase consumer surplus by aligning the incentives of brokers and households, but it will also decrease consumer surplus by reducing competition among lenders. In this chapter, I quantify both opposing forces to capture the net effect of different policies.

The third chapter, co-authored with Nikos Artavanis, Daniel Paravisini, Amit Seru and Margarita Tsoutsoura, develops a new approach to isolate and quantify the extent to which deposit withdrawals are due to liquidity, exposure to policy risk, or expectations about how other depositors will behave. We use high frequency micro-data on insured time-deposits from a large Greek bank over a long time period that spans quiet periods as well as events with large policy uncertainty. We use variation induced by maturity expiration of time deposits around the large policy uncertainty events to filter deposit withdrawals due to direct exposure to policy risk from those due to expectations about behavior of other depositors. In response to a policy uncertainty shock that doubled the short-run CDS price of Greek sovereign bonds, the early deposit withdrawal probability quadrupled. About two-thirds of this increase is driven by direct exposure to policy risk with the remainder due to changes in expectations of behavior of other depositors. We quantify these effects in terms of forgone interest rates and changes in short-run CDS prices. Our estimates imply effects that compare well with anecdotes from other recent prominent episodes of depositor withdrawals.

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# Chapter 1

# The Role of Brokers in the UK Mortgage Market

## 1.1 Introduction

When originating a mortgage, households can directly contact lenders via their branch network and online platforms. Alternatively, households can hire certified experts, in the form of mortgage brokers, to help them decide which options best fit their needs and assist them with the application process. In the UK, almost 50% of households consult with mortgage brokers when deciding on their mortgages.[1] To compensate brokers for their services, households often pay a −sometimes significant− fee. However, these downstream charges are not the only source of revenue for brokers in this market. They also receive commission payments from lenders whenever they originate one of their mortgages. This form of compensation may

[1]Brokers also play a key role in other developed countries. In the US, mortgage brokers originated over 44% of residential mortgages before the crisis (National Association of Mortgage Brokers, http://www.namb.org) and about 33% after the crisis (Alexandrov and Koulayev, 2018). Similarly 53% of Australians rely on mortgage brokers (Mortgage and Finance Association of Australia's (MFAA), and according to the Canadian Mortgage and Housing Corporation (CMHC) 55% of first-time buyers in Canada use a broker when originating their mortgage.

influence brokers' advice, causing them to steer consumers towards high-commission mortgages. If these mortgages are also more expensive or worse in other dimensions that consumers may value, commissions can potentially generate an agency problem between brokers and households and reduce consumer welfare in this market.

Using a novel loan-level dataset for all mortgage originations in the UK, I analyze the role of brokers in this market and the key trade-offs consumers may face given incentives and market structure. I find evidence suggesting that broker sales react to changes in lenders' financial incentives. After controlling for a rich set of fixed effects, I find that products with a 13% (£100) higher commission for a broker have, on average, a 2% higher share in the broker's sales portfolio. Therefore, despite demand-side incentives that might discipline brokers to act in the best interest of households (e.g., repeated sales and reputation concerns), brokers seem responsive to supply-side monetary incentives.

The data also shows that brokers allow small, challenger banks to introduce their products at a lower cost (e.g., less need for an extensive branch network). In exchange, challenger banks pay, on average, higher commissions to brokers. They also offer the cheapest deals for many products in the market. After accounting for observable characteristics, households originating their mortgage through a broker are 7 percentage points more likely to choose a product from these new lenders. In an industry that is very concentrated upstream, brokers seem to improve competition by making households aware of better products that would otherwise not be discovered given challenger banks' limited advertisement and lack of extensive branch networks.

I also find that, despite the rise of price comparison websites and online sales, nearby bank branches still matter for household choices. The number of branches in a given county is strongly correlated with lenders' share of non-intermediated sales, suggesting borrowers using lenders' in-house distribution channels value proximity of the nearest branch. Moreover, in counties where lenders have a low branch density, they tend to pay higher commissions to brokers in order to increase their market share via intermediated sales. Brokers offer lenders a way to introduce their products in areas where setting up a branch is costly and consumer take-up of online distribution channels remains low. However, in areas where lenders already have a high branch density, brokers can steal business from lenders' in-house distribution channels. These results suggest brokers and bank branches are substitutes. Because households can bypass the intermediary and go directly to lenders, the relationship between brokers and lenders in this market is both vertical (brokers provide an alternative distribution channel for lenders) and horizontal (brokers compete downstream with lenders' in-house distribution channels).

The rest of the chapter proceeds as follows. Section 1.2 describes the data and the institutional setting. I present some stylized facts particular to the UK mortgage market. Section 1.3 shows motivating empirical evidence on potential trade-offs and conflicts of interests in the data. In Section 1.4, I conclude by discussing the need for a model to study the trade-offs in this market and how the different roles brokers play can be affected by regulation.

## 1.2 Institutional Setting and Data

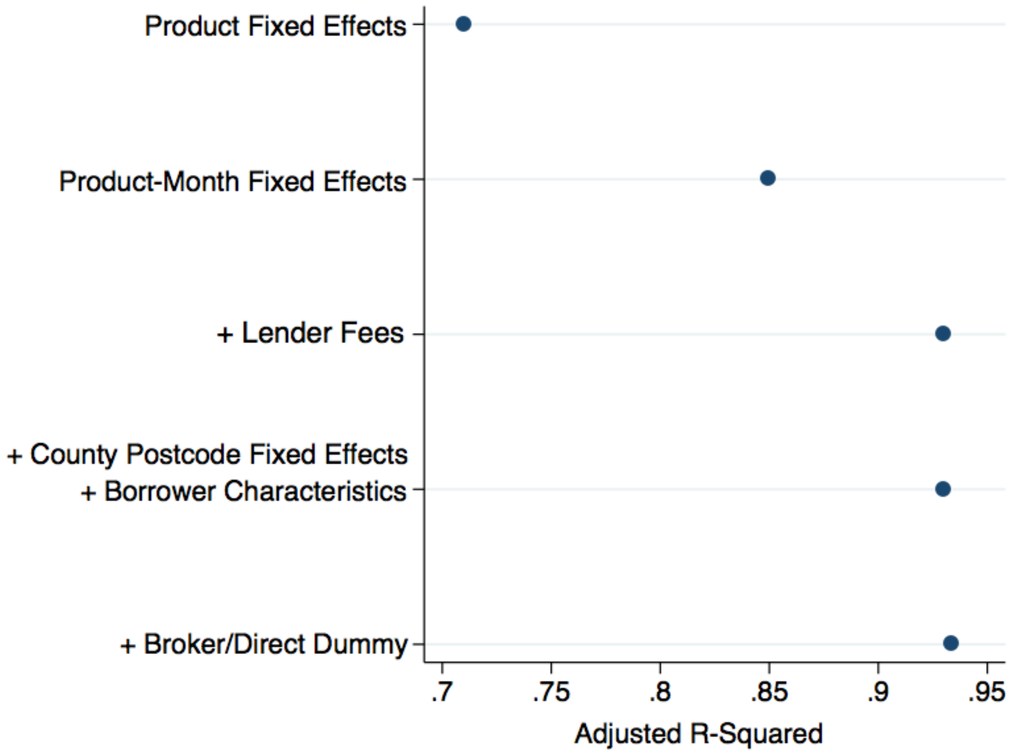
### 1.2.1 The UK Mortgage Market

The UK mortgage market has several institutional features that differentiate it from mortgage markets in the US, Canada, and Continental Europe. For example, the UK has no long-term fixed-rate mortgages. Most products feature a relatively low (usually fixed) interest rate for an initial period of usually two, three, or five years followed by a (usually floating) reset rate that is significantly higher. Reset rates last until the end of the mortgage term, unless borrowers decide to refinance. Additionally, most mortgage contracts include early repayment charges, which typically account for 5% or 10% of the outstanding loan and are in place until the end of the initial fixed period. Given the significant size of these charges and the jump in the reset rate, most borrowers refinance around the time when the initial duration ends, making remortgaging a relatively frequent event in this market (see, e.g., Cloyne et al., 2017).

Another important aspect of the UK mortgage market is individual-based pricing or negotiation between the lender and the borrower is limited. All borrowers purchasing the same mortgage product pay close to the advertised rate. Lenders' pricing of default risk in this market seems to be driven by loan-to-value ratios (see, e.g., Best et al., 2018), whereas the pricing of refinancing risk is embedded in the duration of the initial fixed period (see, e.g., Benetton, 2018). Therefore, products with the same maximum loan-to-value and initial fixed period should have very similar interest rates for a given lender. I test this assertion by regressing loan-level interest rates on an extensive set of dummy variables. Figure 1-1 reports the adjusted R-squared that results from such regressions. I consider a product to be a triplet of the maximum loan-to-value, initial period, and lender, and I find that product-month fixed effects and the corresponding lender fees account for more than 90% of the variation in mortgage rates. The adjusted R-squared does not increase once I control for borrower characteristics (age, income, credit score, employment status) and location of the property. Moreover, the residual variation cannot be explained after including a dummy for the mortgage being originated through a broker.

In terms of market structure, the UK mortgage market is very concentrated upstream. The six largest lenders in the market account for more than 75% of mortgage originations. Panel A in Figure 1-2 shows the consolidation process that these lenders, the so-called "Big Six," have experienced over the last decades. Through a series of mergers and acquisitions, they have been able to achieve significant

Figure 1-1: Explained variation in mortgage pricing




Note: the chart reports the adjusted $R^2$ of regressions of household level interest rates and fees on a set of dummy variables. First row includes only dummies for the product (interaction of lender, maximum loan-to-value band and initial fixed period). Second row adds fixed effects for each month. Third row adds dummies for lender fees (other price). Fourth row includes dummies for the location of the house and borrower characteristics (income, age, credit score). Finally, fifth row adds a dummy accounting for whether the mortgage was originated by a broker or directly through the lender's in-house distribution channels.

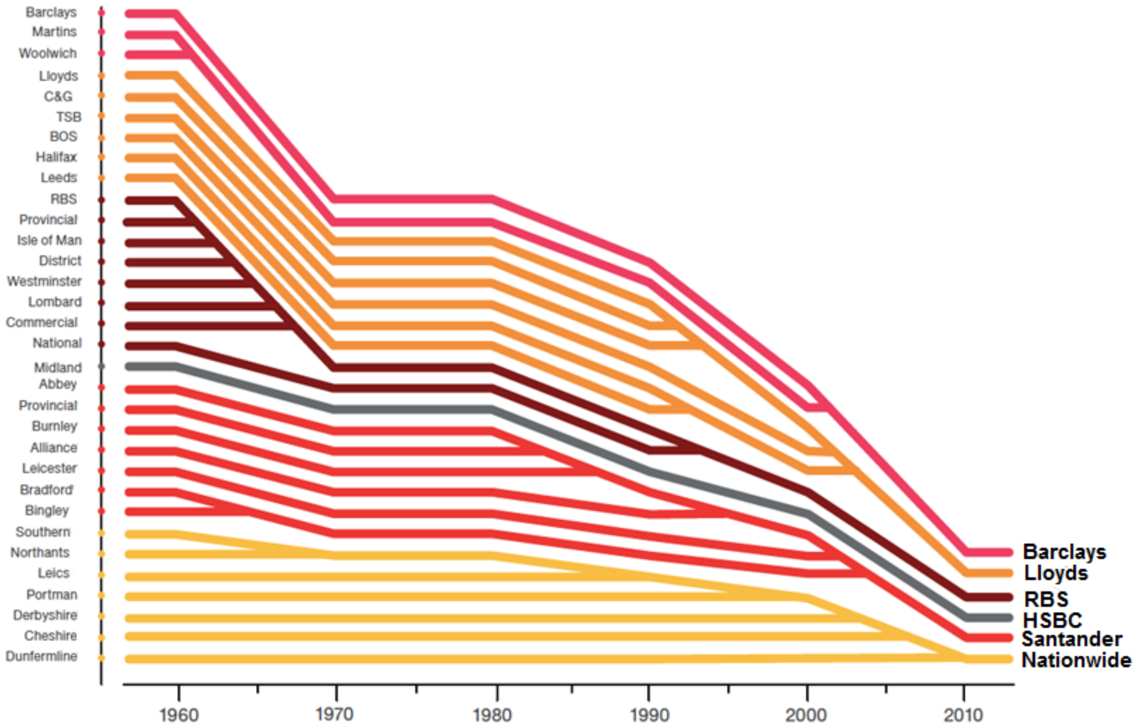
market power at a national level. However, the last several years have also seen significant entry in the market from the so-called "Challenger Banks." Panel B in Figure 1-2 presents the timeline for the main entrants in the mortgage market. Many of these entrants have a very limited branch network and promote their products mostly through on-line distribution channels and intermediaries. This strategy has proven successful partly because of the strong presence of mortgage brokers in the UK market. In 2017, more than 70% of first-time-buyers and 60% of home-movers originated their mortgage through an intermediary. Brokers also have a significant market share in the remortgaging market, especially for those borrowers who refinance with a different lender. Although many individual brokers are present in the form of one-person firms, the broker market is dominated by the largest 20 broker companies. These brokerage firms account for more than 60% of all new originations and have direct communication with lenders. I will discuss the relationship between lenders and broker companies in more detail when describing the data in the next subsection.

### 1.2.2 Data

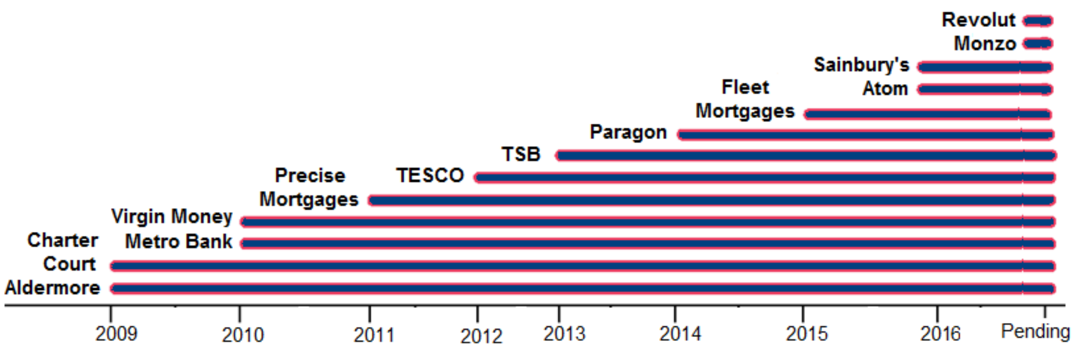
My main dataset is the Product Sales Database (hereafter, PSD), which is a comprehensive regulatory dataset containing the universe of residential mortgage originations in the UK. These data are collected quarterly by the Financial Conduct Authority (FCA) and are only available to restricted members of staff and associated researchers at the FCA and the Bank of England. For the purposes of this paper, I focus on the year 2015 and the first half of 2016. During this period, I observe for each mortgage origination details on the loan (interest rate, loan amount, initial fixed period, lender, fees), the borrower (income, age, credit score), and the property (value, location). I also have information on the distribution channel, that is, whether a broker intermediates the sale and, if so, the identity of the brokerage.

Figure 1-2: Consolidation and Entry in the UK Mortgage Market

PANEL A: Consolidation in the UK banking sector over the last 50 years




PANEL B: Entry in the UK banking sector over the last 10 years (not exhaustive)




Notes: Panels A shows mergers and acquisitions for the Big Six lenders in the UK. Panel B presents a non-exhaustive timeline of recent entrants in the UK mortgage market. Graphs use data adapted from PwC Report "Who are you calling a challenger?", Bankers Magazine, and Quarterly Bulletin, Q4, Bank of England, 2010, plus additional dates from lenders' own websites.

Table 1.1 summarizes the data. I observe more than 2 million contracts of which almost 90% are mortgages with initial fixed periods of two, three, and five years. Given the importance of refinancing in this market, the finding that more than 50% of borrowers in my sample are either external or internal remortgagors is not surprising. The average interest rate is 2.57 percentage points, and lenders charge on average an origination fee of £467. The average loan is almost £160,000 with a loan-to-value of 60%, a loan-to-income of 3.1, and an average maturity of 25 years. Borrowers are, on average, 38 years old, have an annual income of £62,000. Borrowers are richer and have higher credit scores than the average UK resident.

Table 1.1: Summary Statistics (All Borrowers).

| | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Panel A: Loan Characteristics | | | | | |
| Interest Rate (%) | 2,236,025 | 2.57 | 0.79 | 1.26 | 6.2 |
| Lender Fee (£) | 2,236,025 | 467 | 631 | 0 | 2405 |
| Loan Value (£1000) | 2,236,025 | 159 | 129 | 49 | 903 |
| Loan-to-Value (%) | 2,236,025 | 60 | 23 | 15 | 98 |
| Maturity (Years) | 2,236,025 | 25 | 8 | 2 | 45 |
| Initial Period (Years) | 2,236,025 | 3.22 | 2.4 | 1 | 10 |
| Panel B: Borrower Characteristics | | | | | |
| First-Time-Buyers | 2,236,025 | 0.19 | 0.39 | 0 | 1 |
| Home-Movers | 2,236,025 | 0.23 | 0.42 | 0 | 1 |
| Internal Remortgagors | 2,236,025 | 0.22 | 0.41 | 0 | 1 |
| External Remortgagors | 2,236,025 | 0.36 | 0.48 | 0 | 1 |
| Gross Income (£1000) | 1,506,724 | 62.13 | 48.2 | 10 | 523 |
| Age (Years) | 1,506,724 | 38 | 9.6 | 18 | 85 |
| Loan-to-Income | 1,506,724 | 3.12 | 1.2 | 1.3 | 5.2 |
| Credit Score | 984,471 | 482 | 66.3 | 250 | 765 |

I complement the PSD data with novel information on broker companies that is also collected by the FCA. For each mortgage origination in the PSD, I observe commission payments (made by lenders to brokers for a given sale), broker fees (paid by borrowers), and supplementary details on contract agreements between lenders and brokers. Table 1.2 summarizes the data. Panel A compares the fraction of intermediated sales and the average per-sale broker remuneration across borrower types. More than 70% of first-time-buyers originate their mortgage through a brokerage. Intermediation is also the most popular distribution channel in the home-movers and external remortgagors markets, with shares above 60%. Only 11% of internal remortgagors (those refinancing with the same lender) hired a broker when renewing their mortgage. On average, a broker will receive over £800 per mortgage, with most of the revenue coming from lenders' commissions and only a small fraction (if any at all) from broker fees. Figure A-1 plots the distribution of broker fees, revealing that most broker companies charge borrowers zero fees for their services. On the other hand, commissions from lenders are quite generous. Figure A-2 shows the distribution of commission rates across borrower types. No within-lender-broker variation exists for a given period, implying commissions are the same for all products within each lender-broker pair. However, significant heterogeneity exists across brokers and across time, with commission rates ranging between 0.3% and 0.8% of the loan.

Panels B and C of Table 1.2 report the average number of agreements between brokers and lenders and the fraction that were formed or broken during my sample period. The average lender deals with 13 broker companies, whereas the average brokerage sells products from 18 lenders. However, there is heterogeneity both across brokers and across lenders. For example, one lender has no dealings with brokers, whereas another lender has agreements with all brokers. Likewise, some broker companies have very few lenders in their network, whereas others include almost

Table 1.2: Summary Statistics for Intermediated Sales and Broker-Lender Agreements.

PANEL A: Intermediated sales and broker payments.

| | All Borrowers | First-Time Buyers | Home Movers | Internal Remortgagors | External Remortgagors |
|---|---|---|---|---|---|
| Intermediated | 46% | 72% | 64% | 11% | 63% |
| Commission (£) | 723 | 661 | 845 | 708 | 543 |
| Commission Rate (% loan) | 0.41 | 0.42 | 0.41 | 0.41 | 0.37 |
| Broker Fee (£) | 141 | 167 | 164 | 3 | 129 |
| N | 2,236,025 | 426,958 | 510,833 | 797,430 | 500,804 |

Panel B: Agreements between largest lenders and broker companies.

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| Number of Brokers per Lender | 13 | 7 | 0 | 23 |
| Number of Lenders per Broker | 8 | 3 | 3 | 14 |

Panel C: Changes in agreements between 2015Q1-2016Q2.

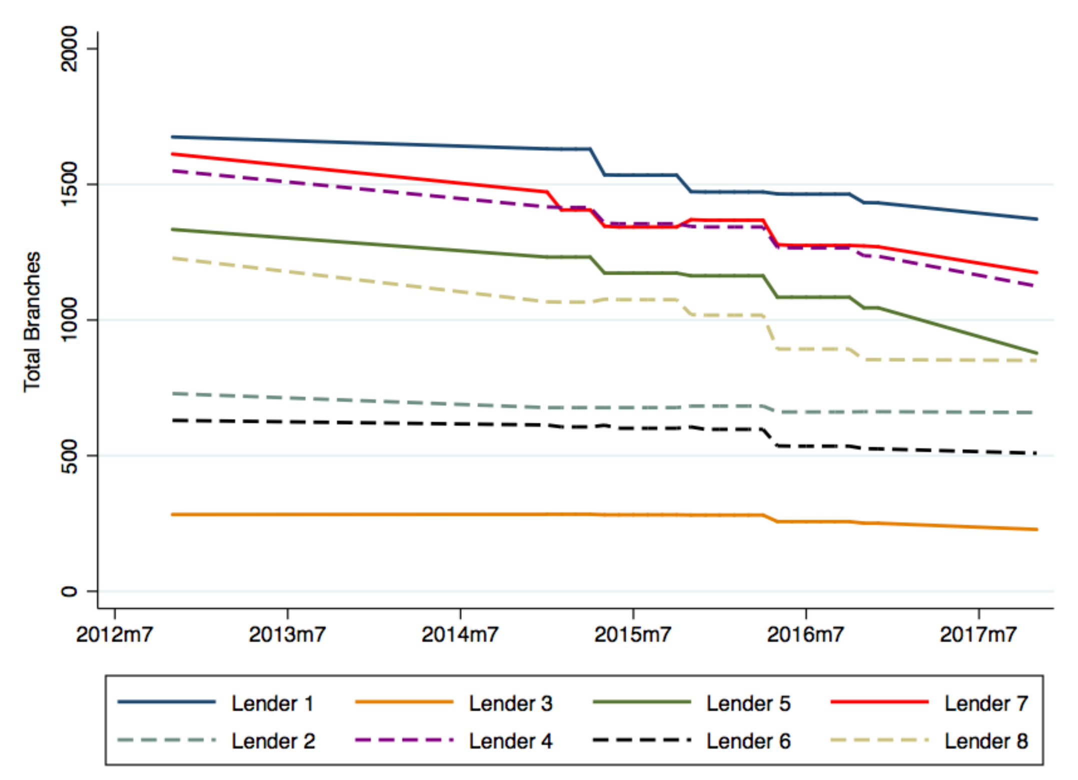
| | |
|---|---|
| Lender-Broker Links Broken | 11% |
| Lender-Broker Links Formed | 18% |

Note: Panel A summarizes the percentage of borrowers who originate their mortgage through a broker and the average per-sale commissions and fees brokers receive by lenders and households, respectively. Panels B and C report all agreements between the largest 16 lenders and 23 broker companies, which account for 87% of the first-time-buyers market. These constitute the set of lenders and brokers that I will use later when estimating the model.

every lender. There is variation in broker-lender networks across time. Throughout my sample period, there are 18% new agreements and 11% of links are broken.

Finally, I collect quarterly postcode-level data on all bank branches in the UK from Experian's Goad and Shop*Point datasets. This panel allows me to identify branch openings and closures for all lenders in my sample. Figure 1-3 plots time-series variation in the number of branches for the largest lenders. Aggregate total branches fall by almost 17% during my sample period. Despite the general downward trend, branch openings and closures are very heterogeneous across lenders and geographical areas (see Figure A-3). For example, London and other large urban

Figure 1-3: Total Branches for largest lenders




Note: Data obtained from Experian Shop*Point and Goad datasets. Total branches account for both openings and closures during the sample period.

conurbations experience large openings for some lenders, whereas some rural areas are essentially bank-branch deserts.

Overall, the combination of these three sources of data provides me with a very rich, loan-level dataset that is ideal for analyzing the effects of broker remuneration on the market. This paper is the first to exploit these combined datasets and the first one to address the role of brokers in this market.

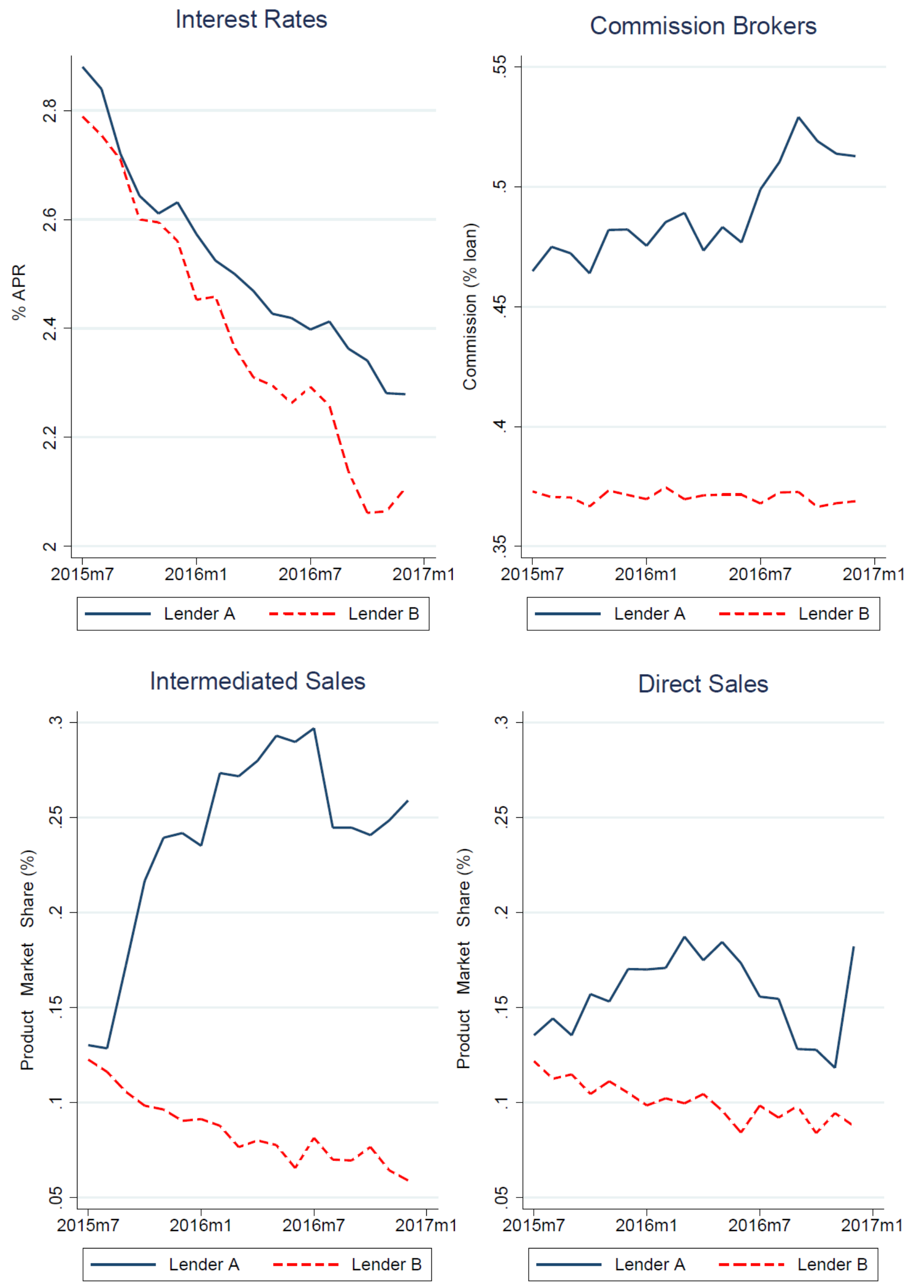
## 1.3 Motivating Evidence

In this section, I document in more detail evidence in favor of the economic trade-offs and conflicts of interest that can potentially exist in the presence of commissions in this market. On the one hand, commissions may distort brokers' advice. On the other hand, they can increase competition and efficiency upstream, leading to overall lower prices. I now present motivating evidence suggesting both sides of the trade-off are present in the UK mortgage market, and that the data supports the inclusion of these forces in the model.

### 1.3.1 Brokers' Advice and Commissions

Commissions from lenders can potentially bias brokers' recommendations towards high-commission products. This distortion can be detrimental for borrowers if products offering high payments to brokers are also more expensive. Figure 1-4 illustrates this concern with a conceptual example using two lenders offering one of the most popular products in the market: a two-year fixed, 75% loan-to-value mortgage. Lender B's product is always cheaper, but Lender A's product pays a higher commission to brokers. Despite being more expensive, Lender A's product has a higher market share via direct sales. Unobservable characteristics, such as more advertisement or lax screening, could explain this gap in direct sales between lenders

Figure 1-4: Example of (Potential) Distortion in a "Vanilla" Mortgage




Note: This figure illustrates prices, commissions, and sales for two different lenders offering one of the most popular products in the market (2-year fixed, 75% LTV). Prices include interest rates and lender fees, and commission rates are expressed as a percentage of the loan.

A and B. The distortion that I would like to address in this section relates to the even larger difference in market shares observed for intermediated sales. In particular, in this subsection, I provide evidence showing that differences in commission payments partly explain the gap in broker market shares.

It is not obvious that commissions will influence brokers' sales choices. In the UK mortgage market, mechanisms are in place that discipline brokers and help ensure they act in their customers' best interests. For example, given the high-frequency of remortgaging in the UK market, repeated sales can align borrowers' and brokers' incentives. Brokers may maintain a good relationship with households in order to ensure they return for future mortgage transactions. Indeed, in a recent consumer survey, 68% of households said they were satisfied with their broker and would use the same intermediary in the future.[2] Brokers can also be motivated by reputation concerns. Consumer surveys find that 23% of borrowers chose their broker because a real estate agent recommended it, and 29% because a friend or relative suggested it. Therefore, in a market where referrals seem to play a critical role, brokers are less likely to engage in misconduct for fear of not being recommended in the future. All in all, whether brokers are reacting to commissions despite repeated sales and reputation concerns remains an empirical question.

In an attempt to capture the effect of commissions on brokers' product choices, I estimate the following fixed-effects specification at the product-broker-month-county level:

$$Share_{bjtc} = \alpha + \theta\, Commission_{blt} + \delta_{jtc} + \gamma_{btc} + \psi_{blc} + \epsilon_{bjtc}\,, \tag{1.1}$$

where the dependent variable is the percentage share of product $j$ in broker $b$'s sales portfolio at month $t$ in county $c$. The independent variable $Commission_{blt}$ is the per-sale commission rate that broker $b$ receives from lender $l$ in month $t$. To solve some of the endogeneity concerns when regressing product shares on commissions,

[2]See Question M56 in the FCA's consumer survey *Financial Lives Survey 2017*.

I control for confounders by absorbing a rich set of fixed effects at the county level. I include product-time-county fixed effects to account for time-varying product characteristics that could affect brokers' product preferences, such as interest rates, advertisement, and fees. I also add broker-time-county fixed effects to control for time-varying broker characteristics that could influence brokers' choices, such as their borrower clientèle. Finally, I also add broker-lender-county fixed effects to account for preexisting dealings between a broker and a lender that could result in preferential treatment. This four-differences approach deals with the obvious endogeneity concerns; however, the estimate for $\theta$ could still be biased if broker-product-time-county-varying confounding variables exist. I will further discuss these endogeneity issues when estimating the model. At that stage, I will try to address these concerns using an instrumental variables approach exploiting time-variation in cost-shifters at the broker-lender level.

Table 1.3 presents estimates for equation 1.1. The first column uses the entire sample, and the second column focuses exclusively on first-time-buyers. Both specifications control for a rich set of fixed effects, resulting in a positive and significant coefficient with values of 0.163 for all borrowers and 0.271 for first-time buyers. Thus, products with a 13% (£100) higher commission rate for a broker have, on average, almost a 2% higher market share within a broker's portfolio. Table 1.3 shows suggestive evidence that, after controlling for the obvious confounders, brokers seem to be reacting to changes in commission rates.

Estimates in Table 1.3 exploit within-broker-product variation across time within a county. Results suggest changes in a product's commission will, on average, increase the products' share within a broker's sales portfolio. However, a broker's advice can also be biased across different products. For instance, brokers may be more likely to recommend products with shorter fixed initial periods that will require households to refinance more frequently. Brokers receive another commission payment each time borrowers need to remortgage. Brokers also have incentives to push borrowers toward higher loan-to-value products. Because commissions are expressed as a percentage of the loan amount, brokers may persuade households to borrow as much as possible.[3]

Table 1.3: Product Market Shares and Commissions.

| Dependent Variable: Product Market Share in Broker Sales (%) | All Borrowers (1) | Only FTBs (2) |
|---|---|---|
| Commission Rate | 0.163* | 0.271* |
| (% loan) | (0.097) | (0.180) |
| Product-Time-County FE | Yes | Yes |
| Broker-Time-County FE | Yes | Yes |
| Broker-Lender-County FE | Yes | Yes |
| Observations | 327,750 | 153,416 |
| Adjusted R-squared | 0.953 | 0.937 |
| Average Dependent Variable (%) | 0.53 | 0.47 |
| Average Commission Rate (%) | 0.40 | 0.41 |
| Average Total Commission per Loan (£) | 776 | 802 |

Note: The dependent variable is the product share in a broker's sales portfolio each month in a county. The commission rate is the percentage of the loan paid by the lender to the broker for the sale of a product. Column (1) uses all borrowers, while Column (2) considers only first-time-buyers. Standard errors in parentheses are clustered at the broker and county levels, and (*) corresponds to a p-value lower than 0.1.

[3]In the US, the media and consumer groups have argued that brokers advice to households to borrow beyond their means exacerbated the financial crisis. See, for example, Pleven and Craig, "Deal Fees under Fire Amid Mortgage Crisis; Guaranteed Rewards of Bankers, Middlemen Are in the Spotlight," Wall Street Journal, January 17, 2008; and "Steered wrong: Brokers, borrowers, and subprime loans," *Center for Responsible Lending*, 2008. Similar concerns have been raised in Europe by the Basel Committee on Banking Supervision's Report, "Customer suitability in the retail sale of financial products and services," 2008.

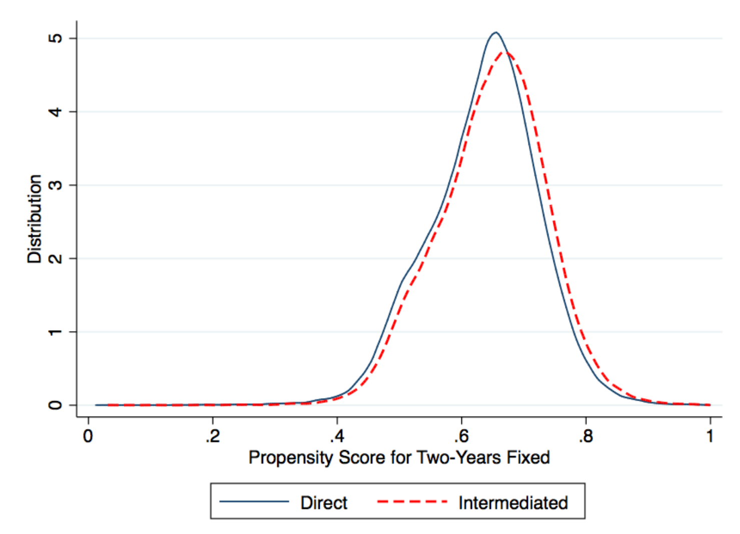
Both types of distortions are, however, difficult to identify empirically due to selection into intermediation. Indeed, the data shows brokers selling more two-year fixed mortgages (vs. three- and five-year fixed) and higher loan-to-value products than the direct sales channel. Still, unobservable (to the econometrician) borrower characteristics could explain these choices. Households originating their mortgages through brokers may have different preferences than those going directly to lenders, and brokers could be selecting the best products conditional on such (unobservable) preferences. To get a sense of any evidence in the data that might suggest selection into brokerage, I calculate borrowers' propensity scores for buying mortgages with (1) high loan-to-value and (2) a short initial fixed period. I use as predictors the borrower's characteristics (income, age, credit score, and whether it is a joint application), property characteristics (house price and location), and month of the year. Figure 1-5 plots these propensity scores separately for direct and intermediated sales. Based on observable characteristics, borrowers going through brokers are slightly more likely to buy a mortgage with high loan-to-value and short initial period. However, I cannot reject that distributions for both channels are statistically different. Unobservable product and borrower characteristics can be driving the observed differences in choices between direct and intermediated sales. Brokers' preferences over product characteristics could also be an explanation. In the model in Section 2.2, I explicitly account for borrowers' selection into intermediation and brokers' incentives both within and across product types. I am able to separately identify the borrower and broker preferences over product characteristics, other than commissions.

### 1.3.2 Upstream Competition and Commissions

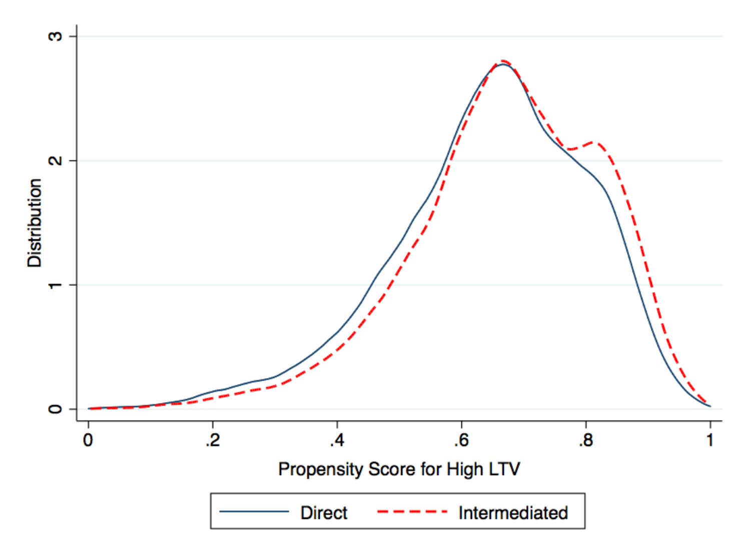
Despite the recent uptake of online distribution channels in many markets, bank branches still play a crucial role in mortgage originations in the UK. Panel A in

Figure 1-5: Selection into Intermediation

PANEL A: Probability of Getting a 2-Year Mortgage




PANEL B: Probability of Getting a High Loan-to-Value Mortgage



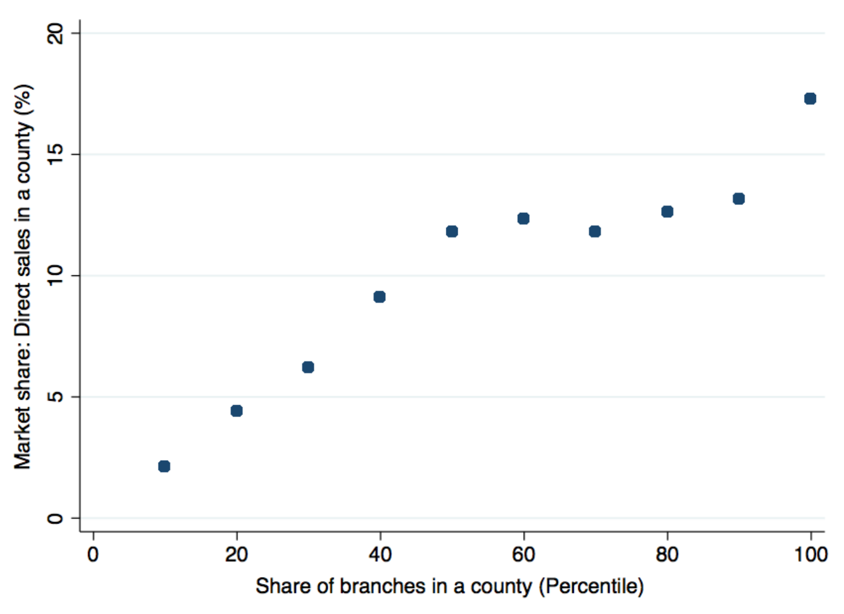

Notes: Panel A shows for each sales channel the probability that a first-time-buyer get a two-year mortgage based on its observable characteristics (age, income, credit score, partner, house price, location) and month dummies. Panel B plots the analogous probability for choosing a mortgage with a loan-to-value greater than 85%.

Figure 1-6 shows that lenders with a more significant concentration of branches in a given county account for a higher share of direct sales in that same county. This strong positive correlation between direct sales and branch presence still holds after adding lender and area fixed effects to account for local demand and lender preferences. Moreover, recent changes in regulation implemented by the Mortgage Market Review (MMR) in April 2014 have intensified the importance of bank branches as a distribution channel. The MMR requires lenders to provide advice for all sales that require any "interaction" with borrowers. Lenders have been very conservative in their interpretation of these "interaction trigger" and now provide lengthy advice to almost all of their borrowers, except for internal remortgagors. Although some lenders give the option of speaking to an advisor over the phone, most borrowers are redirected to the nearest branch for an appointment with a specialized advisor to discuss their mortgage application. Both face-to-face and telephone interviews of almost two hours on average. However, no such requirement exists for borrowers originating their mortgages via brokers. Lenders seem to be taking advantage of this fact and are using commissions to promote their products to intermediaries in areas where borrowers would have to travel a significant distance to their nearest branch for an interview. Panel B in Figure 1-6 shows that lenders are also more likely to pay higher average commission rates in counties where they have a lower concentration of branches. In such cases, commissions and brokers can increase welfare by (1) lowering lenders' distribution costs, (2) reducing borrowers' origination costs and (3) increasing households' available choice sets, especially in the so-called "bank-branch deserts."

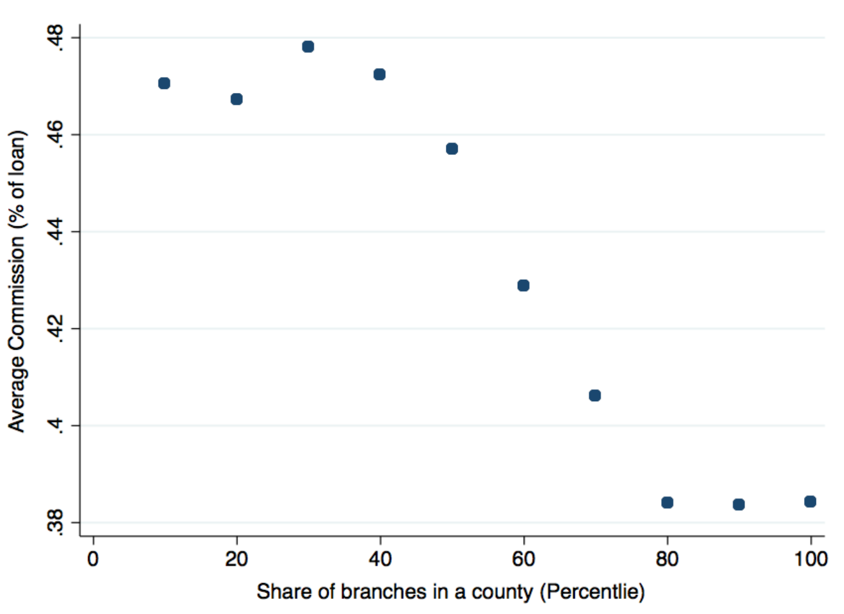
Moreover, commissions also allow challenger banks to introduce and promote their products in the market without the need to set up extensive (and expensive) branch networks. Panel A in Figure 1-7 plots average interest and commission rates for challenger and non-challenger lenders over my sample period, and Panel B

Figure 1-6: Branches, Direct Sales and Commissions

PANEL A: Correlation between branches and direct sales



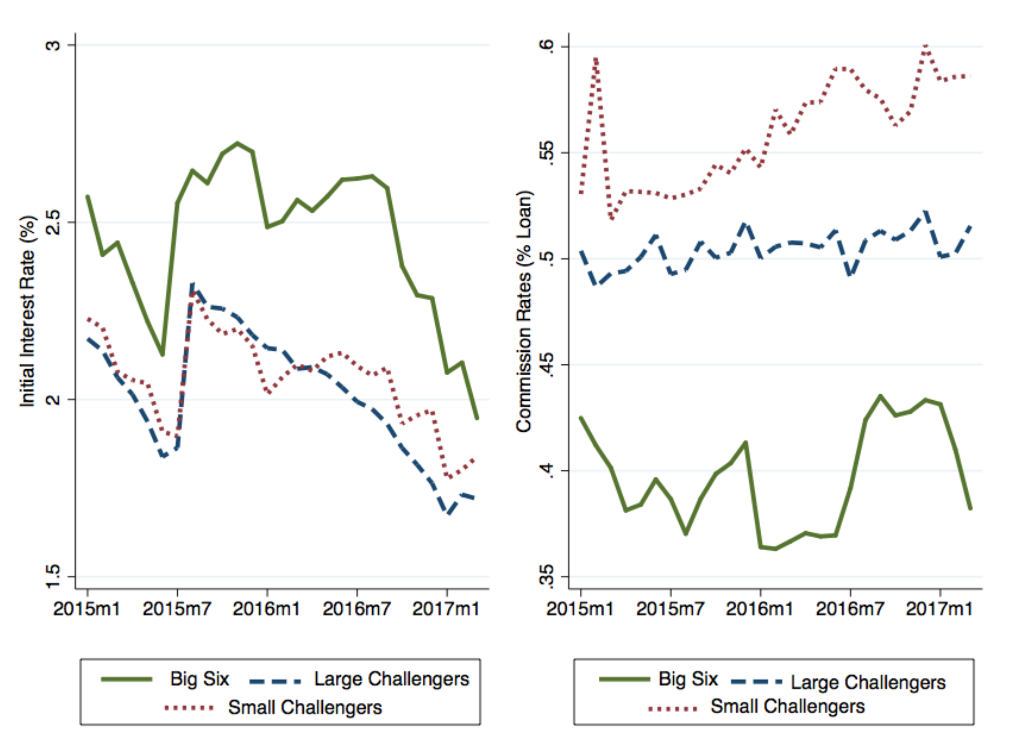

PANEL B: Correlation between branches and average commissions



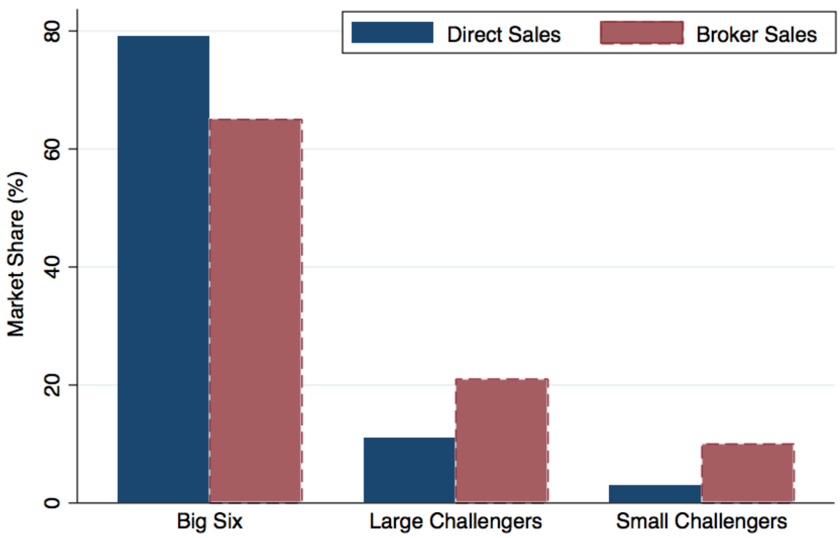

Note: On the X-axes I sort all county-lender pairs according to the lender's concentration of branches in the county. In Panel A, I then average direct sales for each lender within a county. In Panel B, I calculate the average commission rates for each lender within a county.

Figure 1-7: Commissions and Market Shares across Lenders

PANEL A: Average commissions for the Big Six and challenger banks.




PANEL B: Market shares across lender types and sales channels.



in Figure 1-7 shows the corresponding market shares for direct and intermediated sales channels. On average, challenger banks pay higher commission rates and account for a higher market share in brokers' sales than in direct sales. To formalize this relationship between challenger banks and intermediated sales, I estimate the following specification:

$$Challenger_{ijt} = \alpha + \delta \, Intermediated_{ijt} + \beta X_{ijt} + \epsilon_{ijt} \,, \tag{1.2}$$

where $Challenger_{ijt}$ is a dummy equal to one if household $i$ at time $t$ purchased mortgage product $j$ from a challenger bank, and zero otherwise. The independent variable $Intermediated_{ijt}$ is a dummy variable equal to one if the household originated the mortgage through a broker, and zero if it used the direct channel instead. Covariates $X_{ijt}$ control for observable borrower, product, geographical, and time-period characteristics.

Table 1.4 shows estimates for equation 1.2. After controlling for borrower and product characteristics and year-month and county fixed effects, first-time-buyers going to a broker have a 7% higher probability of originating their mortgage through a challenger bank. Although this relationship can be driven by unobservables and selection into intermediation, brokers seem to be increasing challenger banks' market shares. Given that for many products in the market, challenger banks offer better rates than the Big Six, commissions can benefit households via their allocative role in the broker channel, inducing higher matching rates between borrowers and challenger banks.

## 1.4 The Need for a Model

The results in the preceding subsections 1.3.1 and 1.3.2 point to a key trade-off emerging from the presence of brokers in this market. On the one hand, brokers'

Table 1.4: Probability of Getting a Product from a Challenger Bank.

| Dependent Variable: Challenger (0/1) | All Borrowers (exc. Internal Remortgagors) (1) | First-Time-Buyers Only (2) |
|---|---|---|
| Intermediated | 0.0476*** | 0.0674*** |
| | (0.001) | (0.003) |
| Max. LTV Band FE | Yes | Yes |
| Fixed Period FE | Yes | Yes |
| County FE | Yes | Yes |
| Year-Month FE | Yes | Yes |
| Borrower Characteristics (income, age, credit score) | Yes | Yes |
| Observations | 489,352 | 159,486 |
| R-squared | 0.24 | 0.33 |

Note: The unit of observation is at the household level. Dependent variable is a dummy equal to one if the borrower chose a mortgage from a challenger bank. Robust standard errors in parentheses such that (***) corresponds to a p-value lower than 0.01.

advice can be distorted towards high-commission products, potentially reducing consumer surplus. On the other hand, brokers allow challenger banks to introduce their products without the need to invest in an extensive branch network, increasing competition upstream and potentially leading to lower prices. Moreover, brokers also allow established banks to promote their products in areas where they have limited branch density, reducing their distributional costs and eventually resulting in efficiency gains and lower prices. Finally, as shown in section 3.2.1, consumers currently pay very low fees (in many instances, no fee at all) when hiring a broker. These low charges are possible only because brokers are getting most of their revenue directly from lenders. Commission payments decrease the price consumers pay for valuable expert services that reduce household search costs and increase the information on available products. Given these trade-offs, the net effect of commissions on consumer surplus depends on which of all these forces dominates in equilibrium.

To evaluate the overall impact of regulating broker payments, it is necessary to empirically assessing the relative sizes of these effects on consumer surplus. This may prove to be difficult for three reasons. First, no counterfactual scenario regulating commissions exists in this market. This limitation precludes evaluating the performance of such a policy in this context. The second challenge arises due to selection into intermediation. Consumers decide whether to hire a broker, based on observable and unobservable (to the econometrician) characteristics of both the borrower and the broker. Therefore, in the presence of this endogenous choice, reduced-form methods would require strong assumptions when evaluating such behavior, which could ultimately bias the resulting estimates. Finally, contract negotiations between lenders and brokers endogenously determine commission payments in this market. To evaluate the effects of a hypothetical cap or ban on such commissions, understanding the incentives and the trade-offs lenders and brokers face when deciding whom to include or exclude from their sales networks and what commissions to set in such agreements is necessary.

In Chapter 2, I present and quantify a structural model of the UK mortgage market that features all trade-offs discussed above. Such a framework will help overcome the empirical limitations described in this section and will enable me to quantify the net effect on consumer surplus of restricting upstream commissions. The goal of the next chapter is to evaluate policies similar to those implemented by regulators worldwide.

# Chapter 2

# Regulating Broker Compensation in the UK Mortgage Market

## 2.1 Introduction

In many financial markets, expert advisors often receive commission payments from upstream firms. In theory, this form of compensation can generate an agency problem between experts and households by distorting advice towards higher-commission, more expensive products. Motivated by consumer detriment due to biased advice, regulators worldwide have recently restricted financial relationships between upstream firms and expert advisors.[1] Although these policies might help align experts' incentives with those of consumers, they will also have supply-side equilibrium effects on competition and efficiency in the market. The empirical evidence on these equilibrium effects is, however, very limited. This chapter contributes to this

[1] Examples of these initiatives include the Retail Distribution Review in the UK, which resulted in a ban on all upstream commissions for retail investment advice. The Netherlands and Australia have also introduced comparable bans on commission payments for complex financial products, and other countries such as Canada are currently considering the possibility of taking similar measures. In the US, the Consumer Financial Protection Bureau recently introduced new loan originator compensation requirements under the Truth in Lending Act. These new requirements restrict mortgage brokers' upstream payments.

debate by modeling and quantifying the effects on welfare and market structure of regulations restricting payments between lenders and brokers in mortgage markets. Understanding the financial relationships between lenders and mortgage brokers is important both because of the central role mortgage markets have in the consumer credit landscape (where brokerage is often households' most preferred option) and because of the economic and policy implications of similar restrictions in other markets (e.g., insurance, retail investment, and real estate).

With the empirical evidence presented in Chapter 1 in mind, I develop a structural model of the UK mortgage market that I later estimate and use to quantify the net effect of restricting commission payments on welfare. The model features (1) utility-maximizing households in need of a mortgage for the purchase of a residential property, (2) heterogeneous multi-product lenders selling differentiated mortgage products and competing on interest rates, and (3) broker firms providing advice to households on available products and processing all application and origination paperwork. On the supply side, I endogenize commission payments in this market by modeling negotiations between a broker and a lender as a Nash bargaining game. Each pair bargains over the lender's inclusion in the broker's network. In the event of an agreement, the pair sets a per-sale commission, and the broker can originate the lender's mortgages. Once all negotiations end, each lender chooses interest rates to maximize its expected profits. On the demand side, I model households' choice of distribution channel as a discrete choice between hiring a broker or going directly to lenders' in-house distribution channels (e.g., branches). This decision depends on the households' search costs and their expected payoffs from each channel. After choosing a distribution channel, the household needs to decide on a mortgage product. I model this part of demand as a discrete logit with households' preferences being a function of interest rates, product characteristics, and latent demand. Broker preferences over commissions and other product characteristics will also matter for those households that selected the intermediated channel.

Demand estimates show the following: (1) Brokers have downstream market power and can extract surplus from consumers, confirming the existence of an agency problem between households and brokers; (2) average household search costs account for almost 20% of consumer surplus, implying the average household finds it very costly to originate a mortgage on its own; and (3) households going directly to lenders have a preference for nearby branches. This taste for branch proximity disappears for households hiring a broker. Consumers originating their mortgages via the direct channel face stronger lender market power (at the local level) than those choosing the intermediated channel. Thus, changes in competition across lenders have a differential impact on households, depending on their choice of sales channel.

On the supply side, I find that lenders' marginal costs are on average greater for higher loan-to-value bands and products with longer initial fixed periods. Additionally, estimates show that lenders' marginal costs differ depending on the sales channel, with broker sales being less costly than direct sales. Thus, brokers improve efficiency in the market by reducing costs both for lenders (via lower marginal costs) and households (via lower search costs). Finally, the estimated bargaining parameters reject take-it-or-leave-it offers as a model for setting commission payments in this market.

Next, I use these estimates to simulate welfare effects of policies restricting brokerage services and commissions. A counterfactual simulation with no brokers results in a drop of 51% in consumer surplus. This decrease is driven by a 156% increase in search costs for households, a 13% increase in lenders' marginal costs, and a 35% increase in the Herfindahl-Hirschman Index (HHI). The decrease in competition results from consumers going direct having a preference for nearby branches and only the largest lenders having a dense branch network. Overall, the combination of these three equilibrium effects results in 24% higher prices and consumers being worse off than in the baseline with broker services.

Next, I consider counterfactual scenarios with a complete ban on commissions (motivated by recent regulations) and three different caps. Two countervailing forces largely determine my results: broker and lender market power. Households choosing the intermediated channel face broker market power, resulting from brokers' capacity to extract surplus from the household. Households originating their mortgage directly with lenders experience local lender market power, driven mainly by the presence of nearby branches. When compared with the baseline with no restrictions on commissions, a ban reduces broker market power at the expense of increasing lender market power. In this situation, the price of expert services increases for households, causing 115% more households to choose lenders' in-house distribution channels and increasing search costs by 83%. Due to the lack of extensive branch networks, the share of challenger banks goes down by 16% with the HHI increasing by 21%. Lenders' average marginal cost goes up by 7%, causing prices to rise by 11%. The net effect of these forces is a 25% decrease in consumer surplus.

Alternatively, I find that a cap equal to the median commission payment in the baseline case with no restrictions generates a 10% increase in consumer surplus. In this scenario, the decrease in broker market power is sufficiently large to compensate for the increase in lender market power. The intuition is that a cap still allows brokers to get revenue from lenders, causing household broker fees to increase but not as much as in the case of a ban. Therefore, although the share of direct sales increases by 30%, the competition effect of challenger banks dominates and prices fall by 5%. Overall, these findings are evidence in favor of capping, rather than banning, commission payments in markets where consumers can access the good not only through intermediaries, but also directly from upstream firms. The trade-offs for competition and efficiency need to be considered when implementing similar policies in other markets where consumers face high search costs and brokers and lenders have market power.

**Contributions to the Literature.** This paper contributes mainly to three strands of literature. First, it complements existing approaches in household finance (Campbell and Cocco, 2003; Campbell, 2012; Best et al., 2018; DeFusco and Paciorek, 2017) by analyzing the role that brokers play in borrowers' demand in mortgage markets (often dominated by intermediated sales). Woodward and Hall (2010, 2012) consider broker fees when analyzing originations in the US mortgage market. They find evidence of significant price dispersion in broker fees and show that groups that are likely less informed pay higher brokerage fees. Jiang et al. (2014) also study the role of mortgage brokers on mortgage delinquency between 2004 and 2008. They find that brokers originated lower-quality loans, which were 50% more likely to be delinquent than bank-originated loans. These papers focus on the interactions between brokers and borrowers, and how brokers' financial incentives can generate biased advice and be detrimental for consumers. I contribute by explicitly accounting for supply-driven equilibrium effects that may increase consumer surplus via more upstream competition, lower search costs, and lower prices. This paper is also the first to develop a structural model to quantify welfare effects from regulations imposing restrictions on brokers' financial incentives. In that sense, my work adds to the recent trend of using structural techniques to analyze markets with financial products, such as pensions (Hastings et al., 2017), insurance (Koijen and Yogo, 2016), retail deposits (Egan et al., 2017), corporate lending (Crawford et al., 2018b), credit cards (Nelson, 2017), and mortgages (Benetton, 2018).

Second, this paper fits into a vast literature on the role of intermediaries. Intermediaries can create value by guaranteeing quality and certifying information (Biglaiser et al., 2017; Biglaiser and Li, 2018), which can alleviate information asymmetries in many markets, such as labor markets (David, 2008, Stanton and Thomas, 2015) and insurance markets (Anagol et al., 2017). Intermediaries can also lessen trading frictions (Gavazza, 2016), reduce search costs (Salz, 2017), promote innovation and adoption of new technologies (Howells, 2006), and facilitate entry (Ahn et al., 2011). This paper is closest to settings in which intermediaries take the form of expert advisors and adds to the growing empirical literature that examines agency problems in expert services. For example, in the prescription drug market, Iizuka (2007, 2012) and Ho and Pakes (2014) find doctors react to financial incentives when dispensing generic drugs. Financial advisors are also not immune to conflicts of interest, with many of them having misconduct records and being repeat offenders (Egan et al., 2018). In the housing market, Levitt and Syverson (2008) show how real estate agents exploit their informational advantage to their financial benefit when advising clients on the timing and sales price of their houses. Similarly, Guiso et al. (2018) find evidence of distorted advice when analyzing lenders' in-house mortgage recommendations to borrowers. Financial incentives can also amplify the effects of high search costs by inducing brokers to steer consumers towards inferior products (Egan, 2018).

Though closely related, this paper differs from prior work on expert advisors in that it estimates welfare effects from a policy restricting supply-side financial incentives. A recent theoretical literature that, similar in spirit to this paper, analyzes market effects in the presence of commission payments to financial advisors (e.g., Inderst and Ottaviani, 2009, 2012a,b,c; Inderst, 2015; Heidhues et al., 2016; Martimort et al., 2017). However, given the possible trade-offs in the market, the overall effect on consumers of banning such commissions is theoretically ambiguous. The empirical literature on the topic is almost inexistent. Grennan et al. (2018) study payments between pharmaceutical firms and physicians. They use a structural model to estimate the equilibrium response of prices and quantities to a ban on these financial incentives and find a positive effect on consumer welfare of such policy. This paper differs from their approach in that it analyzes intermediation services in financial markets, which face different trade-offs than those in the healthcare sector. For example, in many financial markets, consumers can directly access providers without the need to consult with an expert advisor, which is often not the case for medical treatments. Therefore, in market structures where consumers can bypass the intermediary, the exposure of households to market power from providers and intermediaries differs from settings similar to that in Grennan et al. (2018). These differences lead to contrasting welfare effects of policies restricting upstream payments.

Finally, my analysis relates to the recent empirical literature on bargaining. Many of the existing papers focus on the healthcare sector and the interactions between hospitals, insurance companies, suppliers, and firms (see, e.g., Grennan, 2013, Gowrisankaran et al., 2015, Ho, 2009, Ho and Lee, 2017a, Ho and Lee, 2017b, Grennan and Swanson, 2016), and on the telecommunications industry and the relationships between television channels, programming distributors, and viewers (see, e.g., Crawford and Yurukoglu, 2012, Crawford et al., 2018a). This paper is the first to introduce bargaining to analyze vertical payments in credit markets. Moreover, this work also contributes to the literature by modeling a bargaining game in markets where consumers have the option to bypass the intermediary and directly purchase the good from providers via their in-house distribution channels. This type of vertical structure is also analyzed in Donna et al. (2018) for the Portuguese outdoor advertising industry. Similarly to their setting, in my framework when providers and intermediaries negotiate, they acknowledge that their relationship is both vertical (intermediaries provide an alternative distribution channel for providers) and horizontal (intermediaries compete with providers' in-house distribution channels). I exploit this vertical-horizontal structure in a novel identification strategy using geographical and time variation in lenders' branch networks and their outside options to access consumers.

The rest of the chapter proceeds as follows. In Section 2.2, I develop a general equilibrium model for the mortgage market capturing the key trade-offs described in Chapter 1. In Section 2.3, I discuss estimation and identification of the demand and supply. Section 2.4 presents the estimation results. Section 2.5 performs counterfactual and welfare analysis of restricting upstream payments. Section 2.6 concludes.

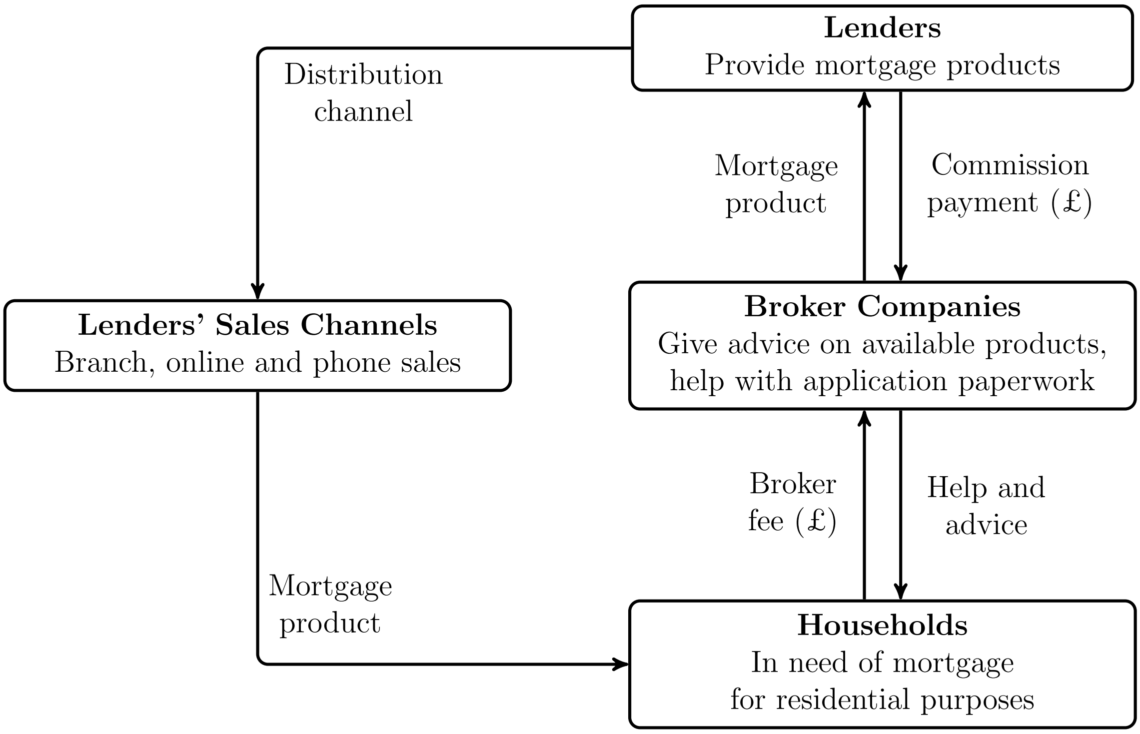
## 2.2 A Model of the UK Mortgage Market

### 2.2.1 Set-up

In this section, I develop a structural model of the UK mortgage market that predicts: (i) household demand for mortgage products, (ii) household demand for brokerage services, (iii) interest rates offered by lenders, and (iv) negotiated lender-broker-specific sales commissions. I later estimate this model and use it as a tool to simulate counterfactual policy analysis.

The model focuses on the interactions between lenders, brokers, and households in the UK mortgage market. Figure 2-1 describes the vertical and horizontal relations in this market between all main players. A *household* consists of one or two potential borrowers in need of a mortgage for the purchase of a residential property. A *lender* is a bank or building society selling differentiated mortgage products to households. A *broker* is a firm that helps households get a mortgage by providing advice on available products and sorting out application and origination paperwork with the lender. The timing of events is as follows. First, brokers negotiate with lenders for the terms of lenders' inclusion in the brokers' networks. If successful, these bilateral negotiations determine the set of commissions paid by lenders to

Figure 2-1: Vertical and Horizontal Relations in the UK Mortgage Market




Note: The diagram displays the main vertical relations in the UK mortgage market. Households in need of a mortgage can pay a fee and hire a broker company to provide them with advice on available products and help them with all paperwork involved in the application and origination of the mortgage. The broker will also receive a commission payment from the lender for each sale. Households can also bypass the broker and access the lender's distribution channels directly via bank branches and online and phone sales.

brokers for the sale of any given product. Next, lenders set prices in the form of interest rates for all their mortgage products. Finally, households decide on a sales channel, that is, whether to hire a broker or use lenders' in-house distribution channels (e.g., branches). I will refer to the former as the intermediated channel and to the latter as the direct channel. Once households have chosen a sales channel, they acquire one of the available mortgage products through that channel. In this setting, lender-broker bargaining and lenders' mortgage pricing constitute the supply side of the market, whereas households' choice of sales channel and mortgage product captures the demand side.

### 2.2.2 Demand

Assume there are markets labeled $t = 1, ..., T$, each with households indexed by $i = 1, ..., I_t$ and with heterogeneous search costs and preferences across product characteristics. I define a market as half-year in my data, and each household can only be active in one market and purchase only one product. In each market there are $l = 1, ..., L_t$ lenders, each selling $J_{lt}$ horizontally differentiated mortgage products, indexed by $j = 1, .., J_{lt}$. Likewise, each market has $B_t$ brokers, indexed by $b = 1, ..., B_t$.

#### Mortgage Product Choice

In the last stage, after selecting a sales channel, households choose one of the available mortgage products. I follow the characteristics approach (Lancaster, 1979) and assume households' mortgage demand is a function of observable household characteristics, random preferences, product attributes, and a vector of preference parameters. I also assume that the problem households face when choosing a mortgage product will differ depending on their chosen sales channel, which is predetermined at this stage.

**Direct Channel.** Consider household $i$ in market $t$ that has opted for lenders' in-house distribution channels. I make the parametric assumption that the indirect utility of such household has the following linear form:

$$V_{ijlt}^{D} = \alpha\, r_{jlt} + \beta\, X_{jl} + \xi_{jlt} + \lambda\, Branches_{ilt} + \epsilon_{ijlt}\,, \tag{2.1}$$

where $r_{jlt}$ is the interest rate of product $j$ offered by lender $l$ in market $t$; $X_{jl}$ are time-invariant product characteristics including lender, maximum loan-to-value, and initial fixed period; $\xi_{jlt}$ captures unobservable product-lender-market characteristics affecting household utility in a market (e.g., advertising, screening); and $\epsilon_{ijlt}$ is an idiosyncratic taste shock. Finally, $Branches_{ilt}$ accounts for the number of branches that lender $l$ has in household $i$'s county, and $\lambda$ is the associated preference parameter. By adding branches in the horizontal differentiation dimension, I account for costs associated with application and origination processes that households may face, along the lines of Hastings et al. (2017) and Benetton (2018).

Household $i$ will purchase mortgage product $jl$ if and only if it attains the highest utility among all available products in the household's consideration choice set, $C_{it}$, which I assume is household specific and restricted by household characteristics. That is, household $i$ will choose product $j$ from lender $l$ if (1) it is part of the available choice set, and (2) $V^D_{ijlt} > V^D_{ikst}, \forall ks \in C_{it}$. Consider $V_{11}, V_{21}, ..., V_{jl}, ..., V_{JL}$ to be the utilities for all product-lender alternatives, where J and L are the number of products and lenders in choice set $C_{it}$, respectively. Then, the probability that alternative $jl$ is chosen at a purchase occasion is:

$$s_{ijlt} \; = \; Pr \, ( \, jl \;\; chosen \, | \, C_{it}) \; = \; Pr \, ( \, V^D_{ijlt} > V^D_{ikst} \quad for \;\; all \;\; ks \in C_{it}) \, . \qquad (2.2)$$

**Intermediated Channel**. Consider now household $i'$ has hired broker $b$ in market $t$. Let $b(i')$ denote this broker-household pair. I assume that each broker-household pair $b(i')$ is a composite agent that maximizes the joint indirect utility, which I assume to be a weighted average of the indirect utility of the household, $V^b_{ijlt}$, and that of the broker, $W_{bjlt}$. Moreover, I make the parametric assumption that the indirect utility of the pair $b(i')$ for the purchase of product $j$ from lender $l$ in market $t$ takes the following form:

$$
\begin{aligned}
V_{b(i')jlt} \;&=\; (1-\theta_b)\,\underbrace{(\beta\, X_{jl} + \alpha\, r_{jlt} + \xi_{jlt} \;+\; \epsilon_{ijlt}\,)}_{\text{Household's Utility } (V^b_{ijt})} \\
&\quad +\; \theta_b\,\underbrace{(\,\gamma_1\, c_{lbt} \;+\; \gamma_2\, X_{jl} + \zeta_{blt})}_{\text{Broker's Utility } (W_{bjlt})}\,,
\end{aligned}
\tag{2.3}
$$

where the indirect utility of the broker includes a percentage commission $c_{lbt}$ that broker $b$ receives from lender $l$, as well as product characteristics over which the broker may have some preferences. For example, brokers may prefer products with shorter initial fixed periods. These type of products incentivize households to refinance more frequently, which in turn leads to more business (and commissions) for brokers. Moreover, brokers may prefer higher loan-to-value products because commissions are expressed as a percentage of the loan. I also account for the possibility of brokers' preferences being affected by unobservable (to the econometrician) broker-lender-market characteristics, $\zeta_{blt}$, such as preferential treatment. Parameter $\theta_b$ in equation 2.3 captures the average downstream market power of broker $b$ and the share of surplus a broker can extract from her average client. This parameter captures the magnitude of the agency problem households face when dealing with broker $b$ and the influence/negotiation power the latter has over the consumer. If $\theta_b$ is equal to zero, then then the broker is fully benevolent in the sense that demand-side incentives are so large that brokers' and households' incentives are fully aligned. If, on the other hand, $\theta_b$ is equal to one, then supply-side incentives fully dominate, and the broker can extract all surplus from households. Finally, households' indirect utility is analogous to that of equation 2.1 in the direct channel, with the exception that bank branches do not play a role when getting a mortgage through a broker.[2]

[2]Reduced-form evidence in Section 1.3.2 suggests that branch presence matters only for direct sales. Moreover, when adding this coefficient in the estimation for broker sales, the effect is small and not significantly different from zero. After controlling for commissions, branch proximity does not seem to play a role when originating a mortgage through a broker.

Each broker-household pair maximizes the joint indirect utility subject to their available choice set, $C_{b(i')t}$. This choice set is broker-household specific, and it is restricted by household characteristics (as in the direct channel), but also by broker $b$'s network of lenders. At this stage, a broker can only originate mortgages with lenders with whom she reached an agreement in the previous bargaining stage. I denote this subset of lenders $N_{bt}$. Therefore, broker-household $b(i')$ will choose product $j$ from lender $l$ in $N_{bt}$ if (1) it is part of the available choice set $C_{b(i')t}$, and (2) $V_{b(i')jlt} > V_{b(i')kst}$, $\forall\ ks \in C_{b(i')t}$. Finally, the probability that product $jl$ is chosen, $s_{b(i')jlt}$, conditional on the available choice set, $C_{b(i')t}$, is analogous to the one defined in equation 2.2 for the direct channel.

### Sales Channel Choice

Before choosing a mortgage product, households need to decide whether to go directly to lenders' in-house distribution channels or hire a broker. I assume each household $i$ has a search cost $\kappa_i$. This search cost is a fixed cost that households incur when gathering information on all products available to them in market $t$. I assume search costs are heterogeneous and assigned via i.i.d. draws from a distribution $F_\kappa$. If household $i$ decides to use the direct sales channel, it will incur the search cost $\kappa_i$ to learn about available products and to deal with the administrative aspects of the application. Household $i$ can also choose the brokerage option. In this case, the household is matched to broker $b$ with probability $\pi_{bit}$ and has to pay a broker fee $f_{bit}$ for the broker's services. I assume (1) households do not search across brokers, and (2) no competition exists among brokers. Therefore, I consider broker fees as exogenous.[3]

Household $i$ will choose the sales channel that provides the highest (net) ex-ante

[3] As already presented in Figure A-1, broker fees in this market are significantly low, with many broker companies offering their services at no cost for the borrower. Thus, households always have the option to hire brokerage services at a zero fee.

expected utility, which depends on the household's search cost, broker fees, and ex-ante expected maximum indirect utility from each sales channel. Let $\hat{\kappa}_i$ be the search cost that makes household $i$ indifferent between both sales channels. This indifference cut-off value is:

$$\underbrace{E\big[\max_{jl}\ V^{D}_{ijlt}\left(\eta\right)|Direct\big]\ -\hat{\kappa}_i}_{\text{Direct Channel}}\ =\ \underbrace{\sum_{b\in B_t}\pi_{b(i)t}\left(E\big[\max_{jl}\ V_{b(i)jlt}\left(\eta\right)\mid b\ \big]-\alpha_i f_{bit}\right)}_{\text{Broker Channel}}, \tag{2.4}$$

where $\eta$ is a vector of all household-preference parameters; $E\big[\max_{jl} V_{ijlt}(\eta)|Direct\big]$ and $E\big[\max_{jl} V_{b(i)jlt}(\eta)|b\big]$ are the ex-ante expected household utilities of household $i$ going directly to the lender and hiring broker $b$, respectively; $\pi_{b(i)t}$ is the probability that household $i$ is matched to broker $b$; and $f_{bit}$ is the broker fee paid by household $i$ when hiring broker $b$. I multiply the fee by the price coefficient, $\alpha_i$ in equations 2.1 and 2.3, to transform money into utils and make the fee comparable to the expected utilities. This indifference condition in equation 2.4 implies that, if household $i$ has a search-cost draw $\kappa_i$ that is greater than $\hat{\kappa}_i$, it will choose to hire a broker. If it has a search-cost draw $\kappa_i$ smaller than $\hat{\kappa}_i$, it will opt for the direct sales channel and search for a mortgage across lenders' in-house distribution channels.

### 2.2.3 Supply

#### Lender Mortgage Pricing

Each market $t$ contains $L_t$ lenders that are for-profit organizations selling mortgage products to households. They maximize expected profits by setting interest rates (prices) for each of their products. I define the set of products offered by lender $l$ in market $t$ as $J_{lt}$. Lender $l$'s profits from a direct sale of product $j$ in market $t$ are:

$$\Pi^{D}_{jt}\ =\ t_j\left(r_{jt}-mc^{D}_{jt}\right), \tag{2.5}$$

where $t_j$ is the initial fixed period for product $j$, $r_{jt}$ is the initial rate for that product in market $t$, and $mc^D_{jt}$ is the marginal cost of selling product $j$ in market $t$ through a direct distribution channel. Similarly, lender $l$'s profits from selling product $j$ in $J_{lt}$ in market $t$ via an intermediated sale from broker $b$ are:

$$\Pi^b_{jt} \;=\; t_j \left(r_{jt} - mc^B_{jt}\right) - c_{lbt} \;, \tag{2.6}$$

where $c_{lbt}$ is the commission paid to broker $b$ in market $t$ for the sale of product $j$ from lender $l$, and $mc^B_{jt}$ is the marginal cost of selling product $j$ in market $t$ through the broker channel. I allow for marginal costs to vary across sales channels, because there could be ways in which brokers reduce lenders' origination costs (e.g., screening, income verification). I also implicitly assume that a household's loan quantity choice is equal to one, and it is not affected by changes in the interest rate. That is, a change in the interest rate will affect households' choice probabilities across products, but not the associated loan amount (conditional on the loan-to-value bands). Therefore, I am only accounting for households' discrete choice in lenders' profits, as opposed to previous work that also endogeneizes households' choice of loan amount (see Benetton, 2018). Finally, I am assuming all households remortgage at the end of the initial period (see Cloyne et al., 2017) and no default.

Using demand choice probabilities as defined by equation 2.2 and cut-off search costs as characterized in equation 2.4, lender $l$'s expected profits from serving household $i$ in market $t$ are:

$$\Pi^l_{it} = \underbrace{F_\kappa(\hat{\kappa}_i) * \sum_{j \in J_{lt}} \left(s_{ijlt} * \Pi^D_{jt}\right)}_{\text{Revenue from Direct Sales}} \;+\; \underbrace{\left[1 - F_\kappa(\hat{\kappa}_i)\right] * \sum_{j \in J_{lt}} \sum_{b \in Nlt} \left(\pi_{b(i)t} * s_{b(i)jt} * \Pi^b_{jt}\right)}_{\text{Revenue from Broker Sales}} \;, \tag{2.7}$$

where $s_{ijlt}$ and $s_{b(i)jt}$ are choice probabilities for household $i$ choosing product $jl$ conditional on choice channel, $F_\kappa(\hat{\kappa}_i)$ represents the probability that household $i$

will choose to go directly to the lender's distribution channel, and $1 - F_\kappa(\hat{\kappa}_{it})$ is the probability that it will decide to hire a broker. Conditional on other lenders' interest rates, lender $l$ will decide in each market $t$ the initial rate for each product $j$ in $J_{lt}$ that maximizes the sum of equation 2.7 across all households in each market. Thus, in each market, lender $l$ solves the following maximization problem:

$$\max_{\{r_{jt}\}_{j \in J_{lt}}} \quad \Pi_t^l \;=\; \sum_{i \in I_t} \Pi_{it}^l(r_{1t}, ..., r_{J_l t}) \,, \tag{2.8}$$

with the corresponding first-order conditions with respect to the interest rate of product $j$ in market $t$ given by:

$$\begin{aligned}
\frac{\partial \Pi_t^l}{\partial r_{jt}} = & \sum_{i \in I_t} \Bigg[ F_\kappa(\hat{\kappa}_{it}) * s_{ijlt} * t_j \\
& + F_\kappa(\hat{\kappa}_{it}) \sum_{k \in J_{lt}} \frac{\partial s_{iklt}}{\partial r_{jt}} * \left[ t_k \left( r_{kt} - mc_{kt}^D \right) \right] \\
& + f_\kappa(\hat{\kappa}_{it}) * \frac{\partial \hat{\kappa}_{im}}{\partial r_{jt}} \quad \sum_{k \in J_{lt}} s_{iklt} * \left[ t_k ( r_{kt} - mc_{kt}^D ) \right] \\
& + \left[ 1 - F_\kappa(\hat{\kappa}_{it}) \right] \; \sum_{b=1}^{B} \pi_{b(i)t} * s_{b(i)jlt} * t_j \\
& + \left[ 1 - F_\kappa(\hat{\kappa}_{it}) \right] \; \sum_{b=1}^{B} \pi_{b(i)t} \sum_{k \in J_{lt}} \frac{\partial s_{b(i)klt}}{\partial r_{jt}} * \left[ t_k \left( r_{kt} - mc_{kt}^B \right) - c_{lbt} \right] \Bigg] \\
& - f_\kappa(\hat{\kappa}_{it}) * \frac{\partial \hat{\kappa}_{it}}{\partial r_{jt}} \quad \sum_{b=1}^{B} \pi_{b(i)t} \sum_{k \in J_{lt}} s_{b(i)klt} * \left[ t_k \left( r_{kt} - mc_{kt}^B \right) - c_{lbt} \right] \Bigg] \\
& = \; 0 \qquad \forall j \in J_{lt} \,.
\end{aligned} \tag{2.9}$$

In (2.9), the first and fourth terms capture the extra profits for both direct and intermediated sales due to a higher interest rate. The second and fifth terms show the effect of higher rates on choice probabilities for all products from lender $l$. Finally, the third and last terms capture the change in the probability of households choosing the direct channel due to higher interest rates. Solving for the interest rate in (2.9) gives the following (I omit the market subscript for simplicity):

$$
\begin{aligned}
r_j^* = \sum_{i \in I_m} \Bigg[ & \underbrace{mc_j^D \, \rho_j^D + \sum_{b=1}^{B} \pi_{b(i)} (mc_j^B + \frac{c_{lb}}{t_j}) \, \rho_j^b}_{\text{Effective average marginal cost}} \\
& - \underbrace{F_{\hat{\kappa}} \, s_{ijl} \, \frac{\rho_j^D}{F_{\hat{\kappa}} \, \frac{\partial s_{ijl}}{\partial r_j} \, + \, f_{\hat{\kappa}} \, \frac{\partial \hat{\kappa}_i}{\partial r_j} \, s_{ijl}}}_{\text{Full mark-up (I)}} \\
& - \underbrace{(1 - F_{\hat{\kappa}}) \, \sum_{b=1}^{B} \pi_{b(i)} \, s_{b(i)jl} \, \frac{\rho_j^b}{(1 - F_{\hat{\kappa}}) \, \frac{\partial s_{b(i)jl}}{\partial r_j} \, - \, f_{\hat{\kappa}} \, \frac{\partial \hat{\kappa}_i}{\partial r_j} \, s_{b(i)jl}}}_{\text{Full mark-up (II)}} \\
& - \underbrace{\sum_{k \neq j \in J_l} \frac{1}{t_j} \left( F_{\hat{\kappa}} \, \frac{\partial s_{ikl}}{\partial r_j} \, + \, f_{\hat{\kappa}} \frac{\partial \hat{\kappa}}{\partial r_j} s_{ikl} \right) \, \frac{\Pi_k^D \rho_k^D}{F_{\hat{\kappa}} \, \frac{\partial s_{ijl}}{\partial r_j} \, + \, f_{\hat{\kappa}} \, \frac{\partial \hat{\kappa}_i}{\partial r_j} \, s_{ijl}}}_{\text{Other products via direct}} \\
& - \underbrace{\sum_{k \neq j \in J_l} \frac{1}{t_j} \sum_{b=1}^{B} \pi_{b(i)} \left( (1 - F_{\hat{\kappa}}) \, \frac{\partial s_{b(i)kl}}{\partial r_j} \, - \, f_{\hat{\kappa}} \frac{\partial \hat{\kappa}}{\partial r_j} s_{b(i)kl} \right)}_{\text{Other products via brokers (I)}} \times \\
& \times \, \underbrace{\frac{\Pi_k^B \, \rho_k^b}{(1 - F_{\hat{\kappa}}) \, \frac{\partial s_{b(i)jl}}{\partial r_j} \, - \, f_{\hat{\kappa}} \, \frac{\partial \hat{\kappa}_i}{\partial r_j} \, s_{b(i)jl}}}_{\text{Other products via brokers (II)}} \Bigg],
\end{aligned}
\tag{2.10}
$$

where $\rho_j^D$ is the effective probability of household $i$ going direct and purchasing product $j$. Likewise, $\rho_j^b$ is the effective probability of household $i$ going to broker and purchasing product $j$. Expressions for both $\rho_j^D$ and $\rho_j^b$ are:

$$\rho_j^D = \frac{F_{\hat{\kappa}} \frac{\partial s_{ijl}}{\partial r_j} \; + \; f_{\hat{\kappa}} \, \frac{\partial \hat{\kappa}_i}{\partial r_j} \, s_{ijl}}{\left[F_{\hat{\kappa}} \frac{\partial s_{ijl}}{\partial r_j} \; + \; f_{\hat{\kappa}} \, \frac{\partial \hat{\kappa}_i}{\partial r_j} \, s_{ijl} + (1 - F_{\hat{\kappa}}) \sum_{b \in B} \pi_{b(i)} \frac{\partial s_{b(i)jl}}{\partial r_j} - f_{\hat{\kappa}} \, \frac{\partial \hat{\kappa}_i}{\partial r_j} \sum_{b \in B} \pi_{b(i)} \, s_{b(i)jl}\right]} \tag{2.11}$$

and

$$\rho_j^b = \frac{(1 - F_{\hat{\kappa}}) \, \frac{\partial s_{b(i)jl}}{\partial r_j} \; - \; f_{\hat{\kappa}} \, \frac{\partial \hat{\kappa}_i}{\partial r_j} \, s_{b(i)jl}}{\left[F_{\hat{\kappa}} \frac{\partial s_{ijl}}{\partial r_j} \; + \; f_{\hat{\kappa}} \, \frac{\partial \hat{\kappa}_i}{\partial r_j} \, s_{ijl} + (1 - F_{\hat{\kappa}}) \sum_{b \in B} \pi_{b(i)} \frac{\partial s_{b(i)jl}}{\partial r_j} - f_{\hat{\kappa}} \, \frac{\partial \hat{\kappa}_i}{\partial r_j} \sum_{b \in B} \pi_{b(i)} \, s_{b(i)jl}\right]}. \tag{2.12}$$

Note that if no brokers exist in the market and all lenders offer only one product, expression (2.10) collapses to the standard mark-up pricing formula:
$r_j^* = \sum_{i \in I_m} \left( mc_j^D - s_{ijl} \times \left( \frac{\partial s_{ijl}}{\partial r_j} \right)^{-1} \right)$.

### Broker-Lender Bargaining over Commissions

In each market $t$, before setting prices and making any sales, brokers and lenders bilaterally meet and bargain á la Nash to determine whether to form an agreement. If successful, they set a per-sale commission that is expressed as a percentage of the final loan amount. $L_t \times B_t$ contracts are possible, and brokers and lenders have complete information about all payoff functions. I assume the negotiated commission for each contract solves the Nash bargaining solution for that contract. Thus, the equilibrium commission vector maximizes the Nash product of each pair's gains from trade, conditional on agreements reached by all other pairs. Moreover, given that the agreement value for a broker dealing with a given lender may change depending on whether she has reached an agreement with another lender with similar mortgage products, I also assume each contract remains the same even if negotiation for another contract fails. Thus, all negotiations within market $t$ are simultaneous and separate, such that commissions set in other meetings are not known but conjectured. This setting is motivated by the model presented in Horn and Wolinsky (1988), and it is commonly used by other empirical papers (see, e.g., Crawford and Yurukoglu, 2012, Grennan, 2013, Gowrisankaran et al., 2015, Ho and Lee, 2017a,b, Crawford et al., 2018a).[4] Despite these assumptions, lenders and brokers' payoffs will still depend on outcomes of bilateral negotiations to which they are not party. I start by considering the ex-ante payoff structures for brokers and lenders, and their resulting participation constraints. I then show the Nash bargaining solution to each contract.

Each broker seeks to maximize his ex-ante expected payoff from serving all households that hire his services. Given lenders' expected rates and households' expected mortgage and sales channel choices, the ex-ante expected utility for broker $b$ in market $t$, as a function of commissions and network structure $N_{bt}$, is:

$$W_{bt}(\boldsymbol{c}_{bt}, N_{bt}) \;=\; \sum_{i \in I_t} \Big(1 - F_\kappa[\hat{\kappa}_i(\boldsymbol{c}_t)]\Big) * \pi_{b(i)t} * \sum_{j \in J_{b(i)t}, N_{bt}} s_{b(i)jlt}(\boldsymbol{c}_{bt})\; W_{bljt}(c_{lbt})\,, \quad (2.13)$$

where $\boldsymbol{c}_{bt}$ is all commissions payments of broker $b$ and $W_{bjlt}(c_{lbt})$ is the broker's utility from originating product $j$ with lender $l$ in market $t$ as defined in equation 2.3. Brokers' ex-ante utility also depends on households' probability of choosing the brokerage channel, $(1 - F_\kappa[\hat{\kappa}_{it}(\boldsymbol{c}_t)])$, which is a function of commission payments for all brokers in market $t$. Similarly, the ex-ante expected profits to lender $l$ in market $t$, conditional on commissions and network structure $N_{lt}$, are:

[4] Recently, Collard-Wexler et al. (2018) have provided a non-cooperative foundation for this bargaining solution based on Rubinstein's model of alternating offer bargaining.

$$
\begin{aligned}
\Pi^l_t(\boldsymbol{c}_{lt}, N_{lt}) = \sum_{i \in I_t} \Bigg( & \underbrace{F_\kappa[\hat{\kappa}_{it}(\boldsymbol{c}_t)] \sum_{j \in J_{lt}} \left( s_{ijlt} * \Pi^D_{jt} \right)}_{\text{Revenue from Direct Sales}} \\
& + \underbrace{[1 - F_\kappa[\hat{\kappa}_{it}(\boldsymbol{c}_t)]] \sum_{j \in J_{lt}} \sum_{b \in N_{lt}} \left( \pi_{b(i)t} * s_{b(i)jt} * \Pi^b_{jt}(c_{lbt}) \right)}_{\text{Revenue from Broker Sales}} \Bigg),
\end{aligned} \tag{2.14}
$$

where $\boldsymbol{c}_t$ are all commissions in market $t$ and $\boldsymbol{c}_{lt}$ is a vector with all commissions paid by lender $l$ in market $t$. Lender profits are defined by equations (2.5) and (2.6).

Brokers and lenders' ex-ante expected profits are key in the Nash bargaining model, because they determine the agreement and disagreement payoffs. Using equations (2.13) and (2.7), the exponentiated product of the net payoffs from agreement is:

$$
\begin{aligned}
NP^{lb}_t\,(c_{lbt}|\boldsymbol{c}_{-lbt}) = [\, & \underbrace{\Pi^l_t(c_{lbt}|\boldsymbol{c}_{-lbt}) - \Pi^l_t(0\,|\boldsymbol{c}_{-lbt})}_{\text{Gains from trade for lender } l} \,]^{\beta_{lb}} \\
& \times [\, \underbrace{W_{bt}(c_{lbt}|\boldsymbol{c}_{-lbt}; N_{bt}) - W_{bt}(0\,|\boldsymbol{c}_{-lbt}; N_{bt} \setminus J_l)}_{\text{Gains from trade for broker } b} \,]^{1-\beta_{lb}},
\end{aligned} \tag{2.15}
$$

where $\beta_{lb}$ is the bargaining power of lender $l$ when negotiating with broker $b$. Setting $\beta_{lb} = 0.5$ assumes symmetric Nash bargaining, and setting $\beta_{lb} = 0$ assumes Nash-Bertrand pricing behavior by lenders. Disagreement payoffs imply all commissions for broker $b$ for the sale of all products from lender $l$ are set to zero. That is, I treat products for each lender as an indivisible block, meaning that if bargaining breaks down between a lender and a broker, the broker cannot originate any of the lender's products and the lender will not be part of the broker's network. Moreover, I assume lenders face no capacity constraints. Hence, in the event of a disagreement between a lender and a broker, the broker can originate a mortgage with his ex-post second choice of lender without facing any restrictions on the lender's side.

I define the Nash bargaining solution as the commission vector $\boldsymbol{c}_t^*$ that maximizes equation (2.15) for each Nash bargaining contract, conditioning on the outcomes of all other contracts. Therefore, each $c_{lbt}^*$ in $\boldsymbol{c}_t^*$ solves the following maximization problem:

$$\max_{c_{lbt}} \quad NP_t^{lb}\,(c_{lbt}|\boldsymbol{c}^*_{-lbt}) \quad \textit{such that}$$

$$(1)\ \Pi_t^l(c_{lbt}|\boldsymbol{c}^*_{-lbt}; N_{lt}) - \Pi_t^l(0\,|\boldsymbol{c}^*_{-lbt}; N_{lt}\setminus b) \ \geq\ 0\ \ (\textit{Lender PC})$$

$$(2)\ W_{bt}(c_{lbt}|\boldsymbol{c}^*_{-lbt}; N_{bt}) - W_{bt}(0\,|\boldsymbol{c}^*_{-lbt}; N_{bt}\setminus J_l) \ \geq\ 0\ \ (\textit{Broker PC})\,,$$

where $\boldsymbol{c}^*_{-lbt}$ is the equilibrium commission vector, excluding the commission of the lender-broker pair in the negotiation. (1) and (2) are participation constraints for the lender and broker, respectively. They need to be imposed because an agreement is not mandatory and either broker or lender can unilaterally walk away. Expanding the participation constraint of lender $l$ dealing with broker $b$, I get:

$$\begin{aligned}
\Delta\Pi_t^l(c_{lbt}|\boldsymbol{c}^*_{-lbt}) = \sum_{i\in I_t} \Bigg[ & \underbrace{\Big(1 - F_\kappa[\hat{\kappa}_{it}(c_{lbt}|\boldsymbol{c}^*_{-lbt})]\Big) \sum_{j\in J_{lt}} \pi_{b(i)t}\ s_{b(i)jlt}(c_{lbt}|\boldsymbol{c}^*_{-lbt})\ \Pi_{ijt}^b(c_{lbt})}_{\text{Expected profits from dealing with broker } b} \\
& + \underbrace{\Big(\, F_\kappa[\hat{\kappa}_{im}(c_{lbt}|\boldsymbol{c}^*_{-lbt})] - F_\kappa[\hat{\kappa}_{it}(0|\boldsymbol{c}^*_{-lbt})]\,\Big)}_{\text{Change in sales channel choices}} * \\
& * \underbrace{\sum_{j\in J_{lm}} \Big( s_{ijlt}\ \Pi_{ijt}^D - \sum_{b'\neq b} \pi_{b'(i)t}\ s_{b'(i)jlt}(\boldsymbol{c}^*_{-lbt})\ \Pi_{ijt}^{b'}(\boldsymbol{c}^*_{-lbt}) \Big)}_{\text{Gains/losses from other sales channels}} \Bigg] \geq 0\,.
\end{aligned} \tag{2.16}$$

Equation (2.16) implies that, for the lender's participation constraint to be non-binding, commission payments need to be below a certain threshold, $\bar{c}_{lbt}$. Similarly, I can expand the participation constraint of broker $b$ dealing with lender $l$:

$$
\begin{aligned}
\Delta W_{bt}(c_{lbt}|\boldsymbol{c}^*_{-lbt}) = \sum_{i \in I_t} \pi_{b(i)t} \Bigg[ & \underbrace{\Big(1 - F_\kappa[\hat{\kappa}_{im}(c_{lbt}|\boldsymbol{c}^*_{-lbt})]\Big) \sum_{j \in J_{lt}} s_{b(i)jlt}(c_{lbt}|\boldsymbol{c}^*_{-lbt})\, W_{b(i)jt}(c_{lbt})}_{\text{Profits from selling products from lender } l} \\
& + \underbrace{\Big(1 - F_\kappa[\hat{\kappa}_{it}(c_{lbt}|\boldsymbol{c}^*_{-lbt})]\Big) \sum_{\substack{k \notin J_{lt} \\ l' \neq l}} s_{b(i)kl't}(c_{lbt}|\boldsymbol{c}^*_{-lbt})\ W_{b(i)jt}(c_{l'bt})}_{\phantom{x}} \\
& \qquad \text{Gains/losses from other product sales + changes in sales channel choices} \\
& - \overbrace{\Big(1 - F_\kappa[\hat{\kappa}_{it}(0|\boldsymbol{c}^*_{-lbt})]\Big) \sum_{\substack{k \notin J_{lt} \\ l' \neq l}} s_{b(i)kl't}(0|\boldsymbol{c}^*_{-lbt})\ W_{b(i)jt}(c_{l'bt})}^{\phantom{x}} \Bigg] \\
& \geq 0\,.
\end{aligned}
\tag{2.17}
$$

Equation (2.17) shows that for the broker's participation constraint to be non-binding, commission payments need to be above a certain threshold, $\underline{c}_{lbt}$. Therefore, for a broker and a lender to begin negotiations, the maximum commission a lender is willing to pay must be higher than the minimum commission a broker is willing to accept, that is, $\bar{c}_{lbt} > \underline{c}_{lbt}$. A lender's decision to reach an agreement with a broker is affected by downstream competition between brokerage services and the lender's in-house distribution channels (e.g., branches). A lender may decide to exclude brokers operating in areas where it has an extensive branch network and his outside option (i.e., direct sales) is much higher. On the other hand, a broker may decide to exclude a lender from her network if the profits she gets from selling other products is sufficiently larger. The intuition is that when jointly agreeing on a mortgage with households, brokers need to split the surplus as given by equation 2.3.

When distortion parameter $\theta_b$ is very low (e.g., the broker has limited bargaining power), the household's utility dominates the broker's utility, and mortgage choices for the pair are driven by households' preferences. However, if brokers refrain from including low-commission lenders in their networks, households' will be forced to choose among choice sets that are beneficial for brokers. The downside is that households will anticipate the more restricted network and may decide to switch to direct sales instead. The latter effect may be small for some lenders, causing brokers to exclude them from their network if their commission is not sufficiently high.

Given each pair's maximization problem, three outcomes are possible in terms of agreement and optimal commission. First, if $\bar{c}_{lbt} < \underline{c}_{lbt}$, no agreement is reached and the broker is not allowed to originate mortgages with that lender. Second, if, on the other hand, $\bar{c}_{lbt} \geq \underline{c}_{lbt}$ and both participation constraints are not binding, each pair chooses an optimal commission rate, $c^*_{lbt}$, such that the first derivatives with respect to commission payments are equal to zero, $\partial log\left(NP_t^{lb}\right) / \partial c_{lbt} = 0$. Finally, if at least one of the participation constraints is binding, the optimal commission is either $\bar{c}_{lbt}$ or $\underline{c}_{lbt}$.

## 2.3 Estimation and Identification

### 2.3.1 Demand

#### Household Preference Parameters

I assume demand taste shocks, $\varepsilon_{ijlm}$ and $\epsilon_{b(i)jlm}$, in the indirect utilities are identically and independently distributed across households, products, and lenders with a type I extreme value distribution. Conditional on going through the direct channel, the probability of household $i$ choosing product $j$ from lender $l$ in market $t$ is:

$$s_{ijlt} \equiv Pr\ (\ jl\ \ chosen \mid C_{it}) = \frac{exp\left(\bar{V}_{ijlt}\right)}{\sum_{ks \in C_{it}} exp\left(\bar{V}_{ikst}\right)}\ , \tag{2.18}$$

where $\bar{V}_{ijlt}$ is household indirect utility in equation 2.1 excluding the error term $\varepsilon_{ijlt}$. If household $i$ hires broker $b$, the probability of choosing product $j$ from lender $l$ in market $t$ is:

$$s_{b(i)jlt} \equiv Pr\ (\ jl\ \ chosen \mid C_{b(i)t}) = \frac{exp\left(\bar{V}_{b(i)jlt}\right)}{\sum_{ks \in C_{b(i)t}} exp\left(\bar{V}_{b(i)kst}\right)}\ , \tag{2.19}$$

where $\bar{V}_{b(i)jlt}$ is broker-household indirect utility as defined in equation 2.3 without the error term $\epsilon_{b(i)jlt}$. Given these choice probabilities, the log-likelihood for direct and intermediated channels is:

$$ln\ (L_i|\eta_i, \delta^G_{jlt}, \delta_{blt}) \ \ = \ \sum_{jl \in C_i} \mathbb{1}_{ijlt}\Big(\mathbb{1}^D_i\ ln(s_{ijlt}) + \sum_{b \in B_t} \mathbb{1}^b_i\ ln(s_{b(i)jlt})\Big)\ , \tag{2.20}$$

where $\eta_i$ is a vector of all demand parameters, $\mathbb{1}_{ijlt}$ is a dummy equal to one if household $i$ buys product $j$ from lender $l$ in market $t$, $\mathbb{1}^D_i$ is a dummy equal to one if household $i$ chooses the direct channel, and $\mathbb{1}^b_i$ is a dummy equal to one if household $i$ hires broker $b$. I include product-lender-market-group fixed effects, $\delta^G_{jlt}$, to account for product mean utility in an income-region group ($G$), that is, the part of utility obtained from product $j$ from lender $l$ in market $t$ that is common across all households $i$ in group $G$. I also add broker-lender-market fixed effects, $\delta_{lbt}$, to control for broker-lender mean utility, that is, the part of the utility obtained from originating a product with lender $l$ that is common across all households going to broker $b$ in market $t$.

**Identification**.– One of the limitations of having transaction data is that households' choice sets and lenders' affordability criteria are unobserved. To identify preference parameters, I create a household-specific counterfactual choice set depending on their observable characteristics. First, I divide households into groups based on geographical regions and year-quarter. I assume households in each group can access all products sold in that region during that quarter, but not those sold in other regions or other quarters. The geographical restriction affects mostly building societies and smaller banks because they often have limited coverage. The time restriction is needed to account for the entry and exit of products. Next, I consider all households that purchased a given product and select those with the lowest credit score, the highest loan-to-income ratio, and the highest age. I carry out this process for every product. I then assume a household will not qualify for that product if (1) it has a credit score lower than the cut-off value, (2) a loan-to-income ratio larger than the cut-off value, or (3) is older than the cut-off value. The rationale for these restrictions is based on lenders' most common set of affordability criteria, which rely on credit scores, loan-to-income, and age. Finally, for the intermediated sales channel, I further restrict the choice set of the household-broker pair to products sold by lenders with whom the broker has reached an agreement in the bargaining stage.

After constructing a counterfactual choice set for each household, I proceed to estimate demand parameters in the log-likelihood described in equation 2.20. To identify household preferences over product characteristics ($\alpha$, $\beta$), I use a two-step instrumental variables approach to explicitly account for possible correlations between interest rates ($r_{jlt}$) and unobservable product characteristics ($\xi_{jlt}$). I use a similar two-step approach to identify broker preferences over commission payments and broker downstream market power ($\theta_b$). This approach allows me to account for correlations between commissions ($c_{lbt}$) and unobservable broker-lender relationships varying over time ($\zeta_{blt}$). In a first step, I maximize the log-likelihood and recover estimates for household preferences over branches ($\lambda$), broker preferences over product characteristics other than commissions ($\gamma_2$), product-lender-market-group fixed effects ($\delta^G_{jlt}$), and broker-lender-market fixed effects ($\delta_{lbt}$). I can separately identify broker and household preferences as long as household-preference parameters for product characteristics remain constant across sales channels. I can identify the coefficient on bank branches as long as households value nearby branches only when originating their mortgage directly through lenders. That is, for households going through brokers, branches do not play a role.

In a second step, I regress the estimated product-lender-market fixed effects ($\hat{\delta}^G_{jlt}$) on interest rates and product characteristics:

$$\begin{aligned}\hat{\delta}^G_{jlt} = \; & [\, \alpha^G \, r_{jlt} + \psi^G_1 \, High\, LTV \; + \psi^G_2 \, Two\text{-}Year\; Fixed \,] \times \mathbb{1}[i = Income\text{-}Region\; G] \\ & + \; Lender\; FE + \; Market\; FE \; + \varepsilon_{ijlt} \; ,\end{aligned} \tag{2.21}$$

where $High\ LTV$ is a dummy equal to one if LTV is 85% or higher. Because interest rates are potentially correlated with unobservable product characteristics included in the error term, I use an instrumental variable approach in order to get consistent estimates of demand parameters $\alpha^G$, $\psi^G_1$, and $\psi^G_2$. In particular, I use two cost shifters as instruments for the interest rate. I use risk weights associated with capital requirements, which vary across time, lender, and loan-to-value bands. I also use the rate for euro interest rate swaps for two, three, and five years. Swap rates vary across time and type, and are a hedging instrument lenders use when selling mortgages with fixed periods of two, three, and five years, respectively. Both instruments allow me to exploit variation across markets, lenders and products. For identification, I am assuming these instruments are uncorrelated with unobserved product characteristics once I control for lender and market fixed effects.

Moreover, I regress the estimated broker-lender-market fixed effects ($\hat{\delta}_{lbm}$) on commissions and broker dummies:

$$\hat{\delta}_{lbt} = \sum_b \mathbb{1}[i = Broker\ b] \left( \frac{\theta_b}{1-\theta_b} \gamma_1 \ c_{lbt} \right) + \mu_{bt} + \phi_{lt} + \nu_{bl} + \varepsilon_{lbt} \ , \tag{2.22}$$

where $\mathbb{1}[i = Broker\ b]$ is a dummy equal to one for broker $b$. I normalize $\gamma_1$ to one, and absorb a rich set of fixed effects captured by $\mu_{bt}$, $\phi_{lt}$, and $\nu_{bl}$. As a robustness check and in order to control for possible correlations between the broker-lender-market commissions and unobservable (to the econometrician) broker-lender-market relationships that might affect brokers' choices, I use supply-shifters instrumental variables. I use as cost shifters for lenders and brokers the business rates (taxes) in counties where the lender has its headquarters and the broker has its principal place of business. This instrument exploits variation across markets, lenders, and brokers. For identification, I assume these instruments are uncorrelated with unobserved time-varying broker and lender characteristics once I control for lender, broker, and market fixed effects.

### Household Search Cost Distribution

I assign households to groups, $G$, based on their income quartile $q$, region $g$, and market $t$. I assume a household $i$ in group $G$ knows the average ex-ante expected maximum utility that households in the same group get from each sales channel.[5] These ex-ante expected utilities can be computed using choice probabilities as given

[5] Recent consumer surveys at the Financial Conduct Authority have shown that 67% of borrowers only consulted one broker when originating their mortgage. In another survey for UK financial products, Finney and Kempson (2008) find most consumers only consulted at most one source of information before making a purchase. Chater et al. (2010) reach a similar conclusion after studying several European countries. Moreover, the FCA's Financial Lives Survey 2017 indicates 23% of borrowers chose their broker because a real estate agent recommended it and 29% because it was recommended by a friend or relative. This indicates that this referral is influential for some consumers. Given households' limited search for a broker and the importance of referrals, the assumption that households only know the average utility similar households got when choosing the brokerage channel seems reasonable.

by equation 2.2 for both direct and intermediated sales. Let $\hat{\kappa}_G$ be the search cost that makes household $i$ in group G indifferent between both sales channels. The payoffs from both channels are defined by:

$$\begin{aligned} Direct\,Channel &= \left(\sum_{i\in G}^{I_G} E\big[\max_{jl}\ \ V_{ijlt}\left(\eta\right)|Direct\big]\right) - \kappa_G \\ Broker\,Channel &= \sum_{b\in G}\pi_{b(G)t}\sum_{i\in G}^{I_G}\left(E\big[\max_{jl}\ \ V_{b(i)jlt}\left(\eta\right)\mid b\,\big] - \alpha_G f_{Gbt}\right), \end{aligned} \tag{2.23}$$

where $\eta$ is a vector of all preferences parameters estimated in the mortgage choice problem; $E\big[\max_{jl}\ \ V_{ijlt}\left(\eta\right)|Direct\big]$ and $E\big[\max_{jl}\ \ V_{b(i)jlt}\left(\eta\right)\mid b\,\big]$ are the ex-ante expected household utilities of household $i$ in $I_G$ going directly to the lender and hiring broker $b$, respectively; $\pi_{b(G)t}$ is the probability that a household in group $G$ is matched to broker $b$; and $f_{Gbt}$ is the broker fee paid by households in group $G$ when hiring broker $b$. I multiply the fee by the price coefficient, $\alpha_G$, in equation 2.21 to transform money into utils and make the fee comparable to the expected utilities. This indifference condition in equation 2.23 implies that, if household $i$ in group $G$ has a search-cost draw $\kappa_i$ that is greater than $\hat{\kappa}_G$, it will choose to hire a broker. Similarly, if it has a search-cost draw $\kappa_i$ smaller than $\hat{\kappa}_G$, it will opt for the direct sales channel and search for a mortgage across lenders' in-house distribution channels.

To estimate the mean and standard deviation of the search cost distribution across subgroups, I use equation 2.23 and the preference parameters estimated in the previous subsection. First, it is necessary to compute for each household the average expected ex-ante utility that it will receive from each sales channel. For the direct channel, following Small and Rosen (1981), household $i$ will get an ex-ante expected maximum utility equal to:

$$E\Big[\max_{jl}\ V_{ijlt}\left(\hat{\eta}\right)|Direct\Big] \ = \ ln\left[\sum_{ks\in J_{it}} exp\ \left(V_{ijlt}\left(\hat{\eta}, Direct\right)\right)\right], \tag{2.24}$$

where $\hat{\eta}$ is the vector of demand-preference parameters estimated in the previous subsection.

For broker sales, each broker-household pair maximizes the joint utility as defined by equation 2.3. Therefore, I need to split the ex-ante expected maximum utility of the pair into that of the broker and that of the household. To do so, I first simulate draws from the distribution of the household's error term for each product assuming a type I extreme value distribution. For each draw, I compute the utility of the broker-household pair for each product in the pair's choice set and select the product that gives the pair the highest utility. I then compute the household's utility for that choice. Finally, I take the average of the maximum household utilities across draws, which will give me a numerical approximation of the household's expected ex-ante utility from that broker.

After computing all ex-ante expected maximum utilities for all channels and all income-region groups, I can rewrite equation 2.23 as:

$$\hat{U}_G^{Direct} - \hat{\kappa}_G \ = \ \hat{U}_G^{Broker}, \tag{2.25}$$

where $\hat{U}_G^{Direct}$ is the estimated expected maximum indirect utility of going direct, and $\hat{U}_G^{Broker}$ is estimated average expected net maximum indirect utility of choosing the broker channel (after subtracting broker fees and multiplying by the probability of being paired with that particular broker). The probability of household $i$ choosing the direct channel will depend on whether its search cost $\kappa_i$ is smaller than $\hat{\kappa}_i$:

$$P_i^{Direct} = Prob\,(\ \kappa_i \ < \ \hat{\kappa}_G) \ = \int \mathbb{1}(\kappa_i \ < \ \hat{\kappa}_G)\, f(\kappa) d\kappa\,. \tag{2.26}$$

Likewise, the probability that household $i$ will choose the broker channel is:

$$P_i^{Broker} = Prob\,(\ \kappa_i \ > \ \hat{\kappa}_G) \ = \int \mathbb{1}(\kappa_i \ > \ \hat{\kappa}_G)\, f(\kappa) d\kappa\,. \tag{2.27}$$

I assume that search costs $\kappa$ follow a normal distribution with mean $\mu$ and standard deviation $\sigma$. Therefore, the log-likelihood function is:

$$Ln\,[L(\mu, \sigma^2; y_i, \hat{\kappa}_G)] = \sum_i ln\Bigg( \Big[F(\hat{\kappa}_G \mid \mu, \sigma^2)\Big]^{y_i} \Big[1 - F(\hat{\kappa}_G \mid \mu, \sigma^2)\Big]^{1-y_i} \Bigg)\,, \tag{2.28}$$

where $F(.)$ is the cdf of $\kappa$, and $y_i$ is a dummy variable equal to one if the household chose to go directly to the lender, and zero if it hired a broker. The value $\hat{\kappa}_i$ is determined by equation 2.25.

**Identification.**– Identification of the search cost distribution parameters, $\mu$ and $\sigma$, comes from variation in consumer choices and their expected utilities.

### 2.3.2 Supply

#### Lender Marginal Costs

The estimation of lenders' marginal costs is based on the optimal pricing formula derived in Section 2.2.3. Using the estimated preference parameters and cut-off search costs, I can back out from equation 2.10 the average effective marginal costs ($AMC_{jt}$), which are a weighted average of the marginal costs from direct and intermediated sales. I then assume that marginal costs from intermediated sales are a function of product characteristics, whereas marginal costs from direct sales are the same as those of intermediated sales plus a premium. I regress the estimated average marginal costs on product characteristics (weighted) and normalized commission rates. I obtain a two-step estimator of the cost parameters at the product level with the following linear specification:

$$AMC_{jt} = \varphi_1 X_{jt}\, \rho^D_{jt} + \varphi_2 X_{jt} \sum_{b=1}^{B} \pi_{bt} \rho^b_{jt} + \varphi_3 \sum_{b=1}^{B} \frac{c_{lb}}{t_j}\, \pi_{bt} \rho^b_{jt} + \tau_t + \varepsilon_{jt}\ , \tag{2.29}$$

where $AMC_{jt}$ is the average marginal costs; $X_{jt}$ are the same product characteristics that affect borrower demand (loan-to-value band,initial period and lender); $\rho^D_{jt}$ and $\rho^B_{jt}$ are weights defined in equations 2.11 and 2.12 respectively; $c_{lb}$ are commission payments; $t_j$ is the initial period; $\tau_t$ are market fixed effects; and $\varepsilon_{jt}$ is a structural error capturing unobservable variables that might affect average marginal costs (e.g., screening, advertising). This two-step estimation allows be to differentiate between the marginal costs of direct and intermediated sales.

**Identification.**– I recover effective average marginal costs by inverting lenders' optimal first-order conditions. Then, to separately identify direct and intermediated marginal costs, I exploit variation across product choice probabilities conditional on sales channels and changes in household choices of direct versus intermediated channels. I also require that, for intermediated sales, the lender has to pay an additional commission to brokers. Finally, to address any concern about endogeneity in $\rho^D_{jt}$ and $\rho^b_{jt}$ due to omitted variable bias, I use product characteristics and $\rho$ values of other lenders as an instrument for a lender's own product characteristics and $\rho$ values.

**Broker-Lender Bargaining Parameters**

The bargaining parameters depend on the protocol of the bargaining game and the gains from trade of both lenders and brokers, as defined in section 2.2.3. Given estimates for demand preferences, household search costs, and marginal costs, I can compute both agreement and disagreement payoffs as described in the model for all broker-lender pairs for which I observe an agreement in equilibrium. I choose the values of $\beta_{bl}$ that minimize the distance between observed equilibrium commissions and the estimated optimal commissions from the model, as determined by the first-order conditions in the bargaining game.

**Identification.**– For each broker-lender pair, I invert the first-order conditions in each pair's bargaining problem. At this stage, the only unknowns are the bargaining parameters. To identify them separately from the outside options, I exploit geographical and time variation in lenders' branch networks. These sources of variation will affect lenders' and brokers' outside options, but not their bargaining parameters. Moreover, I use the timing of negotiations. Demand realizations and changes in branch networks happen more frequently than commission renegotiations. This provides an additional source of variation to identify bargaining parameters separately from changes in outside options. Finally, I also use cross-sectional variation on commission payments across lenders and brokers, as well as time variation (commissions are renegotiated at least once during my sample period).

## 2.4 Estimation Results

### 2.4.1 Demand Parameters: Preferences and Search Costs

For estimating the demand parameters described in subsection 2.3.1, I use a 25% random sample as a training sample, and then use the remaining 75% of the data for cross-validation. Panel A in Table 2.1 reports the estimated demand parameters of the households' mortgage choice problem for the 25% random sample.

The average point estimate of the coefficient on interest rates across all income-region groups is significant and equal to -0.91, implying borrowers dislike more expensive mortgages. The corresponding average own-product demand elasticity is equal to 3.34, and the cross-product demand elasticity equals 0.02. That is, on average, a 1% increase in the interest rate decreases the market share of the mortgage by 3%, whereas the shares of other mortgages increase by 0.02%. I also find that first-time-buyers value more mortgages with higher leverage ($\psi_1$) and longer initial fixed periods ($\psi_2$). This type of borrower is often credit constrained, and a higher loan-to-value allows for lower down-payments. Longer fixed periods minimize switching costs involved in refinancing, as well as interest rate risk. Borrowers also value the fraction of branches in nearby postcodes when purchasing the mortgage directly from lenders. This effect disappears when borrowers originate the mortgage through a broker.

Panel A in Table 2.1 also presents estimates for brokers' distortions to households' choices (brokers' downstream market power). The average distortion is equal to 0.37, as captured by parameter $\theta$. Figure 2-2 shows the distribution of $\theta$ across broker companies, with values ranging between 0.28 and 0.45. Although brokers are heterogeneous in their influence on borrowers, I can reject the null hypothesis of benevolent brokers ($\theta$ equal to zero) at a 5% significance level for all broker companies. In addition, brokers seem to have a preference for products with higher

Table 2.1: Demand Estimates

PANEL A: Mortgage Choice Parameters

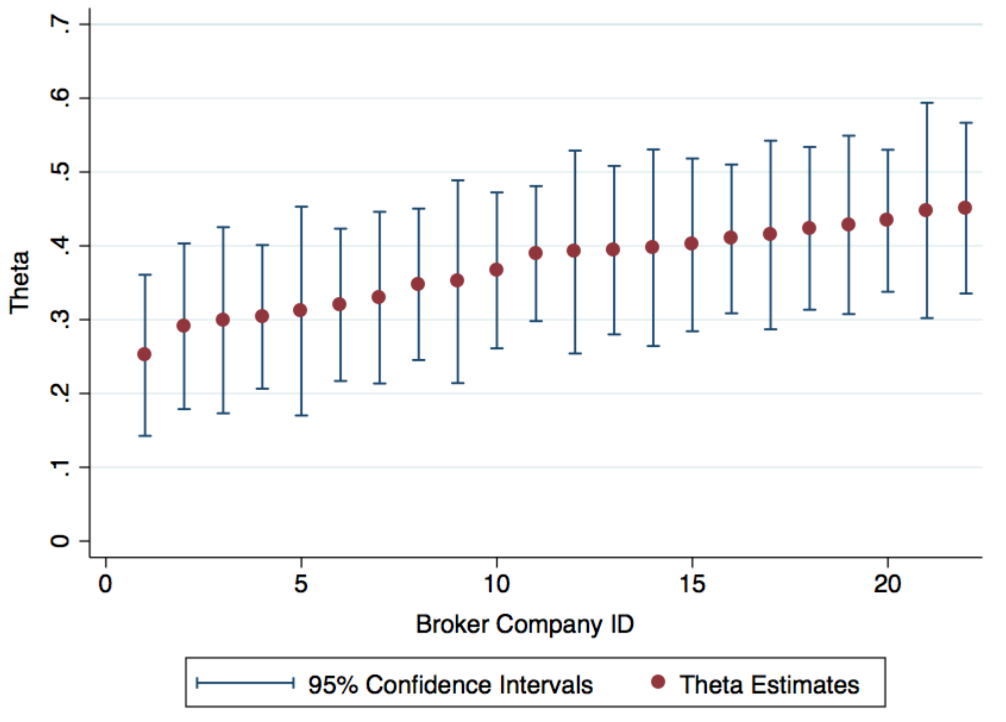
| | Interest Rate Borrower ($\alpha$) | High LTV Borrower ($\psi_1$) | 2-Year Fixed Borrower ($\psi_2$) | Branches Direct ($\lambda$) | Commission Broker ($\bar{\theta}$) | High LTV Broker ($\bar{\gamma}_{21}$) | 2-Year Fixed Broker ($\bar{\gamma}_{22}$) |
|---|---|---|---|---|---|---|---|
| Estimate | -0.91 | 0.45 | -0.21 | 0.33 | 0.37 | 0.14 | 0.27 |
| SE | 0.39 | 0.10 | 0.07 | 0.09 | 0.11 | 0.02 | 0.08 |
| N Likelihood | 7,493,244 | 7,493,244 | 7,493,244 | 7,493,244 | 7,493,244 | 7,493,244 | 7,493,244 |
| N Borrowers | 91,137 | 91,137 | 91,137 | 91,137 | 91,137 | 91,137 | 91,137 |
| N 2nd Stage | 5,208 | 5,208 | 5,208 | - | 483 | - | - |
| Lender FE | Yes | Yes | Yes | - | Yes | - | - |
| Market FE | Yes | Yes | Yes | - | Yes | - | - |
| Broker FE | - | - | - | - | Yes | - | - |
| F-stat | 102 | 102 | 102 | - | 26 | - | - |

PANEL B: Sales Channel Choice Parameters

| | All Borrowers | London | Other Regions | Q1 Income | Q2 Income | Q3 Income | Q4 Income |
|---|---|---|---|---|---|---|---|
| SEARCH COSTS | | | | | | | |
| Mean ($\mu$) | 3.3 | 2.9 | 4.1 | 3.1 | 3.3 | 3.9 | 5.0 |
| Stand. Dev. ($\sigma$) | 0.5 | 0.4 | 0.7 | 0.8 | 0.7 | 0.5 | 0.2 |

Note: Panel A shows the structural demand estimates of the logit model for demand for mortgage products. The model is estimated for a 25% random sample. Standard errors are computed by bootstrapping. The F-stat is the F statistics for the excluded instrument in the second stage instrumental variable regressions for both product-market and broker-lender-market estimated fixed effects. N likelihood is the total number of observations in the first stage (borrower-product pairs). N second stage is the number of observations in the second stages. N borrowers is the total number of borrowers in the 25% random sample. Panel B presents the estimates for the search cost distributions. I use the entire sample for this part of the estimation.

Figure 2-2: Broker Market Power Estimates




Note: The graph shows estimates of distortion parameter $\theta_b$ for the largest 20 broker companies in the market and two categories of small and medium brokers. These parameters are obtained after regressing the estimated broker-lender-market fixed effects on commissions interacted with broker dummies. I also control for market, broker and lender fixed effects. To account for endogeneity concerns, I use supply-side, cost shifters as instrumental variable for commissions. Standard errors are computed by block-bootstrapping.

leverage ($\bar{\gamma}_{21}$) and shorter initial fixed periods ($\bar{\gamma}_{22}$). This preference is not surprising given the financial incentives brokers face. As already described in section 1.3, brokers get fees and commission payments every time households remortgage. Thus, making this event happen as often as possible is in their best interest. Considering that the commission payment is a percentage of the loan amount, brokers can nudge households towards higher loan-to-value products. Results also show evidence of lender geographical market power. The estimate for household preferences for bank branches ($\lambda$) is positive and significant. Moreover, it is 30% of the size of the average estimate for interest rates, implying households going directly to lenders have a strong preference for nearby branches.

In Appendix B I discuss the fit of the model. Figure B-1 compares the distribution of estimated and observed market shares for both training and cross-validation samples. The model fits the out-of-sample data quite well, both in terms of mean and variance. The fit is also good when accounting for product characteristics, namely, lender, initial period, and loan-to-value band. Figure B-2 plots estimated and observed market shares across these dimensions. The main limitation is that the model over-predicts the share of shorter initial period mortgages and has a higher variance for products with loan-to-value bands above 85%.

Panel B in Table 2.1 presents estimates for the mean and standard deviation of borrowers' search cost distributions across income-region groups, as described in section 2.3.1. I use the entire sample to estimate these parameters. I find the average search cost for all first-time-buyers is equal to 3.3, with a variance of 0.5. Panel A in Figure B-3 shows how borrowers in London have a lower average search cost than those in other regions in the UK. Similarly, Panel B in Figure B-3 shows that average search costs increase with income, while the variance decreases.

### 2.4.2 Supply Parameters: Marginal Costs and Bargaining

The first column of Table 2.2 presents average estimates for marginal costs. The average marginal cost is 1.82 percentage points. Small banks have higher average marginal costs, resulting partly from higher capital requirements (Benetton, 2018). Mortgages with longer initial deals and higher loan-to-values are also more expensive on average. The second and third columns of Table 2.2 differentiate between average marginal costs for direct and intermediated sales, with intermediated sales being, on average, 7% less costly to originate than direct sales. Figure B-5 plots marginal cost distributions for both origination channels, illustrating the lower mean and higher variance of broker sales' marginal costs.

Table 2.2: Marginal Costs

| | Total | Direct Sales | Intermediated Sales |
|---|---|---|---|
| All | 1.82 | 1.93 | 1.79 |
| Lender Type | | | |
| Big Six | 1.80 | 1.95 | 1.71 |
| Challengers | 1.84 | 1.87 | 1.83 |
| Small Banks | 2.31 | 2.16 | 2.40 |
| Building Societies | 1.87 | 1.78 | 1.93 |
| Initial Period | | | |
| 2-Years | 1.73 | 1.75 | 1.73 |
| 3-Years | 1.94 | 2.02 | 1.89 |
| 5-Years | 1.98 | 2.10 | 1.84 |
| LTV Band | | | |
| LTV $\leq$ 80 | 1.60 | 1.79 | 1.50 |
| LTV >80 | 2.03 | 2.04 | 2.03 |

Note: Marginal costs are expressed in percentage points and computed for direct and intermediated sales. I report total average marginal costs taking into account direct and intermediated sales for each product in each time period. I also report marginal costs by different product characteristics: lender, initial period and loan-to-value band.

This differential in marginal costs across sales channels is higher for the Big Six, for whom intermediated sales are 12% cheaper. Challenger banks face similar marginal costs, regardless of sales channel, whereas both small banks and building societies find it more costly to originate mortgages through intermediaries rather than through in-house distribution channels. This heterogeneity can be partly driven by the Big Six having intermediary-only online platforms that facilitate the application process and take advantage of economies of scale, which can ultimately reduce the cost of originations via brokers, for example, through quicker income verification. Intermediated sales also have a lower marginal cost for low loan-to-

Table 2.3: Mark-ups

| | Total | Direct Sales | Intermediated Sales (Pre-Commission) | Intermediated Sales (Post-Commission) |
|---|---|---|---|---|
| All | 22% | 28% | 32% | 18% |
| Lender Type | | | | |
| Big Six | 22% | 26% | 36% | 20% |
| Challengers | 19% | 30% | 33% | 17% |
| Small Banks | 13% | 27% | 20% | 7% |
| Building Societies | 24% | 36% | 31% | 16% |
| Initial Period | | | | |
| 2-Years | 19% | 29% | 31% | 15% |
| 3-Years | 24% | 28% | 34% | 19% |
| 5-Years | 25% | 27% | 37% | 23% |
| LTV Band | | | | |
| LTV $\leq$ 80 | 23% | 26% | 38% | 21% |
| LTV >80 | 17% | 20% | 20% | 16% |

Note: Mark-ups are expressed as a percentage of the interest rate. I report average mark-ups for all products and by different product characteristics: lender, initial period and loan-to-value band. I also differentiate between direct and intermediated sales mark-up. For the latter, I consider separately mark-ups before and after commission payments.

value products.

Given marginal costs, I compute average mark-ups and find average mark-up is 22%, which is close to the range that other papers studying the UK mortgage market have reported (see, e.g., Benetton, 2018). Table 2.3 shows the existing variation in mark-ups across lender types and other product characteristics. Most importantly, once I differentiate between mark-ups for direct and intermediated sales (accounting for commission payments), intermediated sales are estimated to be 37%

less profitable for lenders than their in-house direct sales. This finding holds for all lenders and all product types, implying that brokers have some market power when negotiating with lenders and are able to extract surplus from lenders given borrowers' preferences for the brokerage channel.

Finally, given demand and cost estimates, Table 2.4 reports my estimates for bargaining parameters, as described in section 2.3.2. Higher values indicate relatively more bargaining power for lenders. Bargaining parameters are heterogeneous and range between 0.19 and 0.72. These values reject the hypothesis of take-it-or-leave-it offers, because bargaining parameters are neither one, which would imply lenders choose mutually agreeable commissions that make brokers' participation constraints binding, nor zero, which would imply brokers offer commissions that make lenders' participation constraints binding. I find that large brokers have a 50% lower bargaining power when facing the Big Six and building societies than when negotiating with challengers and small banks. Small brokers, on the other hand, are able to equally split the surplus when negotiating with all types of lenders. Among lenders, the Big Six have a bargaining power of 0.72 when dealing with large brokers, but that situation is reversed when negotiating with small brokers. The same happens to building societies. Challengers, however, only have a bargaining power of 0.28 when facing large brokers, but are able to extract 50% of the surplus against small brokers. Similarly, small banks have a higher bargaining parameter in negotiations with small brokers.

## 2.5 Counterfactual Scenarios

In this section, I use the estimates from the model to simulate two sets of counterfactual scenarios. The first set of counterfactual policies restricts the channels through which households can originate a mortgage. First, I consider a policy banning broker

Table 2.4: Lender Bargaining Parameters

| | Large Brokers | Small Brokers |
|---|---|---|
| Big Six | 0.72 | 0.41 |
| Challengers | 0.28 | 0.40 |
| Building Societies | 0.61 | 0.47 |
| Small Banks | 0.19 | 0.31 |

Note: This table reports estimated bargaining parameters for lenders versus large and small broker companies. Larger values of the bargaining parameters indicate relatively more bargaining power for lenders.

services in this market. Next, I implement a ban on direct sales, that is, I make brokers' advice mandatory. In the second set of policy counterfactuals, I consider equilibrium effects from restricting commission payments. from a complete ban to different caps. In all simulations, I make assumptions consistent with a short-run analysis. I assume lenders do not change their available products and that no entry or exit occur in the market. Lenders also do not modify their branch network. I also impose that preferences remain invariant and that lenders' marginal costs are not affected by the policy change. I recognize that some of the assumptions underlying the results in the simulations are strong, but they are necessary to produce policy counterfactuals in this setting.

### 2.5.1 Restrictions on Broker Services and Direct Sales

First, I simulate an equilibrium without any brokerage services. Column (1) in Table 2.5 reports estimates of a counterfactual in which households can only originate their mortgages via lenders' in-house distribution channels. In this scenario, competition decreases with the Herfindahl-Hirschman Index increasing by 35%. Prices go up by almost 25%, and lender profits increase by 12% (even more for the large lenders). Household search costs increase by more than 150%. Larger search costs and higher prices result in consumer surplus decreasing by 51%. This large fall in consumer welfare suggests that the positive roles of brokers (lower search costs and more upstream competition) dominate the negative ones, and households are better off having these intermediaries in the market despite their distorted incentives.

Next, I consider an equilibrium with mandatory brokers' advices (i.e., without any direct sales). Column (2) in Table 2.5 shows estimates of a counterfactual scenario banning direct sales and making expert advice from brokers mandatory. In this simulation, lenders with extensive branch networks lose their local market power (due to household preferences for nearby branches). Competition increases with the Herfindahl-Hirschman Index falling by 27% and the share of the Big Six decreasing by 17%. Moreover, marginal costs go down by 12%, because now all sales are done via brokers (which are more efficient). However, brokers are able to extract most of this gain in efficiency by increasing their commission rates by 42%. This change is driven by a drastic fall in outside options for the Big Six. Overall, lender profits decrease by 20% and prices increase by 9%. The net effect on consumer surplus is a decrease of 6%.

To generate estimates in Column (2), I make two assumptions that might change in the long-run and could affect the overall effect on sumer surplus. First, I assume no entry in the broker market. Given the increase in broker revenues due to higher commissions, it seems reasonable to expect some entry in this market. More brokers would result in lower commissions for banks and, most likely, lower prices for households. This effect will increase consumer surplus. The second assumption is that broker fees to households remain constant. However, if brokers also increased their fees to households, consumer surplus would decrease. The magnitude of this

Table 2.5: Counterfactual Restrictions on Commission Payments

| | Ban on Brokerage %Δ | Ban on Direct Sales %Δ | Ban on Commissions %Δ | Cap at 0.4% %Δ | Fixed at 0.4% %Δ | Fixed at 0.7% %Δ |
|---|---|---|---|---|---|---|
| **Market Structure** | | | | | | |
| HHI | 35% | -27% | 21% | 5% | -3% | 12% |
| Share Big Six | 19% | -17% | 12% | 3% | -2% | 8% |
| **Pass-Through** | | | | | | |
| Prices | 24% | 9% | 11% | -5% | -1% | 8% |
| Marginal Cost | 13% | -12% | 9% | -1% | -4% | 5% |
| Lender Profits | 12% | -20% | 7% | -2% | 0% | 5% |
| Commission Rates | -100% | 42% | -100% | -35% | -17% | 49% |
| **Demand** | | | | | | |
| Share Direct | 357% | -100% | 115% | 30% | -1% | 14% |
| Search Costs | 156% | -100% | 83% | 13% | -1% | 19% |
| Consumer Surplus | -51% | -6% | -26% | 9% | 2% | -11% |

Note: Column (1) reports estimates of restricting brokerage services, so that all mortgages are originated through lenders' in-house distribution channels. Column (2) presents estimates of banning direct sales and making broker advice mandatory. Columns (3) and (4) show estimates for policies imposing a ban and a cap on commissions equal to the median commission. Column (5) sets all commissions equal to 0.4%, and Column (6) fixes commissions at 0.7%.

additional fall will depend on the level of competition among brokers, which I do not model. Thus, Column (2) is a lower bound on the losses.

Overall, banning either broker sales or direct sales will decrease consumer welfare in the short-run. These results suggest that consumers are better off with the baseline model in which there is competition among brokers and branches.

### 2.5.2 Restrictions on Commission Rates

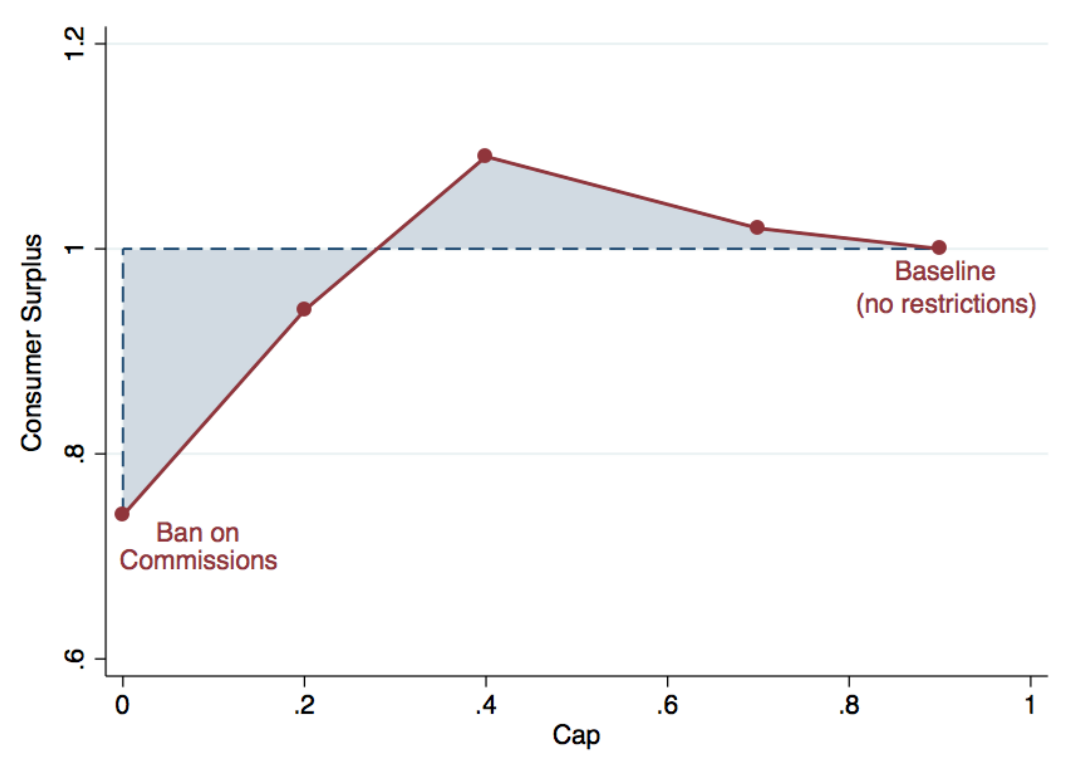
Reduced-form evidence in Section 1.3 suggests brokers react to supply-side incentives. Estimates for brokers' distortion parameters $\theta_b$ in Section 2.4 also reject the hypothesis of benevolent brokers, indicating brokers' choices respond to commission payments. To align households' and brokers' incentives, regulators have imposed restrictions on upstream payments to intermediaries. To address the effects of such policies, I use the estimated model to explore the equilibrium impact of changes in commission rates.

First, I consider equilibrium effects of imposing a ban on commission payments between brokers and lenders. In this counterfactual, I assume broker fees to households' increase such that the average per-sale profit each broker company receives is the same as in the estimated baseline model.[6] In Appendix B, I run the same policy counterfactual but make alternative assumptions on broker pass-through. I obtain qualitatively similar results for different increases in broker downstream fees.

Column (3) in Table 2.5 shows results when implementing a ban on commissions given the assumptions mentioned above. This policy proves to be detrimental for consumers. Market concentration and prices go up, as well as marginal costs and search costs. Consumer surplus falls by more than 25%, and profits for the Big Six increase by more than 27%. To illustrate the mechanism that seems to dominate in this equilibrium, consider a household with large search costs. In the baseline model, this household chooses the brokerage channel. However, because broker fees to households increase significantly in this counterfactual, this household now decides to originate its mortgage via lenders' in-house distribution channels. As shown in the estimated model by the coefficient on nearby branches $\lambda$, lenders' with extensive branch networks are able to get a higher market share from households going direct. When setting interest rates, the Big Six anticipate this increase in direct sales and increase prices, resulting in lower consumer surplus. Given the relevance of branches and other in-house distribution channels in the new equilibrium, challenger banks

[6] I need to make an assumption on broker pass-through since my model does not endogeneize broker fees to households. Since most broker companies in the baseline charge zero fees, it would be unrealistic not to change fees in the counterfactual. Broker companies need to make money, and, if lenders no longer make payments, it seems reasonable to assume household fees will go up.

Figure 2-3: Consumer Surplus and Maximum Commission Rates




Note: A ban on commissions is equivalent to imposing a cap equal to zero. No restrictions on commissions is equivalent to imposing a (non-binding cap) equal to 0.9%. The y-axis plots consumer surplus as defined in subsection 2.3.1.

are likely to invest in their own channels in the long-run. In addition, some broker companies could be forced to exit the market given the decrease in their market share as a result of higher household fees. I do not capture these long-run equilibrium effects in my estimates.

An alternative policy to align households' and brokers' incentives is to impose a cap on commission payments. I assume this cap to be equal to the average commission in the baseline model (0.4% of the loan amount). This regulation allows brokers to still get some revenue from lenders, and therefore broker fees to households do not increase as much as in the case of a ban. This policy also has implications for the network of broker-lender pairs. For some pairs, their new optimal commission, $c^*_{lbt}$, as defined in Section 2.2.3, is below the cap, $c^{cap}_t$. For these cases, nothing changes and the link still holds. For other pairs, the cap violates the broker's participation constraint and the link is broken. Finally, for some pairs, the cap could be binding, and the link holds with an equilibrium commission equal to $c^{cap}_t$. Column (4) in Table 2.5 reports estimates for a regulation imposing a cap. Direct sales increase only by 30% and search costs only go up by 13% (both significantly less than in the case of a ban). Prices fall by 5%, and the overall impact on consumer surplus is positive, with an increase of almost 10%. These results are driven because, despite brokers having narrower networks of lenders and household broker fees going up, households that do hire brokers get, on average, a much better deal than in the baseline model.

Figure 2-3 plots the relationship between consumer surplus and different levels of caps on commissions. This non-monotonic relationship results from a trade-off between broker market power and lender local market power. Households originating their mortgages via brokers face broker market power in the sense that brokers can extract surplus from them (positive values of $\theta$). On the other hand, households going directly to lenders prefer nearby branches. This preference gives lenders local market power, which they can exploit when setting interest rates. A very restrictive cap reduces broker market power at the expense of increasing lender market power. In the case of a ban, the gains of reducing broker market power do not compensate for the welfare loss of increasing lender market power.

The final set of policy counterfactuals considers cases in which, instead of capping commission payments, the regulator fixes commissions to an homogeneous rate. This policy will have the following equilibrium effects. First, a different set of broker-lender links will break. As in the case of a cap, some agreements with higher rates in the baseline will no longer be in place. Additionally, some links with lower rates in the baseline will also no longer hold. Therefore, broker networks will be significantly narrower than in the baseline. This effect will reduce household payoffs from going to brokers and will lead some households to shift to the direct channel (decreasing lender competition and increasing prices). The second equilibrium effect of this policy is that household and broker incentives are more aligned than in the baseline. Household expected utility of going to the broker goes up and some households will shift to the broker channel. However, it is important to highlight that, even though heterogeneity of commissions across lenders no longer distorts brokers' advice, brokers still have their own incentives and these do not necessarily matched those of the household. Theoretically, the overall effect of these policies is ambiguous.

Columns (5) and (6) in Table 2.5 report estimates for regulations fixing commission rates to 0.4% and 0.7%, respectively. Estimates in Column (5) have very similar averages to the baseline with no restrictions. Estimates in Column (6) result in a 11% lower consumer surplus, driven by a larger shift of households into the direct channel. Both policies affect selection into brokers and, consequently, which households are better and worse off because of the regulation. When commission rates are fixed at 0.7%, broker networks are mostly composed by challenger banks. Therefore, households whose payoffs are larger with these banks are more likely to go to brokers. However, these households also have, on average, lower search costs. In equilibrium, households with larger search costs but preferences for the Big Six go direct, while households with lower search costs but preferences for products by the challenger banks go to brokers. The Big Six are able to increase their prices and overall consumer surplus decreases by 11%. In the case where commission rates are set to 0.4%, the two equilibrium effects mentioned above counterbalance each other and the overall impact on consumer surplus is almost analogous to the baseline.

## 2.6 Conclusion

Regulations restricting upstream payments for expert advisors have been at the center of academic and policy debate in the last decades. An ongoing effort seeks to better understand the effectiveness of such policies and the supply and demand channels through which they operate. This paper contributes to this debate by focusing on the UK mortgage market, where brokers play a key role in improving upstream competition among lenders and reducing household search costs. In this market, restrictions on commission payments have a positive effect on consumer surplus by aligning households' and brokers' incentives. However, they also have a negative impact on consumer welfare by increasing downstream fees and making more consumers go directly to lenders. The decrease in demand for expert services increases the market power of lenders with extensive branch networks. As restrictions become more severe, the increase in prices due to less competition upstream dominates the gains from reducing the agency problem between households and brokers. Overall, whenever restricting financial relationships between intermediaries and upstream firms, considering the supply-side equilibrium effects such policies will unravel is vital.

# Chapter 3

# Deposit Withdrawals

[Note: This is co-authored work with Nikos Artavanis, Daniel Paravisini, Amit Seru and Margarita Tsoutsoura. All figures and tables are located at the end of the chapter.]

## 3.1 Introduction

The global financial crisis saw runs on several prominent banks and financial intermediaries. It reopened fundamental old debates on the rationale of a banking system with "run prone" deposits (e.g., Diamond and Dybvig, 1983) as well as on policies that provide stability in the wake of uncertainty (e.g., Drechsler et al., 2018; Egan et al., 2017).[1] Banking regulation that seeks to tackle these issues relies on some assessment of motives driving depositor withdrawals during uncertain and quiet times. Theoretical work has broadly put these depositor withdrawal motives into reasons related to liquidity (idiosyncratic), solvency (fundamentals including policy risk) or expectations about withdrawal behavior of other depositors (coordination). Remarkably, empirical work that isolates and quantifies these motives has been very limited (e.g., Iyer and Puri, 2012). The main obstacles towards this goal have been obtaining detailed high frequency deposit-level data and a credible empirical design in an important setting. This paper aims to fill this important gap.

We develop a new approach to isolate and quantify the extent to which deposit withdrawals are due to liquidity, exposure to policy risk, or expectations about how other depositors will behave. We use daily micro-data on insured time-deposits from a large Greek bank over a long time period

[1] Several theories have also been proposed on advantages that such deposits provide to the financial system during quiet and "sleepy" periods (e.g., Hanson et al., 2015).

that spans quiet periods as well as events with large policy uncertainty. We use variation induced by maturity expiration of time deposits around the large policy uncertainty events to filter deposit withdrawals due to direct exposure to policy risk from those due to expectations about behavior of other depositors. We quantify these effects in terms of elasticities with respect to foregone returns and changes in short-run CDS prices. Doing so allows us to compare the magnitudes of our effects with those found anecdotally in other prominent cases of bank runs (e.g., Northern Rock in UK and Washington Mutual in US) and policy uncertainty (e.g., Italy in the spring and summer of 2018). Much like the setting in Greece, our estimates explain a significant fraction of total depositor withdrawals during these episodes.

Our setting uses daily deposit-level data with detailed contract characteristics on the entire universe of time deposit accounts for retail customers of a large Greek bank. We focus on the time period between 2014 and 2015. This period saw both quiet and uncertain times, as well as withdrawals that in the aggregate drained away almost 30% of time deposits in the Greek banking system. In Greece, 62% of all Greek bank deposits by households are time deposits, being economically relevant for the stability of bank funding sources.[2] This high prevalence of time deposits is not unique to Greece. In Euro area country banks, close to 50% of domestic private non-financial deposits are time deposits with a maturity over one year. [3] Moreover, time deposits are useful from the research design point of view since these contracts have a fixed maturity and "breaking" these deposits prematurely results in a penalty. Any such withdrawal allows us to assess the magnitude of the cost of withdrawal in terms of foregone interest.

Using this setting we start by establishing new facts on depositor withdrawal behavior in "quiet times", when both the bank and sovereign credit default swaps are at their lowest. During such periods there is no uncertainty about bank fundamentals. It is also unlikely that withdrawals during these times are driven by insolvency concerns due to expectations of a large number of other depositors withdrawing. Thus, early withdrawals during such periods allow us to study withdrawal behavior motivated by depositors' idiosyncratic liquidity needs. We find that, on average, about 0.04% of depositors withdraw time deposits early on a daily basis. This implies that 14.6% of time deposits per year are withdrawn early due to liquidity reasons. The foregone annualized return from quiet-time early withdrawals is on average 17% and can be as high as 65% for some borrowers.

[2]See Bank of Greece report on deposit markets, available at https://www.bankofgreece.gr/Pages/en/Statistics/rates_markets/deposits.aspx

[3]See, for example, ECB report on Changes in Bank Financing Patterns, available at: https://www.ecb.europa.eu/pub/pdf/other/changesinbankfinancingpatterns201204en.pdf?3afe7cf6dc78e23e1c8b5201d0dc51ae

This is a period when total deposits in the banking sector (and our bank) were growing, and there was no indication of distress in any price. The magnitudes in early withdrawals during this time imply that depositors exhibit a high willingness to withdraw deposits for liquidity reasons.

Next, we use a novel empirical strategy to isolate depositor withdrawal motives due to changes in their expectations about withdrawal behavior of other depositors (coordination motives). To do so we exploit a large national "announcement event" in Greece as well as deposit heterogeneity in maturity dates after this event. The surprise announcement was an unprecedented call on December 8, 2014 for a Presidential election in Parliament in the following weeks. It marked the beginning of a period of very high expected future policy uncertainty in Greece, including the threat of Greece leaving the Euro zone and of the conversion of deposits from euros to a new Greek currency. The impact of the increased risk on the financial system was large, with the price of the 6-month CDS on Greek sovereign bonds increasing by 136% and the stock market dropping by 12%. Importantly, any policy change could occur only if the Presidential elections failed, national elections were called and there was a change in government at the end of January, 2015. That is, in the weeks after the surprise announcement there was no risk of new policies being implemented.

The announcement event and associated institutional features provide us with a research design to isolate withdrawals due to coordination motives. In particular, for depositors whose deposits matured in the weeks following the surprise announcement, but before any change in government (i.e., between December 8, 2014 and end of January 2015), there was no risk due to new policies. Policies that might have altered fundamentals of Greece or the bank itself were not possible during this maturity period. In addition, we show how the bank faced no liquidity or funding shortages after the announcement, and there were no changes to its assets and liabilities. Therefore, these depositors ("treatment group") could wait until maturity without facing risks associated with policy changes or changes in bank fundamentals. However, this treatment group did face the risk that they would be unpaid if many other depositors withdrew during December and January in anticipation of policy changes in the future. Depositors with maturities further into the future (i.e., after the change in government) had motives to withdraw early in anticipation of policy changes after the election.[4] Thus, all else equal, the only reason for depositors in the treatment group to change their withdrawal behavior during this time period is due to coordination motives. Accordingly, our research design focuses on changes in withdrawal behavior of the treatment group around the announcement event. To make all else equal, we implement a difference-in-difference

[4]Given the structure of the penalty for early withdrawals, depositors are better off withdrawing as early as possible once they are certain they will have to "break" the contract.

specification where we account for liquidity withdrawals using another set of similar depositors with deposits of similar maturity ("control group") around a quiet episode. Our estimates suggest that coordination motives increase the probability of withdrawing early by almost 70% relative to the baseline probability of withdrawing.

Next, we exploit the period around the national election of January 25, 2015 to quantify the motives for withdrawal that are related to changes in fundamentals induced by policy changes. After the election and with a new government in power, new policies could be implemented.[5] Thus, depositors whose deposits matured after the election faced additional risk since policy changes could directly impact fundamentals of Greece and the bank. Under the assumption that coordination motives for these depositors remain the same as those depositors whose deposits matured before the election, we can isolate fundamentals related reasons for depositor withdrawals by comparing depositors with maturity dates before and after the election. As in our previous exercise, we account for liquidity withdrawals using a counterfactual set of depositors with similar maturities during our quiet period. Our estimates suggest that withdrawal motives related to fundamentals increase the probability of withdrawing early by almost 200% relative to the baseline.

Together, these magnitudes illustrate the importance of very different motives in explaining depositor withdrawal behavior. For instance, over 25% of the overall increase in the probability of early withdrawals is due to depositors withdrawing early because they anticipate that other depositor withdrawals, possibly due to likely policy changes in the future, might impact solvency of the bank. The short-run combined effect of coordination and fundamental related motives for withdrawals around the events we study is quite large. During this period, the short-run CDS price of the sovereign bond doubled. It also saw a quadruple increase in withdrawal probability relative to the baseline quiet-time annual withdrawal rate of 14.6%. In other words, if the shock that led to deposit withdrawals had remained constant, it would have depleted the time-deposits of the bank in less than two years. Alternatively, the three motives when scaled to annual frequency, account for 80% of aggregate deposit withdrawals from our Greek bank during the two months after the first announcement event on December 8, 2014.

In auxiliary tests, when we exploit heterogeneity across depositors and contract characteristics, we find that the magnitude of the cross-sectional variation in coordination motives is very small relative to its absolute level. This is consistent with the notion that coordination motives for

[5]According to election polls, there was no uncertainty on the outcome of the election: there would be a new government after January 25, 2015. There was uncertainty, however, on the policies this new government will implement and whether it will keep its electoral promises.

withdrawals are difficult to predict ex-ante using observable characteristics of the borrower base. We do find, however, a strong spatial autocorrelation in withdrawal behavior of depositors across nearby branches in the Northern region of Greece after the announcement event on December 8, 2014. Before that event there is no evidence of depositor withdrawal behavior being correlated across space. After the event, we observe clusters across branches in particular areas in the country, which cannot be explained by observable depositor characteristics in terms of political views, income and demographics. It is worth noting that despite the richness of our data, we are limited in the power of these tests due to requirements on timing and maturity of deposits imposed by our research design.

In the second part of the paper, we quantify the magnitude of withdrawal motives in terms of forgone returns and changes in short-run CDS prices. We exploit the discontinuity in the cost of early withdrawal around pre-scheduled accrued interest repayment dates. On these dates the cost of withdrawal drops to zero. Thus, any early withdrawal around these dates allows us to back out foregone returns of doing so. We estimate a cost-elasticity of withdrawing deposits early of 1.54 in quiet times. Expressed in monetary terms, a drop of €100 in the cost of withdrawing (i.e., 0.26% of deposit amount) increases the baseline probability of idiosyncratic deposit withdrawals by a third. Put another way, these estimates imply that an economically meaningful fraction of depositors are willing to pay a high cost to withdraw insured deposits for liquidity or idiosyncratic reasons.[6] We use these estimates to calibrate the monetary cost of withdrawals due to coordination and fundamental motives.

As noted earlier, around the announcement of elections, an increase of short-run CDS price by around 125% was associated with a sharp increase in withdrawals due to coordination motives. The magnitudes are equivalent to dropping the cost of withdrawing during quiet times by around €300. Alternatively, if the bank wanted to prevent withdrawals due to coordination motives after an increase in CDS prices by more than 100%, it would have to increase interest rates on deposits by 0.8 percentage points. Similarly, an increase in the price of short-run CDS (about 30%) after the elections due to risk about changes to policy dramatically increased withdrawals due to fundamental motives. Put in terms of our calibration, these magnitudes are equivalent to dropping the cost of withdrawing during quiet times by around €600. Alternatively, if the bank wanted to prevent withdrawals due to fundamental motives after an increase in CDS prices by 30%, it would

[6] It is worth noting that the estimates, obtained for time deposits, represent a lower bound on the volatility of demand deposits due to idiosyncratic reasons, since demand deposits do not face a penalty for early withdrawal and are most likely chosen by depositors who are more exposed to liquidity shocks.

have to increase interest rates on deposits by 1.6 percentage points over the next month before maturity (equivalent to a 21% annual return).

It is worth noting that the short-run deposit withdrawal elasticities we estimate are very likely a lower bound on the withdrawal elasticity over a longer horizon. The coordination and fundamental motives for withdrawing plausibly increase as bank deposits shrink. This is certainly consistent with the new Greek government imposing a withdrawal limit of €60 per day as deposits fled the Greek banks, less than six months after the election result. Nevertheless, to gauge external relevance of our estimates as well as to assess their plausibility, we consider how depositor behavior predicted by our estimates compares to actual depositor behavior in the rest of Greece and in other episodes of abnormal deposit withdrawals. Our results predict that, after the increase in CDS prices following December 8, 2014, we should observe 8% of time depositors withdrawing their deposits.[7] Another recent episode involving policy uncertainty and a progressive leakage of depositors took place in Italy in May 2018. Over a two-week political crisis, the CDS price on Italian sovereign bonds increased by 177%. During this period, 31.6% of time deposits with maturities shorter than two years left the Italian banking system. According to our estimates, this increase in the CDS should have resulted in a 10.5% decrease in time deposits. This is a substantial proportion since our estimates only account for time deposits with maturities shorter than one year. We find that we can similarly explain a significant fraction of total depositor withdrawals in the cases of bank runs on Washington Mutual in the US and Northern Rock in UK.

Our paper adds to recent work using micro-data to characterize the depositor behavior. Prior work has had to rely on an ex ante classification by the researcher of whether depositor behavior was a run or driven by fundamentals (Iyer and Puri, 2012; Iyer et al., 2016). Work on coordination motives has also relied on differential effect of an aggregate shock across institutions (Schmidt et al., 2016). In contrast, our approach relies on exogenous variation in the differential costs of running across depositors in the same institution. Doing so occurs naturally in the context of time-deposits and allows the data to tell whether depositor behavior is triggered by coordination or fundamental motives. Since the cost of running in time deposits is observable by the researcher, our approach has the added advantage that allows a quantitative evaluation of the cost of withdrawing deposits. In general, these estimates are hard to obtain without making strong structural assumptions (Dick, 2008, Egan et al., 2017). We contribute to this work by providing a novel approach that allows us to decompose and quantify the liquidity, coordination and fundamental motivations of deposit

[7]Recall that during the two months after this date, our bank lost 10% of its total time deposits and aggregate time deposits in the Greek banking system decreased by almost 8%.

withdrawals.Our estimates can help determine how much should the bank increase interest rates on deposits to keep depositors from withdrawing after changes in CDS prices. In fact, banks often use this mechanism to retain depositors following a change in fundamentals (Acharya and Mora, 2015). Moreover, banks also increase deposit rates when depositor perception of the bank worsens, even when it is not driven exclusively by fundamentals (Chavaz and Slutzky, 2018).

Our work is related to a large literature on bank runs. Theoretical literature discusses information-based runs (see, e.g., Bryant, 1980, Diamond and Dybvig, 1983, Postlewaite and Vives, 1987, Rochet and Vives, 2004, and Goldstein and Pauzner, 2005) and runs based on coordination problems (see, e.g., Jacklin and Bhattacharya, 1988, Chari and Jagannathan, 1988, Calomiris and Kahn, 1991, Chen, 1999, and Diamond and Rajan, 2001). Runs on repo and asset-backed commercial paper (ABCP) for shadow banks have also been documented (see, e.g., Gorton and Metrick, 2012, Acharya et al., 2013, Covitz et al., 2013, and Schroth et al., 2014).

Our paper also contributes to the empirical literature on economic and political uncertainty. Recent empirical papers on the effects of uncertainty on firm incentives include Bloom et al. (2007), Bloom, 2009, Bachmann et al. (2013), and Bloom et al. (2018), with a review in Bloom (2014). There is also a strand of work measuring policy uncertainty (see, e.g., Jurado et al., 2015, Baker et al., 2016).

The rest of the paper proceeds as follows. Section 3.2 describes the data and the institutional setting. Section 3.3 introduces aggregate policy uncertainty and analyzes depositors' withdrawal behavior when exposed to changes in expectations of other depositors' behavior and exposure to policy risk. Section 3.4 considers heterogeneity in our results across depositor and account characteristics, and geographical and political dimensions. Section 3.5 quantifies the effects and compares them to other episodes. Finally, Section 3.6 concludes.

## 3.2 Institutional Setting, Data and Descriptive Statistics

### 3.2.1 Data

Our dataset consists of time deposit accounts for the universe of retail customers of a large Greek bank. Standard contracts for time deposits are characterized by a fixed maturity period over which depositors cannot withdraw funds without incurring a monetary penalty. Time deposit contracts in our bank do not allow for the possibility of partial withdrawals. Each day, a time depositor faces two choices: do nothing (and keep waiting until maturity) or withdraw the entire deposit amount before maturity. In case of an early withdrawal, depositors lose all accrued interests since the last interest payment. This foregone income is deposit-specific and varies over time, being a function of interest rates, account amounts and the number of days left to maturity.

We observe each time deposit at a daily level from January 1, 2014, to March 31, 2015. Each observation has information on account features (interest rate, currency, origination and maturity dates) and depositor characteristics (gender, age, relationship with the bank, income, education). There are additional details on the branch that originated each deposit (postcode, branch ID). Table 3.1 shows summary statistics describing the key variables in our data. The average deposit amount is €27,281 and the average interest rate is almost 2%. Time deposits in our sample have an average maturity of almost six months, with the most popular contracts having a maturity length of one, three, six and twelve months. 77% of accounts are denominated in euros.

Time depositors have an average age of 65 years and are 45% female.[8] The average income of time depositors (as declared in their tax return) is $25,363, while the average income in Greece in 2013 was $8,879 for individuals and $17,270 for households (ELSTAT). Thus, time depositors tend to be among the high earners. Almost one-third of time depositors have at least another credit product with the bank, mainly a mortgage, a consumer loan or a credit card. Depositors tend to hold their time deposits for over two years, renewing them an average of five times. Finally, our bank operates at a national level and has an extensive branch network, which is heterogeneous in size and density across regions.

### 3.2.2 Depositor Withdrawal Patterns

#### Idiosyncratic Withdrawal during Quiet Times

Despite the monetary cost associated with early withdrawal, we observe that within a year 15% of time depositors (0.04% a day) withdraw their deposit amounts at least five days before maturity.[9]

[8] We do not observe whether the account has multiple depositors. All depositor characteristics in our data correspond to those of the main account holder. Given the average age of depositors and the large presence of our bank in rural areas, it seems likely that, when there is a couple owning the time deposit, the main holder is male.

[9] This gap of at least five days is because whenever a time deposit matures on a day that is weekend or holiday, the withdrawal is recorded on the earliest business day close to the maturity day.

The foregone annualized return from these early withdrawals is on average 17% and can be as high as 65% for withdrawals that occur close to the maturity date. The high incidence of early withdrawals and depositors' high willingness to pay to break time deposits are new stylized facts to both academics and regulators. In fact, under Basel III it is common to exclude term deposits from cash outflow calculations for Liquidity Coverage Ratios because it is presumed that depositors are unwilling to pay the associated penalty to withdraw. These stylized facts suggest that deposits are less slow-moving than commonly assumed.

Withdrawal behavior is also heterogeneous across depositors and account characteristics. Figure 3-1 plots 1) the distribution of time deposits in our sample across subgroups based on deposit and depositor characteristics, and 2) the fraction of early withdrawals over the same subgroups. Early withdrawals are more common in accounts with lower interest rates and longer maturity length. Depositors with more products with the bank (for example, mortgages, loans and credit cards) are also more likely to withdraw. We do not find a differential effect in withdrawal behavior across education and age groups. Female and male depositors also have the same fraction of early withdrawals. We also do not observe patterns across origination and maturity dates. Panels A and B in Figure 3-2 plot the total number of time deposits originated in a given week and those maturing during the same period. Depositor behavior when choosing when to open a time deposit and when this deposit matures does not seem to be strategic, on average.

### Withdrawal Around Time Deposit Maturity Expiration

The data exhibits some patterns in withdrawal behavior of depositors over the duration of their contracts. Figure 3-3 shows the fraction of early withdrawals as a function of days to maturity for the most common maturity lengths: six and twelve months. We observe that the relationship between early withdrawals and time to maturity has an inverted-U shape. Depositors are less likely to withdraw at the beginning and end of their maturity period.

The non-monotonic withdrawal behavior over the life of the deposit reflects the benefits and costs of liquidity motivated deposit withdrawal desicions. A depositor will make a time deposit if she does not foresee having a need for the cash in the very short run, which explains why withdrawals are very unfrequent early in the life of a deposit. The probability of unexpected liquidity needs increases over time, consistent with the withdrawal probability increasing over the initial life of the deposit.

The opportunity cost of withdrawing a time deposit, on the other hand, increases over time as the maturity date approaches. Withdrawing a deposit early is equivalent to taking a loan for the remaining maturity of the deposit, at a monetary cost equal to the promised interest. Suppose a depositor makes a one-year term deposit of €100 at a 3% rate. If she holds the deposit until maturity, she receives €103. Withdrawing the deposit two weeks before maturity is equivalent to paying €3 of interest to borrow €100 for two weeks, or borrowing at an annualized rate that exceeds 110%. If the depositor withdraws one week before maturity, the implied interest rate of the loan exceeds 350%. It is thus expected that the probability of early withdrawals drops as the deposit approaches maturity.

Withdrawals within weeks of the maturity date of the deposit can only be rationalized if depositors are extremely impatient. Interest rates exceeding 100% rates are not uncommon in Payday or other high-cost loans that serve liquidity constrained borrowers. The difference is that while typical high-cost loans are for small amounts, below €1,000, the average time deposit in our sample exceeds €50,000. This implies that the economic cost of early withdrawals can be substantial.

### Withdrawal Around Biannual Payments

If a time depositor decides to withdraw her deposit amount before maturity, she will lose all accrued interests between the last interest payment and the time of withdrawal. Our bank calculates accrued interests using a non-linear formula that depends positively on interest rates, Euribor rates and account amounts, and negatively on days left to maturity. Interest payments are heterogeneous across deposit accounts (depend on account characteristics) and vary over time (depend on origination date and maturity length). Accrued interests for time deposits are paid at maturity, except for two dates: January 1 and July 1. On these days, all accounts receive their accrued interests until that moment. Suppose depositor makes a one-year time deposit in March 1 on year T and holds it to maturity until February 28 on year T+1. During the length of her contract the depositor will get three interest payments. The first will consist of all accrued interests between March and June and will be paid on July 1. The second payment, on January 1, will account for all accrued interest between July and December. Finally, at maturity on February 28 on year T+1, the depositor will receive accrued interests for January and February plus the principal.

Depositors may behave strategically when deciding whether to withdraw their deposits around interest payments on January 1 and July 1. To illustrate depositors' incentives around these dates, let us consider a time deposit that has accumulated €100 as accrued interests by June 30. If the depositor decides to withdraw on that day, then she would lose €100. If, on the other hand, she waits one more day, then she will receive €100 on July 1 as her interest payment. She could then withdraw her entire deposit amount without forgoing any accrued interest. This exogenous reset to zero of accrued interests (effectively a fall in the price of early withdrawal) results in a discontinuity in early withdrawals around June 30 and July 1. Panel A in Figure 3-4 illustrates this strategic behavior by plotting accrued interests and the fraction of withdrawals in the weeks before and after interest payments on July 1, 2014. We observe that a fall of €500 in the cost of early withdrawal is followed by a 40% increase in early withdrawals. Panel B in Figure 3-4 shows the drop in the forgone rate of return. Average forgone returns fall from 50% to zero on July 1, incentivizing depositors to strategically withhold early withdrawals until after accrued interests are paid.

### 3.2.3 Institutional Setting and Political Events

We analyze withdrawal behavior of time depositors in the weeks leading to the election of Alexis Tsipras, leader of the anti-austerity left-wing party Syriza, on January 25, 2015 (hereafter $t_1$). These weeks represent a period of political turmoil and policy uncertainty in Greece. Electoral campaign programs of all major parties revolved around the bailout conditions imposed on Greece by the European Union and the International Monetary Fund. The incumbent conservative party, New Democracy, argued in favor of the current austerity measures and Greece's continuation in the European Union. The opposition party, Syriza, supported the renegotiation of Greece's debt and, if better conditions were not agreed upon, the possibility of Greece leaving the European Union.[10] During these weeks, the term *Grexit* started to become common in national and international media, and debates on dramatic policy changes dominated the political arena of the country.

This uncertainty period started on December 8, 2014 (hereafter $t_0$) when Prime Minister Samaras decided to bring forward by two months the following year's Presidential election. This announcement was unprecedented, as it was the first time a Presidential election took place before the end of the incumbent's term.[11] Markets did not anticipate the news. The Athens stock

[10]Syriza's *Radical Left Manifesto* supported the nationalization of banks and promised "an audit of the public debt and renegotiation of interest due and suspension of payments until the economy has revived and growth and employment return".

[11]In Greece, the President is elected for a five-year term by the Parliament. The nominated candidate must achieve a supermajority (200 out of 300 votes) during the first and second rounds. If these were to fail, then the candidate would only need 180 votes in the third, and final, round. From

exchange dropped 13% that same day, being its biggest one-day fall since December 1987.[12] Panel A in Figure 3-5 shows how the 6-month CDS price on Greek sovereign bonds increased by 136% after the announcement at $t_0$. Policy uncertainty rose even further when, three weeks after $t_0$, the Presidential election failed. Overall, the surprise announcement and the failed Presidential election led to significant political turmoil in Greece.[13] Panel B in Figure 3-5 plots the cumulative abnormal returns for Athens Stock Exchange when compared to FTSE Euro 100 during this period. As expected there was a significant drop on the day of the announcement and a subsequent decline in Greek returns afterwards.

In the event of all Presidential voting rounds failing, the Greek Constitution states that the Parliament must be dismissed and a snap election must be called within ten days. Therefore, on December 30 (hereafter $t_A$) Primer Minister Samaras announced that Legislative Elections would be held on January 25 ($t_1$) to elect a new Parliament. After three weeks of campaigning, Syriza won the election, attaining 149 seats in the 300-seat Parliament and being able to form government that same week. Alexis Tsipras was sworn in as Prime Minister the day after the elections. Figure 3-6 summarizes the key events taking place during this period and their political consequences.

After the surprise announcement at $t_0$ and the political turmoil that followed, depositor withdrawal behavior changed significantly. Figure 3-7 plots the daily fraction of early withdrawals over our sample period. Before the announcement at $t_0$, early withdrawals account for 0.04% of total time deposits each day. After $t_0$, we observe the percentage of early withdrawals rising steadily and reaching average daily values of 0.28% of total accounts. This time deposit flight was not exclusive to our bank. Figure 3-8 plots our bank's time deposit index relative to the same index for the entire Greek banking system. Both series follow the same trend, and depositors were withdrawing their deposit amounts throughout the Greek banking system.

The characteristics of depositors withdrawing early also changed during this period. Panels A and B in Table 3.2 summarize depositor characteristics and account features for the average early withdrawal before and after $t_0$, respectively. After the surprise announcement, depositors

1974 to 2008, all Presidential elections were successful with at least the two largest parties reaching a consensus. In 2009, however, the opposition party threatened to challenge the government's Presidential candidate, and early elections were announced before even the Presidential vote had taken place. In December 2014, tensions continued between the government and the opposition party, and for the first time a Presidential election was announced before the end of the incumbent's term.

[12]See, for example: `https://www.theguardian.com/world/2014/dec/09/stock-markets-tumble-as-greece-calls-election`

[13]See, for example: `http://www.bbc.co.uk/news/world-europe-30495578`

withdrawing early have, on average, a longer relationship with the bank and a larger fraction of them are bank employees. Moreover, early withdrawals have greater deposit amounts, lower interest rates and are almost exclusively denominated in euros. These changes suggest that the cost of waiting until maturity increased for depositors. In the next sections we discuss and quantify the different motives driving early withdrawals during this period of policy uncertainty in Greece.

## 3.3 Isolating Depositor Withdrawal Due to Coordination and Fundamental Motives

### 3.3.1 Empirical Strategy

To explain the change in depositor behavior during the period of policy uncertainty between $t_0$ and $t_1$, we differentiate between three motives for early withdrawals: 1) idiosyncratic liquidity motives; 2) expectations about how other depositors will behave; and 3) exposure to policy risk. In order to isolate the effect of each motive, we use difference-in-differences methodologies around the political events taking place at $t_0$, $t_A$ and $t_1$. These dates introduced new motives for early withdrawals and changed depositors' incentives depending on their maturity date. Figure 3-9 maps the events to the different exposures and motives depositors face.

Before $t_0$ it was a "quiet period" with no abnormal levels of policy uncertainty. It was a stable period for the Greek banking and financial sectors. Panels A and B of Figure 3-10 show prices for the Greek CDS across different maturities and the spread of the Greek 10-year bond with respect to the German 10-year bond. In the months leading to the announcement at $t_0$, both time series experienced very low levels and no unusual volatility. During this period, Greece had just returned to the markets, and the general feeling in the press was that of quiet times. Our sample also shows signs of optimism from time depositors. We observe that during these months new deposits have larger deposit amounts and longer maturities. In our empirical strategy, we assume that before $t_0$ all early withdrawals are driven exclusively by idiosyncratic motives (e.g., liquidity needs).

The announcement at $t_0$ marked the start of a period of large policy uncertainty in Greece, as described in Section 3.2.3. After the announcement at $t_0$ the 6-month CDS price on Greek sovereign bonds increased by 136%. This event exposed time depositors with longer maturities to policy risk in the future, since it increased the probability of a change of government and the implementation of new policies affecting fundamentals (both of the bank and the country).

However, time depositors with shorter maturities (before $t_1$) did not face policy risk ("treatment group"), because new policies could not be implemented until after the election at $t_1$. However, the announcement at $t_0$ changed expectations for our treated depositors. In particular, it changed their expectations about the likelihood of the bank failing because of other depositors' withdrawal behavior. In fear of the bank becoming insolvent if enough depositors with longer maturities withdrew their deposit amounts, some depositors with shorter maturities decided to withdraw early. We exploit these differences in risk exposure across depositors based on their maturity date to isolate the change in withdrawals due to expectations about how other depositors will behave. We also show that, during the period between $t_0$ and $t_1$, there were no short-run changes in the bank fundamentals. Both the assets and liabilities of the bank remained unchanged after the announcement at $t_0$. Therefore, we claim that additional withdrawals from depositors with shorter maturities taking place after $t_0$ are driven by coordination motives.

After $t_1$, all depositors faced policy risk, because changes in policies affecting the bank's and the country's fundamentals (e.g., Grexit, capital controls) could be implemented by the new government. To identify changes in withdrawal behavior due exclusively to exposure to policy risk, we exploit the announcement at $t_A$. This was an announcement of the election date $t_1$. Effectively, $t_A$ is a news shock that reveals exposure to policy risk for depositors with short-run maturities. After $t_A$, depositors with maturity dates before $t_1$ knew that they would not be exposed ("control group"), while those with maturity dates after $t_1$ were now certain that they will face policy risk if they wait until maturity ("treatment group"). Before the announcement at $t_A$, both groups of depositors are equally uncertain about their exposure. However, after the exact date of the election is revealed, their exposure changes differently depending on their maturity date. We compare withdrawal behavior of these two types of depositors before and after $t_A$ to isolate changes in withdrawal behavior driven exclusively by exposure to policy risk.

Finally, we need to address two additional challenges to isolate depositor withdrawal motives during the period around $t_0$, $t_A$ and $t_1$. The first relates to the pattern in early withdrawals over the maturity length as described in Section 3.2.2. Due to the inverted U-shape relationship between days to maturity and withdrawal behavior, an event study around the events will result in biased estimates. In particular, it will also capture intrinsic patterns in depositors' withdrawal behavior that are uncorrelated with changes in expectations and exposure to policy risk. To control for these patterns we need a control group with deposit accounts that have the same days to maturity, enabling us to compare deposits at the same point in the inverted U-shape curve.

The second challenge for identification is the interest payments taking place on January 1 (which coincide with $t_A$). As already mentioned in Section 3.2.2, our bank pays accrued interests on January 1 to all time deposits. These payments generate a discontinuity in forgone returns and can lead to strategic withdrawal behavior before and after this interest payment. These additional withdrawals would be uncorrelated with policy uncertainty and could bias our estimates. For this purpose, we use as control group deposits around the interest payment on July 1, when there were no abnormal levels of policy uncertainty.

In the next sections we develop this empirical strategy in more detail.

### 3.3.2 Identifying Coordination Motives: Expectations about Behavior of Other Depositors

In this section, we isolate depositor withdrawal behavior driven exclusively by changes in expectations about other depositors' withdrawals.

#### Difference-in-Differences Approach

We compare withdrawal behavior of depositors with short-run maturity expiration (maturities before $t_1$) before and after the surprise announcement at $t_0$. Before $t_0$, all depositors withdrawals are driven by idiosyncratic motives. As already discussed, between $t_0$ and the national election at $t_1$ new policies (e.g., deposit haircuts, Grexit) could not be implemented. Therefore, after $t_0$, depositors with accounts maturing before $t_1$ face no exposure to policy risk. These depositors could wait until maturity without fear of losing their deposits because of policy changes. However, after $t_0$, depositors with longer maturity expiration changed their expectations about fundamentals (both of the country and the bank) further into the future (when their deposits mature). As a result, some of these depositors with maturities after the election started to withdraw their deposit amounts. The announcement at $t_0$ had an effect on depositors with short-run maturity expiration by effectively changing their expectations about other depositors' (longer maturity expiration) withdrawal behavior.

As our treated group we consider time deposits maturing in the three weeks prior to $t_1$ (window starting three weeks after $t_0$). If depositors in this group decide to withdraw right after $t_0$, then they are willing to give up their accrued interests up to that moment to avoid the possibility of the bank failing because of too many withdrawals from other depositors. Depositors withdrawing early after $t_0$ have higher responsiveness to other depositors' withdrawal behavior than those who decide to wait.

We restrict our sample to deposits maturing over a short window in order to control for endogenous selection of maturity dates and to make accounts comparable in terms of days to maturity. We will compare early withdrawal behavior of these depositors for a three-week period before and after $t_0$. These deposits are not exposed to fundamental policy risk. With this comparison we capture the additional withdrawal behavior due exclusively to changes in expectations about how other depositors behave. The upper panel in Figure 3-11 shows the time periods and maturity dates that we use for our treated group.

To isolate the effect, we need to control for observed patterns in withdrawal behavior across maturity lengths. We also need to take into account interest payments on January 1, 2015. As already described in previous sections, interest payments can generate strategic behavior on deposit withdrawals before and after the payment date, e.g., depositors have incentives to wait until interest are paid on January 1, 2015. Not accounting for either of these patterns would result in a downward bias of our estimates. To address these concerns, we use as a control group time deposits maturing in a three-week window after July 1, 2014, when there was also an interest payment. This period was a time of financial stability, with no abnormal patterns in early withdrawals. To make our control group comparable to our treatment group, we use as a placebo date (hereafter $t_0^{Placebo}$) a day three weeks before interest payments. We will compare depositors in our control group before and after this placebo date. The lower panel in Figure 3-11 shows the time periods and maturity dates that we use for our control group.

To formalize the differential effect on withdrawal behavior across treatment and control groups, we run the following difference-in-differences estimation:

$$Withdrawal_{it} = \delta \, Treated_i + \lambda \, Post_t + \beta \, Treated_i \times Post_t + \gamma' X_{it} + \epsilon_{it} \, , \tag{3.1}$$

where the dependent variable *Withdrawal* is a dummy equal to one if the depositor withdraws funds before maturity. *Treated* refers to deposits maturing during the treatment period (three weeks before $t_1$), as opposed to those in the control group (three weeks after July 1). *Post* is a dummy equal to one for the period after $t_0$ and $t_0^{placebo}$. $X_{it}$ is the set of covariates accounting for depositor and account characteristics. $\epsilon$ is an error term. The coefficient $\beta$ will be our difference-in-differences estimate, capturing the additional increase in withdrawal behavior due exclusively to coordination motives driven by changes in expectations about other depositors' behavior.

### Identification/Assumptions

To identify the difference-in-differences estimates in our specification, we need parallel trends of treatment and control groups before $t_0$ and $t_0^{Placebo}$. Panel A of Table 3.3 shows the fraction of early withdrawals as a percentage of total time deposits before and after $t_0$ and $t_0^{placebo}$ for treatment and control groups. In the three weeks prior to $t_0$ and $t_0^{placebo}$, early withdrawals account for 0.40% of deposits for both treatment and control groups. The pool of depositors and account characteristics in both groups are not significantly different.

For identification we also need that there are short-run changes in the banks' fundamentals after $t_0$. In this exercise we are assuming that all additional withdrawals after $t_0$ are driven exclusively by changes in depositors' expectations about other depositors' withdrawal behavior. Therefore, we need to ensure that during the three weeks following $t_0$ there is (1) no change in the banks' fundamentals, and (2) no changes in factors contributing to idiosyncratic risk. To ensure (1), we check that both the assets and liabilities of our bank are not affected after the event. On the liabilities side, time deposits constitute almost 60% of the bank's liabilities. During our sample period, the bank had access to funds from the ECB and ELA at the same rates. On the asset sides, there was no haircut at the current solvent portfolio, and the pricing of shares of our bank did not change during our sample period. We provide more details supporting assumption (1) in Appendix C.1.

Identification assumption (2) assumes that idiosyncratic withdrawals remain the same before and after $t_0$ and $t_0^{placebo}$. We also assume that the incentives driving the three data patterns described in Section 3.2.1 remain the same for both treatment and control groups throughout our exercise. We check unemployment rates during our period, as well as pension payments. Nothing changed between December and January, when compared to our baseline period. We give more details in Appendix C.2.

### Results

Panel A in Table 3.3 shows that, after the surprise announcement at $t_0$, early withdrawals increased to 1% in the treatment group, while increasing only to 0.66% in the control group. Panel B in Table 3.3 presents the results from estimating Equation 3.1. Column (1) reports the difference-in-differences coefficient to be positive and significant at a 10% significance level. Depositors with short-run maturity expiration and who are not exposed to policy risk are 68% more likely to withdraw their deposit amounts before maturity than the baseline probability. This result holds after controlling for depositor and account characteristics in Column (2). Our claim is that this increase is due exclusively to changes in expectations about other depositors' behavior.

### 3.3.3 Identifying Fundamental Motives: Depositor Exposure to Policy Risk

In this section, we isolate the effect of exposure to policy risk on early withdrawal behavior of depositors.

#### Difference-in-Differences-in-Differences Approach

We exploit the election date announcement at $t_A$, which took place three weeks after the surprise announcement at $t_0$ and three weeks before the national election at $t_1$. After the surprise announcement at $t_0$, depositors knew that there was the possibility of going to elections in the near future (but at least six weeks later).[14] However, the exact date of the election was unknown until $t_A$, when the Prime Minister made the official announcement. He could have delayed the announcement by up to ten days or set the election date a week before or a week after. Therefore, $t_A$ is a news shock on $t_1$ that revealed depositors' exact exposure date to policy risk. Before $t_A$ there was no uncertainty on *who* would win the election, but on *when* this election would take place.[15]

Before $t_A$, time deposits maturing three weeks before and after the election at $t_1$ did not know whether their deposit would be exposed to policy risk or not. We assume maturity dates for these deposits are predetermined at the time of the announcement, since depositors could not have foreseen the upcoming events at the time of origination. This allows us to compare time deposits with maturity dates three weeks before $t_1$ (control group) with those maturing three weeks after $t_1$ (treatment group). After $t_0$, both groups face changes in expectations of other depositors' behavior. After $t_A$, only the treatment group is also exposed to policy risk.

[14] In the event of all Presidential voting rounds failing after the surprise announcement at $t_0$, the Greek Constitution states that the Parliament must be dismissed and a snap national election must be called within ten days. After an unsuccessful third round on December 29, Primer Minister Samaras announced on December 30 (hereinafter $t_A$) that national elections for a new Parliament would take place on January 25 ($t_1$). The current Parliament was therefore dissolved the following day, and the pre-election period began on January 1. After three weeks of campaigning, Syriza won the election and was able to form government.

[15] There was no uncertainty on the outcome of the national election. Polls before and after $t_A$ gave an undisputed victory to Syriza.

Despite having now both treatment and control groups, a difference-in-differences approach will not identify the effect of policy risk. As in the previous exercise, depositors will be in different points in the inverted U-shape curve described in Section 3.2.2, because of differences in days to maturity between treatment and control groups. Estimates would be upward biased, since the number of withdrawals in the control period will always be lower than those in the treatment group. Additionally, we need to account for strategic behavior around interest payments on January 1, 2015.

There is also an additional challenge for identification when compare to the previous exercise in Section 3.3.2. These new concern stems from the fact that accounts in the control group start maturing in the period after $t_A$. By construction, a time deposit that has matured cannot be withdrawn early, leading to an attrition problem in our sample. To account for this trend we use a difference-in-difference-in-differences (DDD) estimator. As our additional control we use time deposits maturing between in the six weeks following the interest payments on July 1, 2014. As $t_A^{Placebo}$ we consider July 1, and as $t_1^{Placebo}$ we consider a date three weeks after interest payments. These accounts allow us to we control for this pattern in the maturing structure of the data. Figure 3-12 illustrates the main events and maturity periods that we exploit for both treatment and control groups.

To formalize the differential effect on withdrawal behavior across treatment and control groups, we run the following triple-differences specification:

$$\begin{aligned} Withdrawal_{it} \quad = \quad & \beta_0 + \beta_1\, Treated_i + \beta_2\, Post_t + \beta_3\, Maturity_i \\ & + \beta_4\, Treated_i \times Maturity_i + \beta_5\, Treated_i \times Post_t + \beta_6\, Post_t \times Maturity_i \\ & + \beta_7\, Treated_i \times Post_t \times Maturity_i + \gamma' X_{it} + \epsilon_{it}\ , \end{aligned} \tag{3.2}$$

where the dependent variable *Withdrawal* is a dummy equal to one if the depositor withdrew funds before maturity. *Treated* refers to time deposits maturing in the six weeks after $t_A$, as opposed to those in the control group that mature in the six weeks after July 1, 2014. *Post* is a dummy equal to one for the period after $t_A$ and the equivalent one in the control group, $t_A^{Placebo}$. *Maturity* refers to deposits maturing after $t_1$ and the equivalent one in the control group, $t_1^{Placebo}$. $X_{it}$ is a set of covariates controlling for depositor characteristics and account features. $\epsilon$ is an error term. The coefficient $\beta_7$ corresponds to the difference-in-differences-in-differences coefficient (DDD), quantifying the additional withdrawals due to exposure to policy risk.

### Identification/Assumptions

To identify the estimates in triple-differences specification, we need parallel trends of treatment and control groups before $t_A$ and $t_A^{Placebo}$. Panel A in Table 3.4 shows the fraction of early withdrawals for both treatment and control groups. In the treatment period, we see that both treatment and control groups follow parallel trends in the periods before the event $t_A$. The same happens between treatment and control groups in the control period around $t_A^{Placebp}$. Moreover, in the period before $t_0$ and $t_0^{placebo}$ all four groups have similar levels of withdrawals.

Another identification concern relates to the interest payment taking place on January 1 and July 1. For our effects to be identified we must have that the average interest payment across control and treatment groups is not significantly different. Panel B in Table 3.4 shows that the interest payments do not vary across all four group of depositors in the period before $t_A$. Finally, as in the previous exercise, we also need to assume that idiosyncratic withdrawals remain the same before and after $t_A$ and $t_A^{placebo}$. That is, we assume that the three data patterns described in Section 3.2.1 remain the same before and after the events.

### Results

Panel A in Table 3.4 shows how the largest increase in the share of early withdrawals corresponds to the period after the news shock $t_A$ for depositors holding accounts with maturity date after $t_1$. The fraction of withdrawals jumps from 1.06%to 2.73%. This increase suggests that depositors discovering their exposure to policy risk faced a higher cost to waiting until maturity and decided to withdraw their deposit amounts early. Panel B in Table 3.4 reports estimates from Equation 3.3. The DDD coefficient is positive and significant at a 1% significance level, and it is larger in magnitude than the one associated with coordination risk. Our results show that policy risk increases the probability of running by 192% when compared to the baseline. This large effect also mitigates concerns regarding our assumption that changes in coordination risk might drive the results.

## 3.4 Heterogeneity Analysis and Other Tests

So far we have shown that, on average, the probability of early withdrawal increases due to coordination and fundamental policy motives. In this section we address whether there is additional heterogeneity in the withdrawal behavior of depositors across different subgroups.

### 3.4.1 Depositor and Account Characteristics

Panel A of Tables 3.7 and 3.8 present estimates for subsamples based on account and depositor characteristics. Columns (1) and (2) split the sample by gender. Withdrawal behavior across men and women is only statistically different when faced with changes in their expectations of other depositors' behavior. When exposed to such changes, men are, on average, more likely to withdraw their deposits before maturity. Columns (3) and (4) split the sample by deposit size (above or below the median deposit amount of 35,000€). Once again, accounts with greater deposit amounts only react significantly differently from accounts with smaller deposit amounts when affected by changes in expectations of the behavior of others. Columns (5), (6) and (7) divide our sample by maturity length. Six-months deposit contracts are the ones driving the results after $t_0$ and the change in expectations. After $t_A$ and changes in exposure to policy risk, three-months and six-months contracts are statistically different from the one-year contracts. Finally, Columns (8) and (9) show that after $t_0$ and $t_A$ there is no differential effect of treatment on deposits in Euros and deposits in foreign currencies.

Panels B of Tables 3.7 and 3.9 show estimates for subsamples depending on depositor-bank relationships. Columns (1) and (2) compare depositors with other financial products with the bank (mortgages, loans, and credit cards) with depositors with no other products with the bank. This split only has a differential effect after $t_A$ and exposure to policy risk. Depositors with other products are significantly more likely to withdraw than those with no additional products. Columns (3) and (4) look at the number of years the depositor has hold at least one time deposit with the bank. Depositors with less than two years relationship with the bank are significantly more likely to withdraw early after both news shocks. Finally, Columns (5) and (6) consider the number of times the time deposit account has been previously renewed. This has no differential effect in any of the specifications.

### 3.4.2 Geographical Heterogeneity

In this section we analyze whether there is geographical heterogeneity in the withdrawal behavior of depositors. Table 3.10 compares results for Athens with the rest of the country. This split of the data is not significant when considering depositor withdrawal after exposure to policy risk. However, when facing changes in expectations on other depositors' behavior, our estimates are driven by depositors outside Athens. Table 3.11 differentiates between depositors in large and small branches. Once again estimates vary significantly only after $t_0$, but not after $t_A$. Finally, we consider geographical heterogeneity across regions based on their political views. Table 3.12 shows results across municipalities that favored Grexit versus those that did not. We find no differential withdrawal behavior across these types of regions.

To further understand geographical heterogeneity after $t_0$ and changes in expectations of other depositors' withdrawals, we consider whether there was a geographical pattern in this change in withdrawal behavior and some suggestive evidence of a contagion effect. In particular, we focus on the presence of clusters in withdrawal behavior across nearby branches. Figure 3-13 plots the spatial autocorrelation across branches, measured by local Moran's $I_i$ and using as weighting matrix the inverse of the distance between branches. We find that after the surprise announcement at $t_0$ there was a significant change in spatial autocorrelation in the northern region of Greece. This correlation in withdrawals of nearby branches in this region is exclusive to the period between $t_0$ and $t_A$ (when depositors with shorter maturity expiration were solely reacting to changes in expectations of other depositors' withdrawals, but were not exposed to policy risk). This spatial autocorrelation disappears after $t_A$, when depositors with shorter maturity expiration also faced exposure to policy risk.

## 3.5 How large are the effects of the various motives?

### 3.5.1 Using cost and foregone return

In this section we exploit the discontinuity in accrued interests on July 1, 2014, to compute the elasticity of withdrawals with respect to changes in forgone returns. For this purpose, we consider time deposits maturing in a three-week window starting three-weeks after the payment at $t_0$. Due to the inverted U-shape relationship between days to maturity and withdrawal behavior described in Section 3.2.2, we need a control group to disentangle normal withdrawal behavior from withdrawals driven exclusively by the exogenous fall in accrued interests. We use as a placebo date a day when there were no exceptional interest payments: October 1, 2014. We compare the withdrawal behavior for deposits with the same days to maturity as the treatment group before and after October 1. These accounts act as a control group for deposits in our treated period. Figure 3-14 shows the main dates that we use in this section for both treatment and control groups. Both groups of depositors have deposits that mature in "quiet times" with no unusual policy uncertainty.

Panel A of Table 3.13 shows the fraction of early withdrawals as a percentage of total time deposits for both treatment and control groups before and after July 1 and October 1, respectively. We observe that withdrawal behavior for both groups of depositors is not significantly different before interest payments, with 0.54% depositors withdrawing early in the treatment group and 0.56% in the control group. After interest payments, the fraction of early withdrawals in the treatment group increased relative to the control group. The percentage of withdrawals in the treatment group rises to 0.86% after interest payments, while withdrawals in the control group drop to 0.46%. This fall in the control group matches the inverted U-shape pattern we described in Section 3.2.2, and it is common across other months when no interest payments were made.

To formalize this differential effect on withdrawal behavior across treatment and control, we run the following difference-in-differences estimation:

$$Withdrawal_{it} \quad = \quad \delta \; Treated_i + \lambda \; Post_t + \beta \; Treated_i \times Post_t + \gamma' X_{it} + \epsilon_{it} \;, \qquad (3.3)$$

where the dependent variable *Withdrawal* is a dummy equal to one if the depositor withdrew funds before maturity. *Treated* refers to deposits maturing during the treatment period when there is an interest payment. *Post* refers to the period after interest are paid on July 1 for the treatment group and the period after October 1 for the control group. $X_{it}$ is the set of covariates accounting for depositor and account characteristics. $\epsilon$ is an error term. The coefficient $\beta$ will be our difference-in-differences estimate, capturing the additional increase in withdrawal behavior due exclusively to a fall in the penalty for early withdrawal.

Results from estimating Equation 3.3 in our sample are reported in Panel B of Table 3.13. Column (1) shows estimates for the baseline specification without covariates. The estimated coefficient $\beta$ is 0.0088, implying that a payment of €494 in accrued interests (equivalent to 1.29% of deposit amount) leads to a 154% increase in the baseline probability of early withdrawal. Column (2) shows that this result holds after controlling for account features (deposit amount, maturity, interest rate, currency) and depositor characteristics (age, gender, bank employee, other products with the bank, previous renewals). Therefore, we find that even in quiet times depositors are very elastic to changes in accrued interests, with a payment of €100 making it 30.4% more likely for depositors to withdraw funds before maturity. Next, we use this estimate for withdrawal elasticity with respect to accrued interests to calibrate in terms of interest rate changes in withdrawals in Sections 3.3.2 and 3.3.3.

We have shown that an interest payment equivalent to 1% of deposit amount leads, on average, to a 120% increase in the baseline probability. Using this result, we can estimate the necessary interest payment that could explain an equivalent increase in withdrawals. We get that, on average, the increase in early withdrawals due to changes in expectations of other depositors' withdrawal behavior is analogous to the one generated by an interest payment of €293 (0.77% of deposit amount and 26% foregone return). Similarly, we can estimate the interest payment that is necessary to explain an equivalent increase in the withdrawal probability due to exposure to policy risk. We find that an interest payment of €612 (1.61% of deposit amount and 72% foregone return) would generate an equivalent increase in the probability of early withdrawal. We interpret these results as the amount the bank will need to increase monthly interest rates to avoid the resulting withdrawal of time depositors in the following month (equivalent to an additional 21% annual return).

### 3.5.2 Using CDS movements

Between the first news shock at $t_0$ and the national election at $t_1$, the 6-month CDS price increased by 219% compared with the previous "quiet period". Right after $t_0$, there was a 136% increase in the short-run CDS price which corresponds to a 68% increase in withdrawals due to changes in expectations on other depositors' withdrawal behavior. Following the same logic, after $t_A$ there was a 27% increase in the price of the short-run CDS, which resulted in 192% additional withdrawals due to exposure to policy risk.

### 3.5.3 Comparing with total Greek deposit withdrawals and other episodes

In the month after $t_0$, 1.21% of depositors will withdraw because of idiosyncratic, liquidity motives. Our estimates predict that there will be 2.04% of depositors that will withdraw due to changes in their expectations of other depositors' behavior. Moreover, there will be an additional 3.55% of depositors that will withdraw early because of their exposure to policy risk. Finally, we also account for 1.2% depositors withdrawing their deposits because of the interest payments after January 1. All in all, we account for 8% of time depositors withdrawing their deposit amounts after $t_0$. In our bank, 10% of time depositors withdrew their deposits in the month after $t_0$. In the entire Greek banking system, 8% of time depositors withdrew their deposit amounts in the month after $t_0$.

## Other Episodes Where Country Fundamentals Changed

Italy has recently also suffered from policy uncertainty due to the unexpected coalition government supported by the populist Five Star Movement and the right-wing League, discussing the possibility of exiting the Eurozone ('Italexit', 'Italeave', or—domestically—'Euroscita'). Prior to the March 2018 elections, both parties had antagonized each other and expressed no intention of cooperating when in government. Coalition negotiations between both parties became public in May, when a draft for a coalition agreement was leaked in the media.[16] These news increased policy uncertainty in the country.

When comparing the Italian episode to our analysis of the Greek elections, we can distinguish between two key events. First event took place on May 15, 2018, when the draft for a coalition agreement was leaked. The second event is the formation of a new government on May 29, 2018. The first event can be compared to our shock at $t_0$, since it created policy risk for depositors with long-run maturity expiration, but not for short-run maturity deposits (since policies could not be implemented until after the appointment of government). Depositors with shorter maturity expiration only faced a change in their expectations on how other depositors will behave. The second event is comparable to our shock at $t_1$, when a new government is appointed and all depositors are exposed to policy risk.

Over this 2-week the CDS price on Italian sovereign bonds increased by 177% during this period of policy uncertainty. During that quarter, time deposits hold by households with maturities shorter than two years decreased by 31.6%.[17] As in Greece, there were no bankruns, only a progressive leakage of depositors out of the system during that period. For an equivalent increase in CDS prices, our estimates predict that, in the month following the election, there will be a 10.5% fall in time deposits maturities shorter than one year.

## Other Episodes Where Bank Fundamentals Changed

Another episode of interest is the bankrun on Northern Rock in 2007. On September 14, 2007, Northern Rock sought and received a liquidity support facility from the Bank of England. The motive for such an emergency measure was the run on deposits of Northern Rock that took place

[16]This draft reclaimed radical changes to the Stability and Growth Pact, along with €250 billion from the ECB. It also supported "the introduction of specific technical procedures for single states to leave the Eurozone and regain monetary sovereignty."

[17]See Bank of Italy's sectoral breakdown of deposits:
https://sdw.ecb.europa.eu/reports.do?node=1000003191

Friday 14 and Monday 17 September, 2007. It all started in August 9, 2007, when interbank and other financial markets froze. Because of Northern Rock's funding model (requiring mortgage securitization), markets anticipated that there was a probability that the bank will run into trouble because of its next securitization being schedule for September 2007. During August 10 and mid-September Northern Rock and the British government and regulators tried to find a solution to the liquidity crisis.[18] During this period, the 5-year CDS price of Northern Rock increased 180%. Northern Rock lost £10 billion of its £30 billion savings book (33% loss), with £4.4 billion in deposits withdrawn on September 14 (21% of total deposit amount).[19] Our model predicts that such an increase in the CDS will result in 11% of time depositors leaving the bank.[20]

Other recent event is related to Washington Mutual (WaMu) and its two bankruns. WaMu's first bank run took place on July 12, 2008, centered in Southern California after the federal government seized IndyMac following a $1.3 billion bank run. The second run started on September 11, 2008, when Moody's rated WaMu's financial strength at D+ and downgraded the company's debt rating to junk status. These news and Lehman Brothers' bankruptcy on September 15, 2008, sparked another bank run. WaMu depositors withdrew $16.7 billion out of their savings and checking accounts over the next 10 days. These withdrawals accounted for 9% of WaMu's total deposits. On September 26, 2008,Washington Mutual filed for bankruptcy. In the month prior to the first bank run, the 5-year CDS of WaMu increased by almost 100%. In September 16, 2008 (last day WaMu was traded on CDS markets), the CDS premium increased by more than 100%. Our estimates predict that such increases in CDS will result in 6% withdrawals of total deposits.

## 3.6 Discussion and Conclusion

In this paper we isolate and quantify deposit withdrawals due to three different motives: liquidity, exposure to policy risk, or expectations about how other depositors will behave. This new approach

[18]The main three options under discussion were: 1) Northern Rock finding a solution to its liquidity crisis on its own by means of short-term money markets and securitization; 2) Northern Rock being taken over by another major retail bank; and 3) Northern Rock receiving a support liquidity facility from the Bank of England and guaranteed by the Government. For details, see: https://publications.parliament.uk/pa/cm200708/cmselect/cmtreasy/56/5607.htm

[19]See, e.g., Financial Times "Northern Rock fall sees outflow of savings," https://www.ft.com/content/2e3bc984-9a07-11dc-ad70-0000779fd2ac

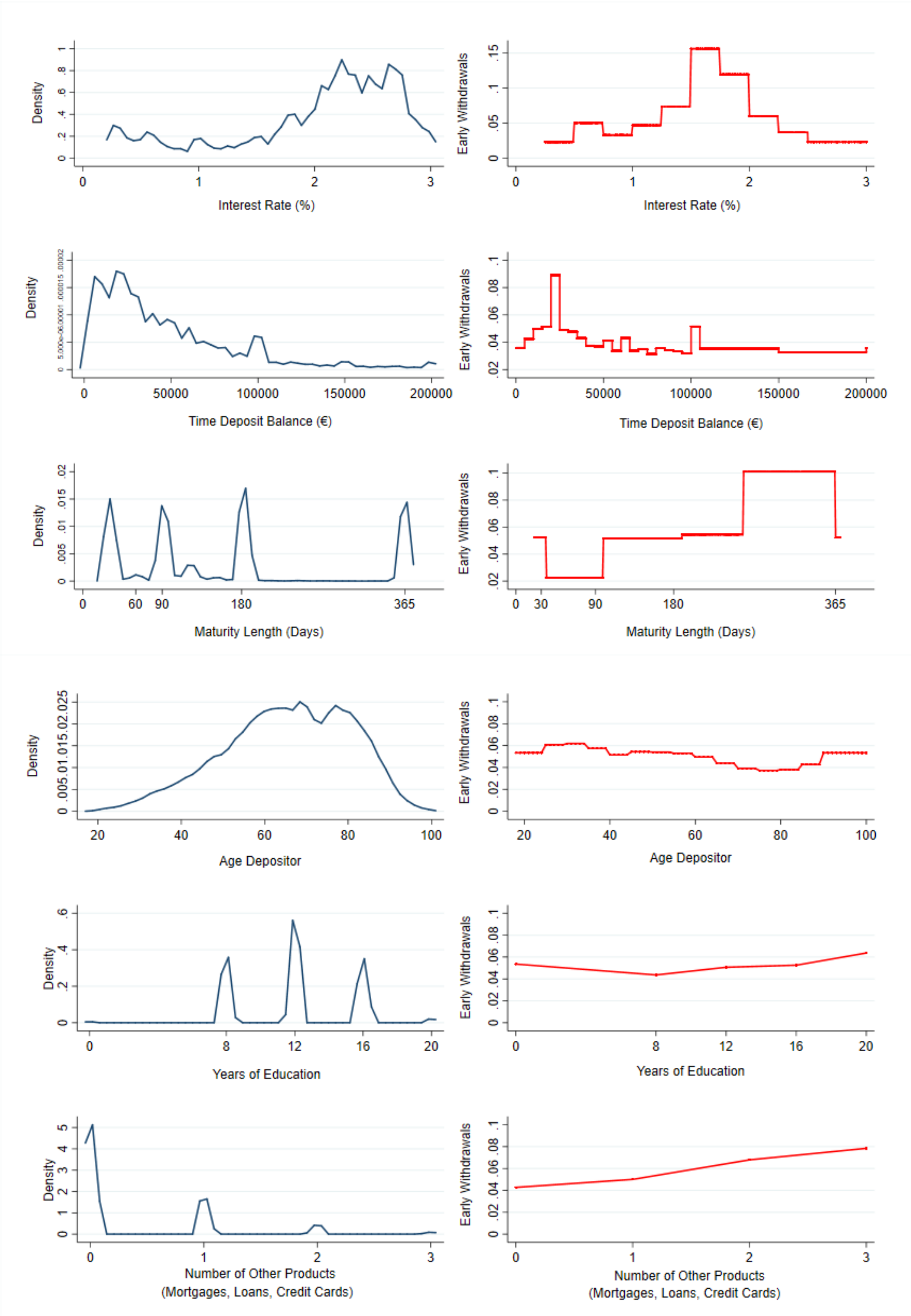
[20]One key difference between Greek and British deposits is the level of insurance. While Greek retail deposits are insured up to €100,000, the UK government only guarantees 100% of the first £2,000 and 90% of the next £33,000. That is, in the UK only £31,700 are insured per deposit.

uses variation induced by maturity expiration of time deposits around the large policy uncertainty events and differentiates between deposit withdrawals due to direct exposure to policy risk and those due to expectations about behavior of other depositors. After a policy uncertainty shock that doubled the short-run CDS price of Greek sovereign bonds, we find that early deposit withdrawal probability quadrupled. According to our estimates, two-thirds of this increase are due to direct exposure to policy risk, while the remainder is driven by changes in expectations of behavior of other depositors. In the last part of the paper, we quantify these effects in terms of forgone interest rates and changes in short-run CDS prices and compare our estimates to episodes of depositor withdrawals in Italy and in two recent bank run episodes.

Table 3.1: Descriptive Statistics Entire Sample

| | Mean<br>(1) | S.D<br>(2) | Min<br>(3) | Median<br>(4) | Max<br>(5) | N<br>(6) |
|---|---|---|---|---|---|---|
| **Panel A: Depositor Characteristics** | | | | | | |
| Age | 65 | 15 | 18 | 66 | 100 | >300,000 |
| Female | 0.45 | 0.5 | 0 | 0 | 1 | >300,000 |
| Income | 25,363 | 20,880 | 1,103 | 21,137 | 197,609 | >40,000 |
| Education (years) | 12 | 3 | 0 | 12 | 20 | >200,000 |
| Other Products | 0.3 | 0.46 | 0 | 0 | 1 | >300,000 |
| Years with Deposit Account | 2.3 | 2.7 | 0.06 | 1 | 56 | >300,000 |
| Bank Employee | 0.04 | 0.2 | 0 | 0 | 1 | >300,000 |
| Athens | 0.34 | 0.47 | 0 | 0 | 1 | >300,000 |
| **Panel B: Deposit Account Characteristics** | | | | | | |
| Interest Rate | 1.94 | 0.95 | 0.01 | 2.2 | 8.19 | >300,000 |
| Initial Balance | 57,281 | 65,490 | 687 | 36,000 | 500,000 | >300,000 |
| TD in Euros | 0.77 | 0.42 | 0 | 1 | 1 | >300,000 |
| Length (days) | 164 | 119 | 21 | 130 | 365 | >300,000 |
| Account Renewals | 6.5 | 10.6 | 1 | 3 | 1513 | >300,000 |
| **Panel C: Total Deposits, Depositors and Branches** | | | | | | |
| Number of Accounts | >100,000 | - | - | - | - | - |
| Number of Depositors | >100,000 | - | - | - | - | - |
| Active TDs per day | >100,000 | - | - | - | - | - |

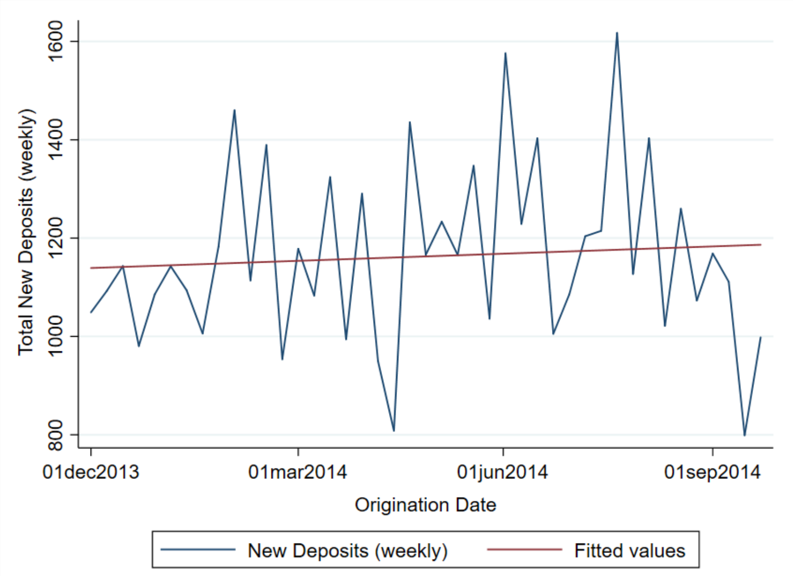
Figure 3-1: Distribution of Characteristics and Withdrawals Across Subgroups



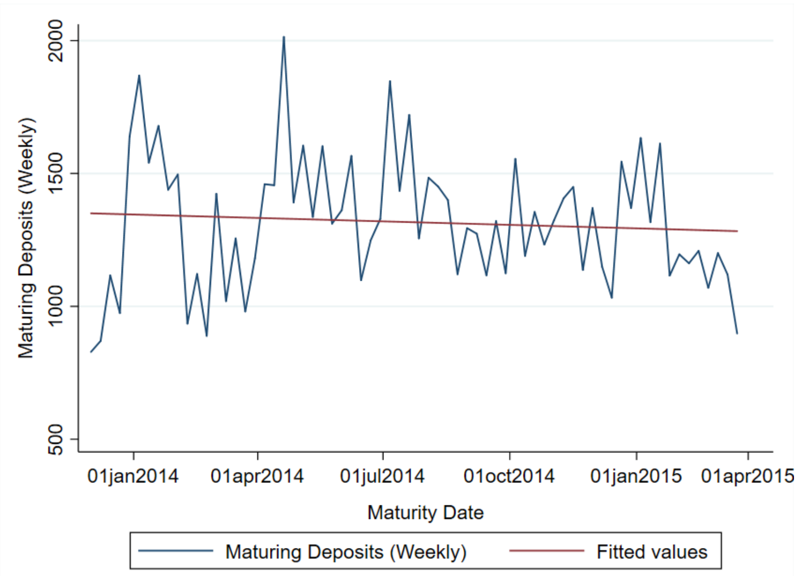

Notes: On the left, density plots for distribution of deposits across deposit and depositor characteristics. On the right, fraction of deposits withdrawn before maturity over same characteristics.

Figure 3-2: Origination and Maturity Dates

PANEL A: Total Deposits Originated Each Week

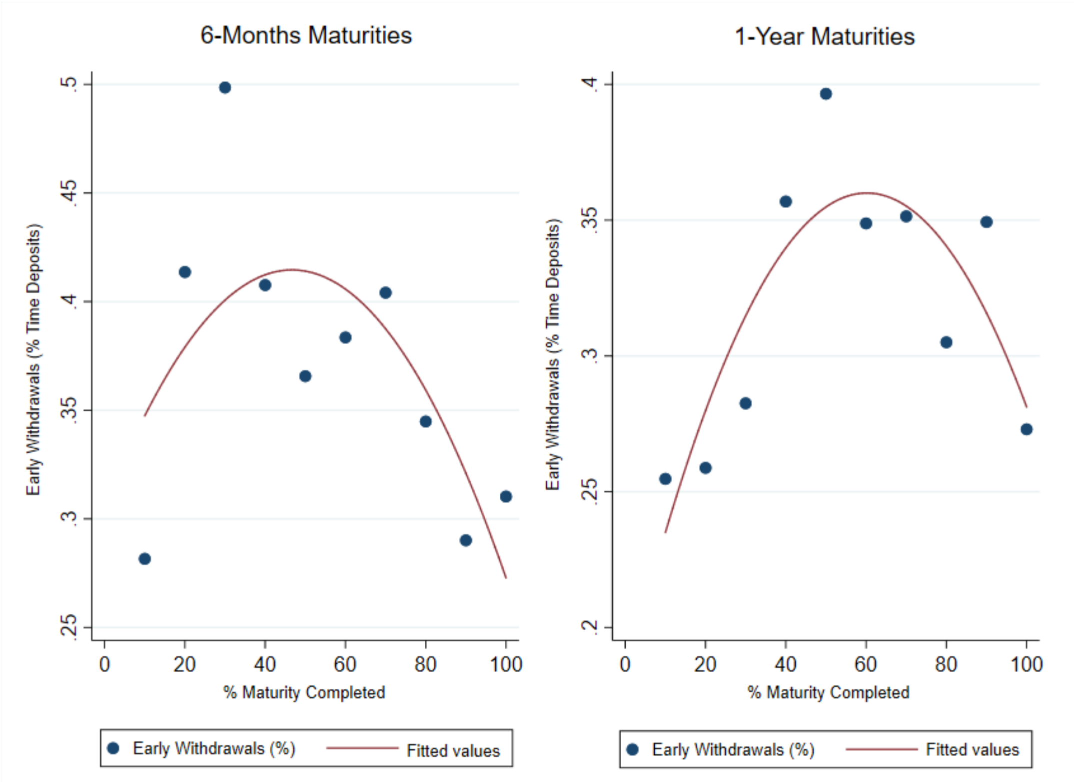



PANEL B: Total Deposits Maturing Each Week




Notes: Panel A shows total deposits originated each week, and Panel B plots total deposits maturing in a given week. Both graphs consider all time deposits in our sample.

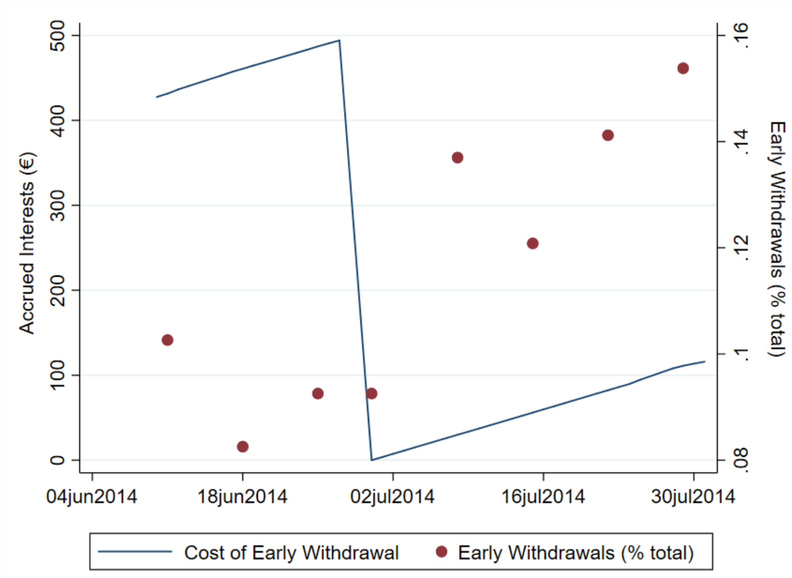
Figure 3-3: Early Withdrawals as a Function of Days to Maturity



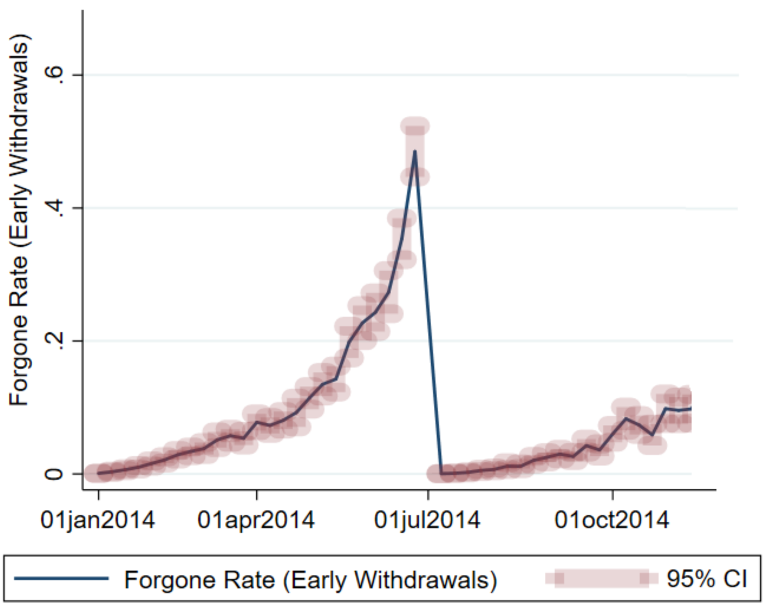

Note: The y-axis shows the percentage of total depositors that withdraw their deposit amounts before maturity. The x-axis is the fraction of maturity length completed at withdrawal. We show this relationship for the two most popular maturity lengths in our sample: three and six months maturities.

Figure 3-4: CDS Prices and Stock Returns Before and After Surprise Announcement ($t_0$)

PANEL A: Accrued Interests and Fraction of Early Withdrawals



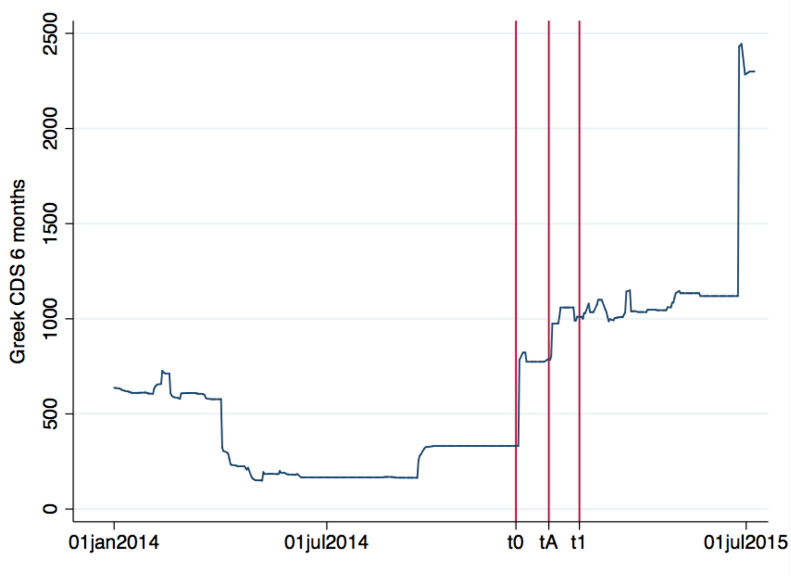

PANEL B: Foregone Returns from Early Withdrawal



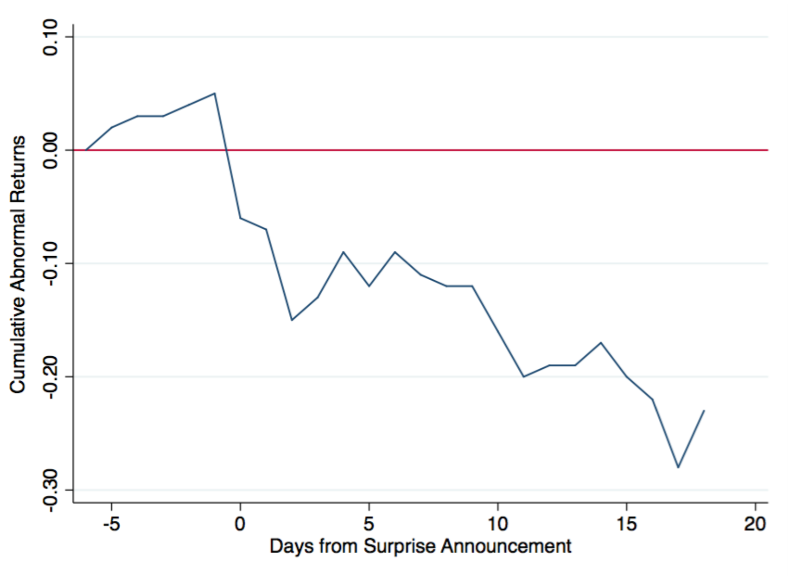

Notes: Panel A shows the cost of early withdrawal measured by total accrued interests (solid line) and the weekly fraction of early withdrawals (scatter plot). On July 1, all time deposits have their accrued interests paid. Panel B plots the foregone rate of return, calculated as (Interest Forgone/Interest Received)^(365/Days to Maturity). The shaded area represent the 95% confidence intervals.

Figure 3-5: CDS Prices and Stock Returns Before and After Surprise Announcement $(t_0)$

PANEL A: Price of 6-Month Greek CDS



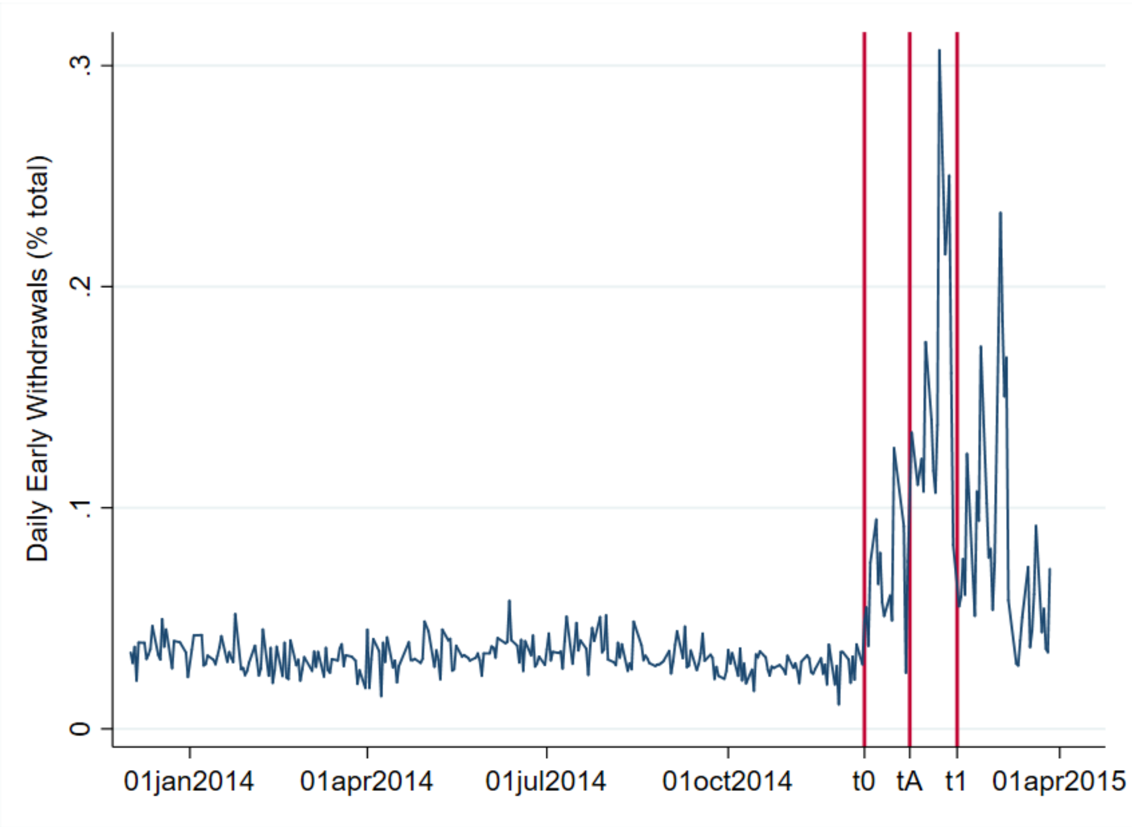

PANEL B: Evolution of Greek Stock Market




Notes: Panel A shows the price of the Greek, 6-month CDS. The vertical lines correspond to the following events: (1) the surprise announcement (t0) on December 8, 2014; (2) the election date announcement (tA) on January 1, 2015; and (3) the national election (t1) on January 25, 2015. Panel B plots the cumulative abnormal returns calculated for Athens Stock Exchange and FTSE Euro 100, with respect to the days from surprise announcement (t0) on December 8, 2014.

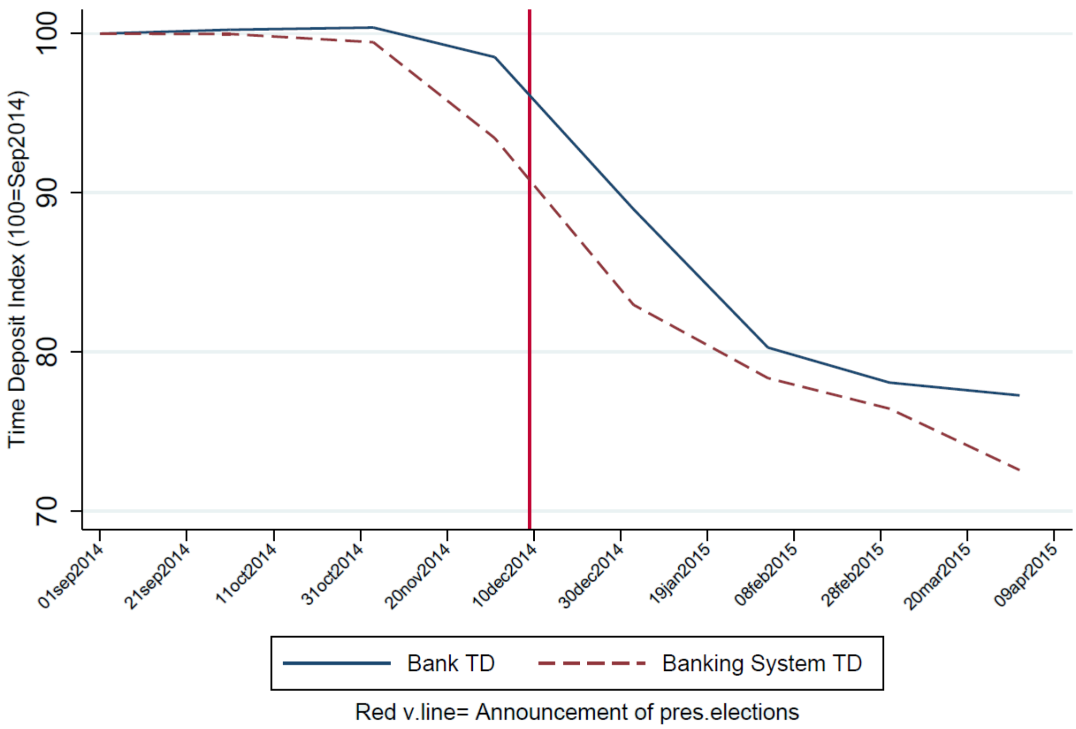
Figure 3-6: Main Political Events

Figure 3-7: Daily Fraction of Early Withdrawals (% of Total Time Deposits)



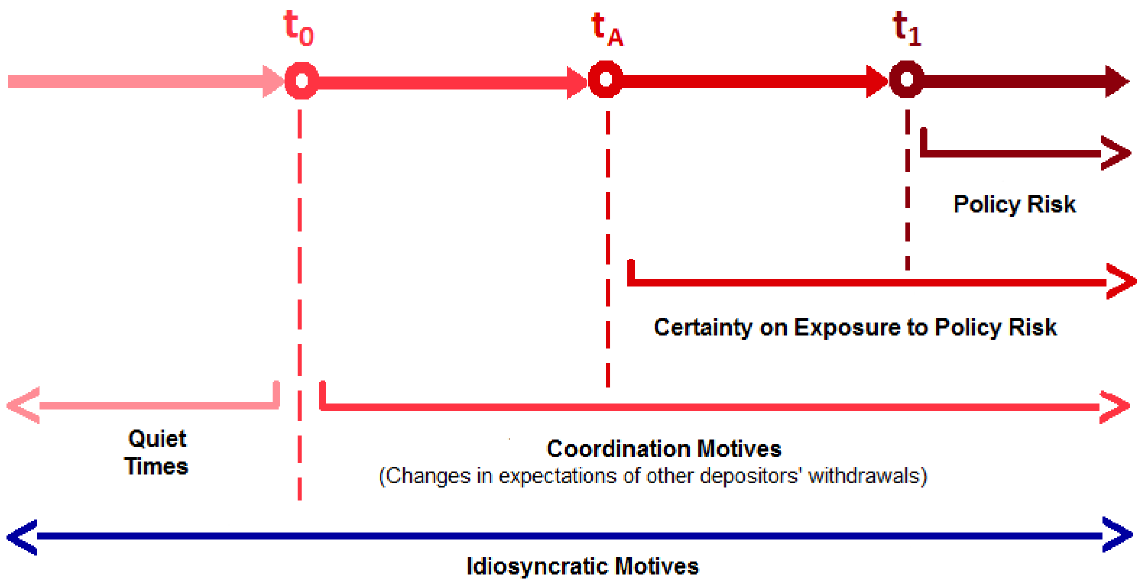

Note: Plot of the percentage of active deposits that were withdrawn that day and had at least five days until maturity. The red vertical line corresponds to the announcement of presidential elections ($t_0$).

Figure 3-8: Time Deposits in Greek Banking System Compared to our Sample




Note: The solid line represents our bank's time deposit index, normalized to 100 for September 2014. The dash line plots the same index for the entire Greek banking system. The red vertical line corresponds to the announcement of presidential elections ($t_0$).

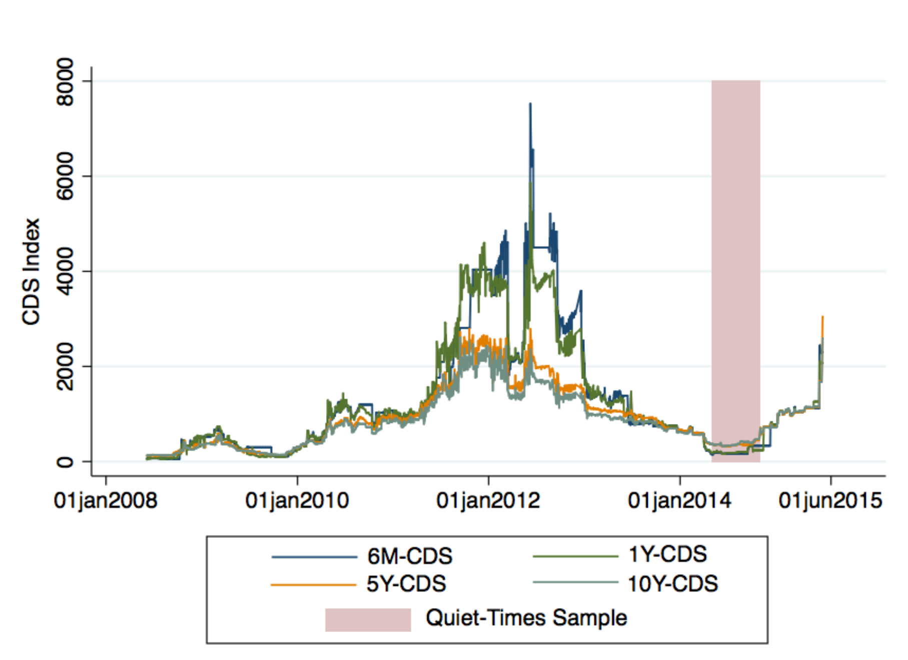
Figure 3-9: Changes in Withdrawal Motives for Depositors with Short-Run Maturities




Note: The diagram relates our main three events to the different withdrawal motives faced by depositors with short-run maturities. Before $t_0$, withdrawals of these depositors are driven only by idiosyncratic motives. After $t_0$, these depositors also have additional coordination motives, driven by changes in their expectations of other depositors' behavior. After $t_A$, depositors receive news about their exposure to policy risk. Finally, after $t_1$ they will also face policy risk in the form of new policies being implemented by the new government.

Figure 3-10: Greek CDS Index and 10-Year Bond

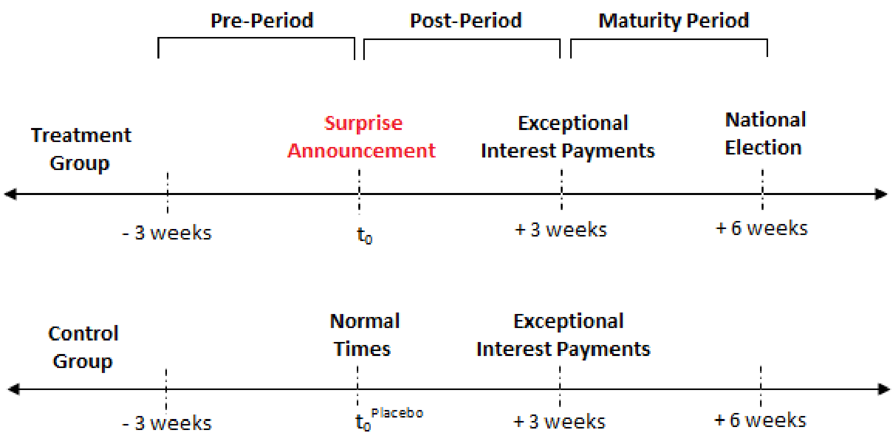
Panel A: Greek CDS for Different Maturities (2010-2015)




Panel B: Greek Bond Spread with respect to German Bond (2010-2015)

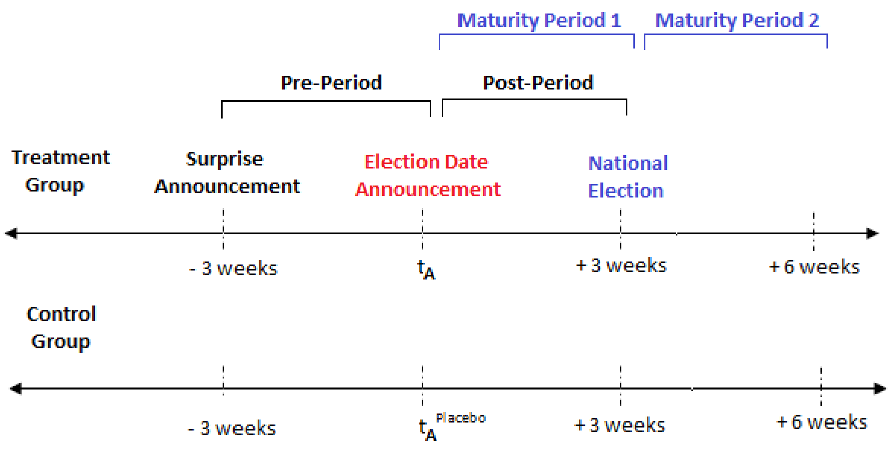

Note: Panel A plots the Credit Default Swap Index for Greece, normalized to 100 for June 2008. The shaded area represents the sample period between March and November 2014. Panel B shows the 10-year Greek bond spread relative to the German 10-year bond.

Figure 3-11: Treatment and Control Groups for Coordination Risk Analysis



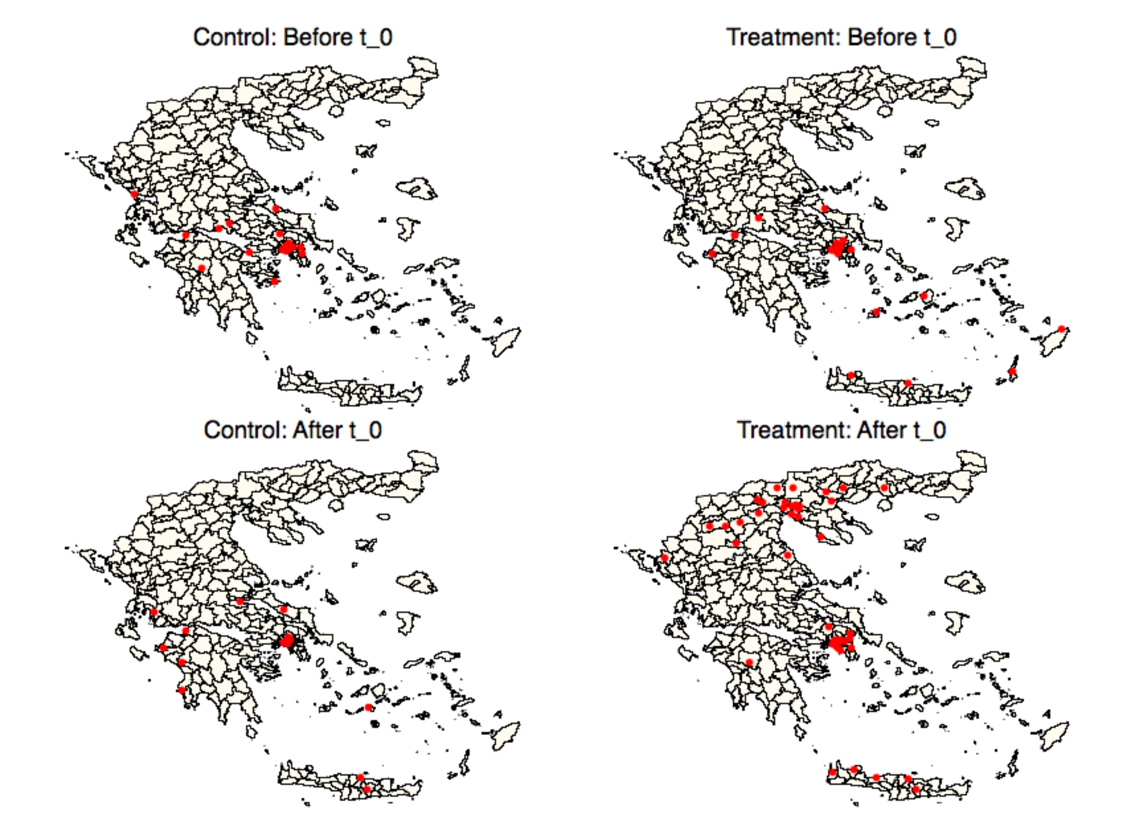

Note: The main event is the surprise announcement at $t_0$. The periods to compare are three weeks before and after the event. The deposits to compare are those maturing between three and six weeks after the event.

Figure 3-12: Treatment and Control Groups for Policy Risk Analysis



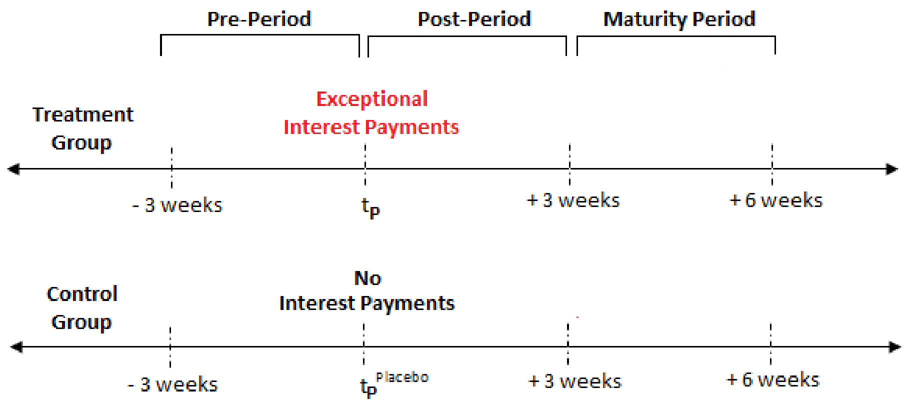

Note: The main event is the election date announcement at $t_A$. The periods to compare are three weeks before and after the event. The deposits to compare are (1) those maturing in the three weeks after the event, and (2) those maturing between three and six weeks after the event.

Figure 3-13: Spatial Autocorrelation in Deposit Withdrawals across Branches




Note: The red dots correspond to branches with deposit withdrawals exhibiting positive spatial autocorrelation with nearby branches, as measured by local Moran's $I_i$. Spatial autocorrelation measures the correlation of a variable with itself through space. In this case, withdrawal behavior in one branch relative to nearby branches. Positive spatial autocorrelation occurs when similar values occur near one another. The two maps to the left correspond to the control period with no news shock. The two maps to the right belong to the treatment period with the news shock at $t_0$. The two top maps represent the period before the announcement at $t_0$, while the two maps at the bottom correspond to the period after the surprise news at $t_0$.

Figure 3-14: Treatment and Control Groups for Cost Elasticity Analysis




Note: The main event is the interest payment at $t_P$. The periods to compare are three weeks before and after the event. The deposits to compare are those maturing between three and six weeks after the event.

Table 3.2: Descriptive Statistics for Early Withdrawals

| | Mean (1) | S.D (2) | Min (3) | Median (4) | Max (5) |
|---|---|---|---|---|---|
| **Panel A: Quiet-Times** | | | | | |
| Daily % Runners | 0.03 | 0.01 | 0.01 | 0.03 | 0.06 |
| Days to maturity | 136 | 104 | 6 | 114 | 364 |
| Length (days) | 257 | 117 | 21 | 360 | 365 |
| Initial Balance | 41,188 | 49,364 | 2,828 | 23,500 | 500,000 |
| Interest Rate | 1.86 | 0.85 | 0.01 | 2.1 | 4 |
| TD in Euros | 0.88 | 0.32 | 0 | 1 | 1 |
| Age | 64 | 16 | 18 | 64 | 100 |
| Female | 0.47 | 0.5 | 0 | 0 | 1 |
| Education (years) | 12 | 3.23 | 0 | 12 | 1 20 |
| Income | 24,450 | 18,678 | 1,900 | 20,433 | 149,569 |
| Bank Employee | 0.03 | 0.18 | 0 | 0 | 1 |
| Years with the Bank | 2.2 | 2.5 | 0.08 | 2.7 | 47 |
| Previous Renewals | 3.5 | 4.7 | 1 | 2 | 97 |
| Other Financial Products | 0.34 | 0.47 | 0 | 0 | 1 |
| Forgone Interest Payment | 308 | 493 | 0 | 175 | 8,180 |
| **Panel B: Uncertainty (after $t_0$)** | | | | | |
| Daily % Runners | 0.12 | 0.07 | 0.02 | 0.10 | 0.28 |
| Days to maturity | 129 | 96 | 6 | 105 | 364 |
| Length (days) | 240 | 109 | 21 | 183 | 360 |
| Initial Balance | 58,583 | 63,591 | 687 | 37,000 | 500,000 |
| Interest Rate | 1.67 | 0.49 | 0.01 | 1.75 | 3.25 |
| TD in Euros | 0.93 | 0.26 | 0 | 1 | 1 |
| Age | 63 | 15 | 20 | 63 | 100 |
| Female | 0.45 | 0.5 | 0 | 0 | 1 |
| Education (years) | 13 | 3.17 | 0 | 12 | 1 20 |
| Income | 25,697 | 19,304 | 1,900 | 21,748 | 193,491 |
| Bank Employee | 0.07 | 0.26 | 0 | 0 | 1 |
| Years with the Bank | 2.8 | 3.5 | 0.08 | 1.8 | 56 |
| Previous Renewals | 4.9 | 6.5 | 1 | 3 | 82 |
| Other Financial Products | 0.39 | 0.49 | 0 | 0 | 1 |
| Forgone Interest Payment | 385 | 531 | 0 | 211 | 8,225 |

Table 3.3: Identifying Coordination Risk

PANEL A: Fraction of Early Withdrawals in Coordination Sample

| | Treatment Group (uncertainty) | Control Group (quiet times) |
|---|---|---|
| Before $t_0$ | 0.40 % | 0.40 % |
| After $t_0$ | 1.00 % | 0.66 % |
| Observations (N) | >8,000 | >8,000 |

PANEL B: Difference-in-Differences Estimation for Coordination Risk

| Early withdrawal (0/1) | (1) | (2) |
|---|---|---|
| Treatment | 0.000 | 0.000 |
| | (0.001) | (0.001) |
| Post $t_0$ | 0.0026*** | 0.0027*** |
| | (0.0009) | (0.0009) |
| DiD | 0.0027* | 0.0027* |
| | (0.0015) | (0.0015) |
| Account Chacteristics | No | Yes |
| Depositor Chacteristics | No | Yes |
| Observations | >30,000 | >30,000 |

Note: Column (2) in PANEL B includes depositor characteristics (gender, age, bank employee, other products, previous relationship with the bank) and account characteristics (deposit amount, maturity, rate, currency). Robust standard errors are in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3.4: Identifying Policy Risk

PANEL A: Fraction of Early Withdrawals in Policy Risk Sample

| | Treatment Period (uncertainty) | | Control Period (quiet times) | |
|---|---|---|---|---|
| | Control Group (No Policy Risk) | Treatment Group (Policy Risk) | Control Group (No Policy Risky) | Treatment Group (No Policy Risk) |
| Before $t_0$ | 0.40 % | 0.49 % | 0.40 % | 0.41 % |
| Between $t_0$ and $t_A$ | 1.00 % | 1.06 % | 0.66 % | 0.64 % |
| Between $t_A$ and $t_1$ | 0.38 % | 2.73 % | 0.37 % | 0.90 % |
| Observations (N) | >8,000 | >8,000 | >8,000 | >8,000 |

PANEL B: Interest Payments in Policy Risk Sample

| | Treatment Period (uncertainty) | | Control Period (quiet times) | |
|---|---|---|---|---|
| | Control Group (No Policy Risk) | Treatment Group (Policy Risk) | Control Group (No Policy Risky) | Treatment Group (No Policy Risk) |
| Interest Payment | €526<br>(680) | €478<br>(602) | €509<br>(707) | €475<br>(603) |

Table 3.5: Difference-in-Differences-in-Differences Estimation for Policy Risk

| Early withdrawal (0/1) | (1) | (2) |
|---|---|---|
| Treatment | 0.0030** | 0.0028** |
| | (0.00122) | (0.00126) |
| Maturity (after $t_1$) | -0.0016 | -0.0016 |
| | (0.0010) | (0.0011) |
| Post (after $t_A$) | -0.0028*** | -0.0028*** |
| | (0.0009) | (0.0009) |
| Treatment $\times$ Post $t_A$ | -0.0033** | -0.0033** |
| | (0.0015) | (0.0015) |
| Treatment $\times$ Post (after $t_A$) | 0.0023 | 0.0025 |
| | (0.0019) | (0.0019) |
| Post $t_A$ $\times$ Maturity (after $t_1$) | 0.0104*** | 0.0104*** |
| | (0.0017) | (0.0017) |
| DDD | 0.0127*** | 0.0127*** |
| | (0.0030) | (0.0030) |
| Account Chacteristics | No | Yes |
| Depositor Chacteristics | No | Yes |
| Observations | >50,000 | >50,000 |

Note: Column (2) includes depositor characteristics (gender, age, bank employee, other products, previous relationship with the bank) and account characteristics (deposit amount, maturity, rate, currency). Robust standard errors are in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3.6: Heterogeneity Analysis for Idiosyncratic Subsamples

PANEL A: Depositor and Account Characteristics

| Early withdrawal (0/1) | Female | Male | Balance <35,000 | Balance >35,000 | 3-month TDs | 6-months TDs | 1-year TDs | Currency Euros | Foreign Currency |
|---|---|---|---|---|---|---|---|---|---|
| Treatment | 0.000 | -0.000 | -0.001 | 0.000 | 0.000 | 0.004* | -0.004* | 0.000 | -0.000 |
| | (0.002) | (0.002) | (0.002) | (0.001) | (0.002) | (0.002) | (0.002) | (0.001) | (0.004) |
| Post Interest | -0.002 | -0.001 | -0.005** | 0.001 | -0.003 | -0.001 | -0.001 | -0.001 | -0.006* |
| | (0.002) | (0.002) | (0.002) | (0.001) | (0.002) | (0.002) | (0.002) | (0.001) | (0.003) |
| DiD | 0.0082*** | 0.0093*** | 0.0105*** | 0.0073*** | 0.0026 | 0.0035 | 0.0166*** | 0.0091*** | 0.0066 |
| | (0.0024) | (0.0024) | (0.0030) | (0.0019) | (0.0028) | (0.0030) | (0.0031) | (0.0019) | (0.0047) |
| Depositor Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Account Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | >15,000 | >15,000 | >15,000 | >15,000 | >8,000 | >10,000 | >12,000 | >27,000 | >3,000 |
| Baseline Prob. of Running | 0.56 | 0.58 | 1.00 | 0.18 | 0.55 | 0.45 | 0.71 | 0.55 | 0.69 |
| Baseline Cost of Running (% TD) | 1.32 | 1.29 | 1.18 | 1.42 | 0.42 | 1.02 | 2.15 | 1.39 | 0.59 |

PANEL B: Depositor-Bank Relationship

| Early withdrawal (0/1) | No Other Products | Other Products | Less than 2 years | More than 2 years | 3 Renewals or Less | More than 3 Renewals |
|---|---|---|---|---|---|---|
| Treatment Group | 0.001 | -0.002 | 0.001 | -0.002 | 0.001 | -0.002 |
| | (0.001) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| Post Interests | -0.0003 | -0.0051** | -0.0028* | 0.0000 | -0.0025 | -0.0005 |
| | (0.00115) | (0.00241) | (0.0016) | (0.0013) | (0.0016) | (0.0013) |
| DiD | 0.0067*** | 0.0144*** | 0.0092*** | 0.0083*** | 0.0103*** | 0.0070*** |
| | (0.0019) | (0.0038) | (0.0026) | (0.0021) | (0.0027) | (0.0021) |
| Depositor Characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Account Characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | >25,000 | >5,000 | >20,000 | >20,000 | >15,000 | >15,000 |
| Baseline Prob. of Running | 0.42 | 0.94 | 0.78 | 0.28 | 0.75 | 0.34 |
| Baseline Cost of Running (% TD) | 1.29 | 1.35 | 1.25 | 1.39 | 1.42 | 1.17 |

Note: Robust standard errors are in parentheses for both Panels A and B ( with *** p<0.01, ** p<0.05, * p<0.1).

## Table 3.7: Heterogeneity Analysis for Coordination Subsamples

PANEL A: Depositor and Account Characteristics

| Early withdrawal (0/1) | Female | Male | Balance <35,000 | Balance >35,000 | 3-month TDs | 6-months TDs | 1-year TDs | Currency Euros | Foreign Currency |
|---|---|---|---|---|---|---|---|---|---|
| Treatment Group | 0.002 | -0.001 | 0.001 | -0.001 | 0.002 | 0.001 | -0.002 | 0.000 | 0.002 |
| | (0.001) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) | (0.003) |
| Post $t_0$ | 0.0036*** | 0.0019 | 0.0014 | 0.0037*** | 0.0005 | 0.0012 | 0.0062*** | 0.0028*** | 0.0008 |
| | (0.0013) | (0.0012) | (0.0015) | (0.0011) | (0.0015) | (0.0013) | (0.0019) | (0.0010) | (0.0024) |
| DiD | -0.0000 | 0.0051** | -0.0000 | 0.0053*** | -0.0017 | 0.0086*** | -0.0010 | 0.0034** | -0.0037 |
| | (0.0022) | (0.0020) | (0.0022) | (0.0019) | (0.0026) | (0.0025) | (0.0025) | (0.0016) | (0.0035) |
| Depositor Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Account Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | >15,000 | >15,000 | >15,000 | >15,000 | >10,000 | >10,000 | >10,000 | >35,000 | >5,000 |
| Baseline Prob. of Running | 0.36 | 0.44 | 0.59 | 0.24 | 0.38 | 0.36 | 0.47 | 0.41 | 0.31 |
| Baseline Cost of Running (% TD) | 1.32 | 1.31 | 1.17 | 1.44 | 0.44 | 1.00 | 2.45 | 1.40 | 0.57 |

PANEL B: Depositor-Bank Relationship

| Early withdrawal (0/1) | No Other Products | Other Products | Less than 2 years | More than 2 years | 3 Renewals or Less | More than 3 Renewals |
|---|---|---|---|---|---|---|
| Treatment | 0.000 | 0.001 | 0.000 | 0.001 | 0.000 | 0.001 |
| | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) |
| Post $t_0$ | 0.0023** | 0.0037* | 0.0011 | 0.0047*** | 0.0011 | 0.0044*** |
| | (0.0010) | (0.0020) | (0.0013) | (0.0013) | (0.0013) | (0.0012) |
| DiD | 0.0016 | 0.0059* | 0.0046** | 0.0002 | 0.0044** | 0.0008 |
| | (0.0016) | (0.0034) | (0.0021) | (0.0020) | (0.0022) | (0.0019) |
| Depositor Characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Account Characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | >20,000 | >10,000 | >15,000 | >15,000 | >15,000 | >15,000 |
| Baseline Prob. of Running | 0.19 | 0.95 | 0.53 | 0.23 | 0.54 | 0.24 |
| Baseline Cost of Running (% TD) | 1.32 | 1.30 | 1.17 | 1.51 | 1.39 | 1.23 |

Note: Robust standard errors are in parentheses for both Panels A and B ( with *** p<0.01, ** p<0.05, * p<0.1).

Table 3.8: Heterogeneity Analysis for Policy Risk Subsamples (Depositor and Account Characteristics)

| Early withdrawal (0/1) | Female | Male | Balance <35,000 | Balance >35,000 | 3-month TDs | 6-months TDs | 1-year TDs | Currency Euros | Foreign Currency |
|---|---|---|---|---|---|---|---|---|---|
| Treatment | 0.001 | 0.004** | 0.001 | 0.005** | 0.001 | 0.009*** | -0.004* | 0.003** | -0.003 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.001) | (0.002) |
| Maturity (after $t_1$) | -0.002 | -0.001 | 0.001 | -0.004*** | -0.000 | 0.004** | -0.008*** | -0.002* | 0.002 |
| | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) | (0.002) | (0.002) | (0.001) | (0.003) |
| Post (after $t_A$) | -0.004*** | -0.002 | -0.003* | -0.003** | -0.002 | -0.001 | -0.005*** | -0.003*** | -0.002 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.002) |
| Treatment $\times$ Post (after $t_A$) | -0.0017 | -0.0046** | -0.0021 | -0.0043** | 0.0002 | -0.0091*** | 0.0007 | -0.00368** | 0.000552 |
| | (0.0021) | (0.0021) | (0.0021) | (0.0021) | (0.0024) | (0.0026) | (0.0026) | (0.0016) | (0.0030) |
| Treatment $\times$ Maturity (after $t_1$) | 0.0033 | 0.0018 | 0.0014 | 0.0034 | 0.0094*** | -0.0090*** | 0.0085*** | 0.0032 | -0.0030 |
| | (0.0027) | (0.0026) | (0.0028) | (0.0025) | (0.0036) | (0.0033) | (0.0029) | (0.0020) | (0.0037) |
| Maturity (after $t_1$) $\times$ Post (after $t_A$) | 0.0107*** | 0.0101*** | 0.0091*** | 0.0116*** | 0.0025 | 0.0036 | 0.0212*** | 0.0112*** | 0.0035 |
| | (0.0023) | (0.0023) | (0.0027) | (0.0020) | (0.0025) | (0.0029) | (0.0030) | (0.0018) | (0.0045) |
| DDD | 0.0136*** | 0.0119*** | 0.0106** | 0.0148*** | 0.0179*** | 0.0260*** | -0.0033 | 0.0129*** | 0.0106 |
| | (0.0043) | (0.0042) | (0.0044) | (0.0042) | (0.0058) | (0.0051) | (0.0049) | (0.0033) | (0.0065) |
| Depositor Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Account Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | >20,000 | >30,000 | >25,000 | >25,000 | >15,000 | >15,000 | >15,000 | >45,000 | >5,000 |
| Baseline Prob. of Running | 0.71 | 0.62 | 0.72 | 0.61 | 0.43 | 0.48 | 1.08 | 0.69 | 0.39 |
| Baseline Cost of Running (% TD) | 1.32 | 1.31 | 1.17 | 1.44 | 0.44 | 1.00 | 2.45 | 1.40 | 0.58 |

Note: Robust standard errors are in parentheses for both Panels A and B ( with *** p<0.01, ** p<0.05, * p<0.1).

Table 3.9: Heterogeneity Analysis for Policy Risk Subsamples (Depositor-Bank Relationship)

| Early withdrawal (0/1) | No Other Products | Other Products | Less than 2 years | More than 2 years | 3 Renewals or Less | More than 3 Renewals |
|---|---|---|---|---|---|---|
| Treatment | 0.001 | 0.008*** | 0.005*** | 0.000 | 0.004** | 0.001 |
| | (0.001) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| Maturity (after $t_1$) | -0.002 | -0.002 | 0.002 | -0.006*** | 0.001 | -0.005*** |
| | (0.001) | (0.002) | (0.002) | (0.001) | (0.002) | (0.001) |
| Post (after $t_A$) | -0.002** | -0.004** | -0.002 | -0.004*** | -0.001 | -0.004*** |
| | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) |
| Treatment × Post (after $t_A$) | -0.0025 | -0.0053 | -0.0052** | -0.0009 | -0.0056** | -0.0008 |
| | (0.0016) | (0.0035) | (0.0021) | (0.0021) | (0.0022) | (0.0020) |
| Treatment × Maturity (after $t_1$) | 0.0036* | -0.0004 | 0.0008 | 0.0049** | 0.0011 | 0.0041* |
| | (0.0020) | (0.0042) | (0.0028) | (0.0023) | (0.0029) | (0.0024) |
| Post (after $t_A$) × Maturity (after $t_1$) | 0.0093*** | 0.0134*** | 0.0090*** | 0.0122*** | 0.0097*** | 0.0111*** |
| | (0.0019) | (0.0035) | (0.0024) | (0.0022) | (0.0025) | (0.0021) |
| DDD | 0.0068** | 0.0283*** | 0.0197*** | 0.0044 | 0.0161*** | 0.0093** |
| | (0.0032) | (0.0070) | (0.0045) | (0.0038) | (0.0046) | (0.0039) |
| Depositor Characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Account Characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | >40,000 | >10,000 | >30,000 | >20,000 | >20,000 | >30,000 |
| Baseline Prob. of Running | 0.59 | 0.87 | 0.64 | 0.70 | 0.65 | 0.68 |
| Baseline Cost of Running (% TD) | 1.32 | 1.30 | 1.17 | 1.52 | 1.39 | 1.23 |

Note: Robust standard errors are in parentheses for both Panels A and B ( with *** p<0.01, ** p<0.05, * p<0.1).

Table 3.10: Heterogeneity Analysis for City of Athens

| Runner (0/1) | (Coordination) City of Athens | (Coordination) Not Athens | (Idiosyncratic) City of Athens | (Idiosyncratic) Not Athens | (Policy) City of Athens | (Policy) Not Athens |
|---|---|---|---|---|---|---|
| Treatment | 0.003 | -0.001 | 0.004* | -0.001 | -0.001 | 0.004** |
| | (0.002) | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) |
| Post Period | 0.005*** | 0.002* | 0.001 | -0.003** | -0.004* | -0.001 |
| | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) |
| Treatment × Period ( DD) | -0.0014 | 0.0048*** | 0.0060* | 0.0101*** | 0.0022 | 0.0035 |
| | (0.0027) | (0.0017) | (0.0032) | (0.0021) | (0.0034) | (0.0023) |
| Post $t_A$ | | | | | -0.0029 | -0.0029*** |
| | | | | | (0.0019) | (0.0010) |
| Treatment × Post $t_A$ | | | | | -0.0035 | -0.0030* |
| | | | | | (0.0027) | (0.0018) |
| Post $t_A$× Post $t_1$ | | | | | 0.0104*** | 0.0105*** |
| | | | | | (0.0033) | (0.0019) |
| DDD | | | | | 0.0175*** | 0.0107*** |
| | | | | | (0.0056) | (0.0036) |
| Depositor characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Account characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | >10,000 | >20,000 | >10,000 | >20,000 | >15,000 | >30,000 |
| Baseline Prob. of Running | 0.38 | 0.40 | 0.29 | 0.70 | 0.66 | 0.67 |
| Baseline Cost of Running (% TD) | 1.22 | 1.37 | 1.30 | 1.32 | 1.35 | 1.31 |

Note: Robust standard errors are in parentheses for both Panels A and B ( with *** p<0.01, ** p<0.05, * p<0.1).

Table 3.11: Heterogeneity Analysis for Small and Large Branches

| Early Withdrawal (0/1) | (Coordination) Small Branches | (Coordination) Large Branches | (Idiosyncratic) Small Branches | (Idiosyncratic) Large Branches | (Policy) Small Branches | (Policy) Large Branches |
|---|---|---|---|---|---|---|
| Treatment | 0.003 | -0.000 | -0.002 | 0.000 | -0.000 | 0.003** |
| | (0.003) | (0.001) | (0.003) | (0.001) | (0.003) | (0.001) |
| Post Period | -0.001 | -0.002 | 0.001 | 0.003*** | -0.001 | -0.002 |
| | (0.002) | (0.001) | (0.003) | (0.001) | (0.002) | (0.001) |
| Treatment × Post Period | -0.0021 | 0.0037** | 0.0091*** | 0.0060* | 0.0031 | 0.0022 |
| (DD) | (0.0036) | (0.0016) | (0.0046) | (0.0019) | (0.0043) | (0.0021) |
| Post $t_A$ | | | | | -0.0020 | -0.0030*** |
| | | | | | (0.0022) | (0.0010) |
| Treatment × Post $t_A$ | | | | | -0.0017 | -0.0036** |
| | | | | | (0.0033) | (0.0017) |
| Post $t_A$× Post $t_1$ | | | | | 0.0071* | 0.0112*** |
| | | | | | (0.0039) | (0.0018) |
| DDD | | | | | 0.0137** | 0.0125*** |
| | | | | | (0.0070) | (0.0034) |
| Depositor characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Account characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | >7,000 | >23,000 | >7,000 | >23,000 | >10,000 | >40,000 |
| Baseline Prob. of Running | 0.49 | 0.38 | 0.70 | 0.53 | 0.66 | 0.67 |
| Baseline Cost of Running (% TD) | 1.35 | 1.31 | 1.34 | 1.30 | 1.35 | 1.31 |

Note: Branch size is defined as those below and above the median in their number of time deposit accounts. Small branches are those with 200 or less daily TD accounts on average, and large branches are those with more than 200 daily TD accounts on average. Robust standard errors are in parentheses for both Panels A and B ( with *** p<0.01, ** p<0.05, * p<0.1).

Table 3.12: Heterogeneity Analysis on Political Views

| Early withdrawal (0/1) | (Coordination) Against Grexit (<50%) | (Coordination) Pro-Grexit (>50%) | (Idiosyncratic) Against Grexit (<50%) | (Idiosyncratic) Pro-Grexit (>50%) | (Policy) Against Grexit (<50%) | (Policy) Pro-Grexit (>50%) |
|---|---|---|---|---|---|---|
| Treatment | 0.002 | -0.000 | -0.001 | 0.000 | 0.002 | 0.003* |
| | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) | (0.002) |
| Post Period | 0.002* | 0.003** | -0.004** | -0.000 | 0.000 | -0.003** |
| | (0.001) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) |
| Treatment × Post Period (DD) | 0.0019 | 0.0032* | 0.0094*** | 0.0086*** | 0.0028 | 0.0022 |
| | (0.0024) | (0.0018) | (0.0029) | (0.0022) | (0.0032) | (0.0023) |
| Post $t_A$ | | | | | -0.0028** | -0.0028** |
| | | | | | (0.0014) | (0.0012) |
| Treatment × Post $t_A$ | | | | | -0.0041* | -0.0028 |
| | | | | | (0.0023) | (0.0019) |
| Post $t_A$ × Post $t_1$ | | | | | 0.0090*** | 0.0113*** |
| | | | | | (0.0026) | (0.0021) |
| DDD | | | | | 0.0167*** | 0.0103*** |
| | | | | | (0.0051) | (0.0038) |
| Depositor characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Account characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | >10,000 | >20,000 | >10,000 | >20,000 | >15,000 | >35,000 |
| Baseline Prob. of Running | 0.32 | 0.45 | 0.75 | 0.46 | 0.55 | 0.73 |
| Baseline Cost of Running (% TD) | 1.34 | 1.31 | 1.32 | 1.30 | 1.34 | 1.30 |

Note: Robust standard errors are in parentheses for both Panels A and B ( with *** p<0.01, ** p<0.05, * p<0.1).

Table 3.13: Estimating the Elasticity of Depositors to Interest Payments

PANEL A: Fraction of Early Withdrawals

| | Treatment Group (interest payments) | Control Group (no interest payments) |
|---|---|---|
| Before Interest Payment | 0.54 % | 0.56 % |
| After Interest Payment | 0.86 % | 0.46 % |
| Observations (N) | >8,000 | >8,000 |

PANEL B: Difference-in-Differences Estimation

| Early withdrawal (0/1) | (1) | (2) |
|---|---|---|
| Treatment | -0.00024 | -0.00016 |
| | (0.001) | (0.001) |
| Post Interest Payment | -0.0016 | -0.0016 |
| | (0.001) | (0.001) |
| DiD | 0.0088*** | 0.0088*** |
| | (0.002) | (0.002) |
| Account Chacteristics | No | Yes |
| Depositor Chacteristics | No | Yes |
| Observations | >30,000 | >30,000 |

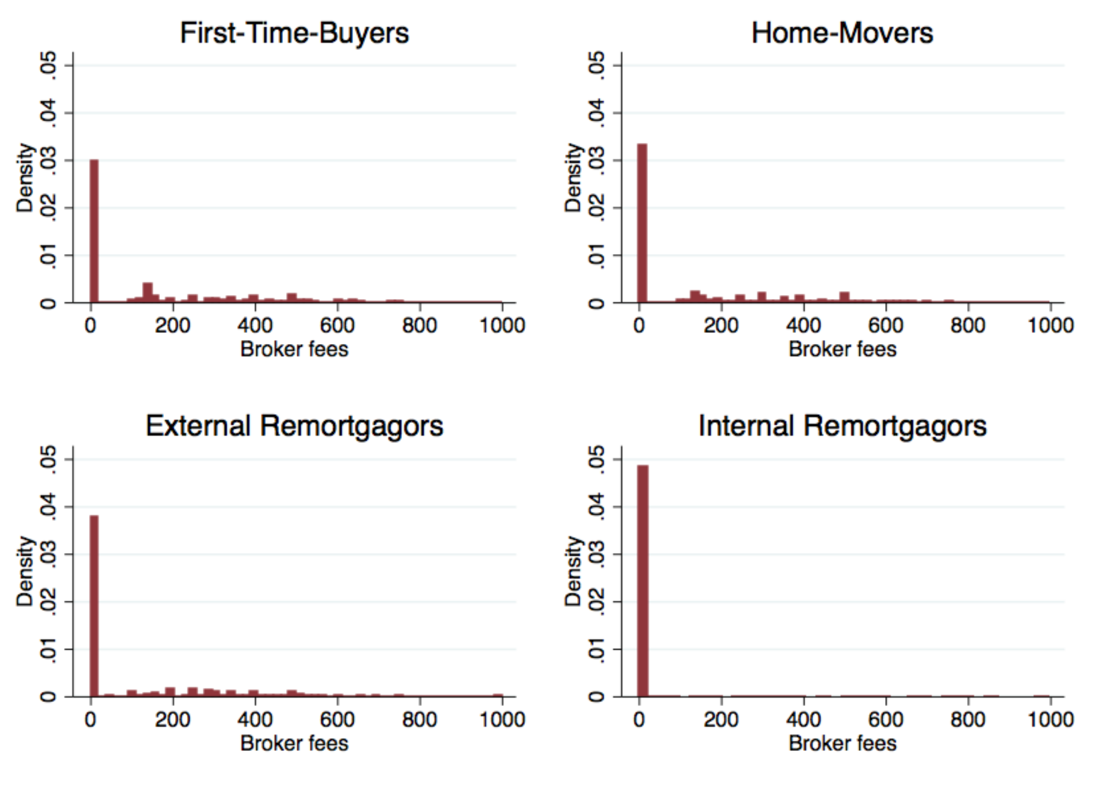
Note: Column (2) in PANEL B includes depositor characteristics (gender, age, bank employee, other products, previous relationship with the bank) and account characteristics (deposit amount, maturity, rate, currency). Robust standard errors are in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

# Appendix A

# Appendix Chapter 1

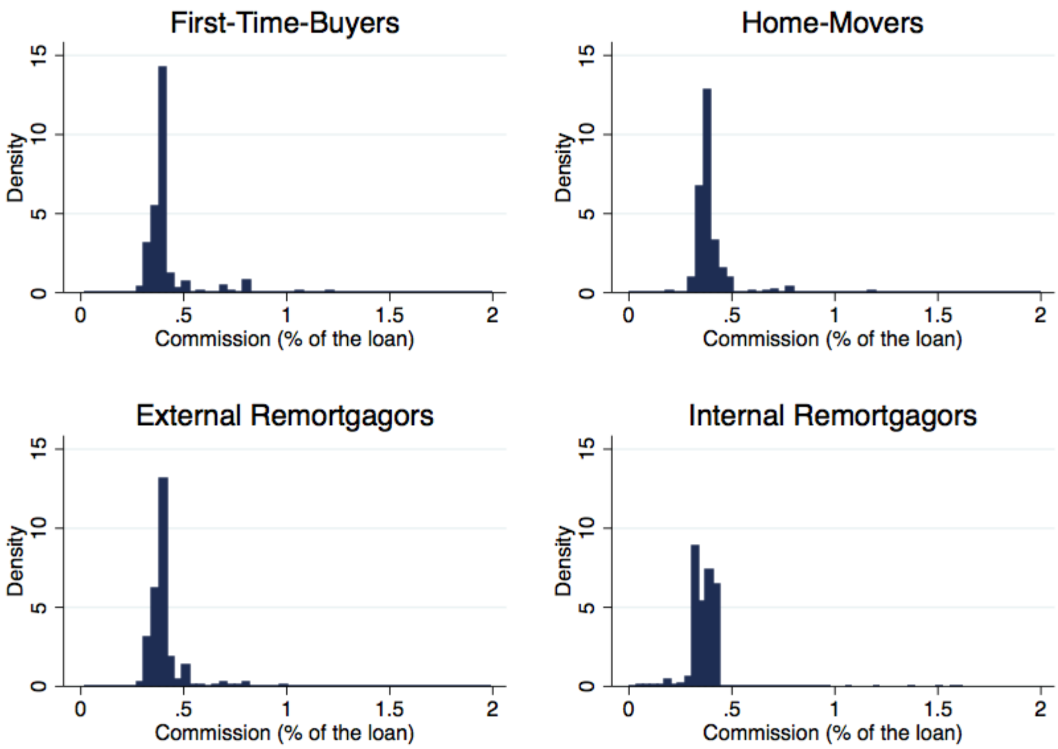
## A.1 Distribution of Fees and Commissions

Figure A-1: Distribution of Broker Fees Across Borrower Types




Note: Broker fees are expressed in pounds. Internal remortgagors are borrowers refinancing with the same lender, while external remortgagors are borrowers refinancing their mortgage with a different lender.

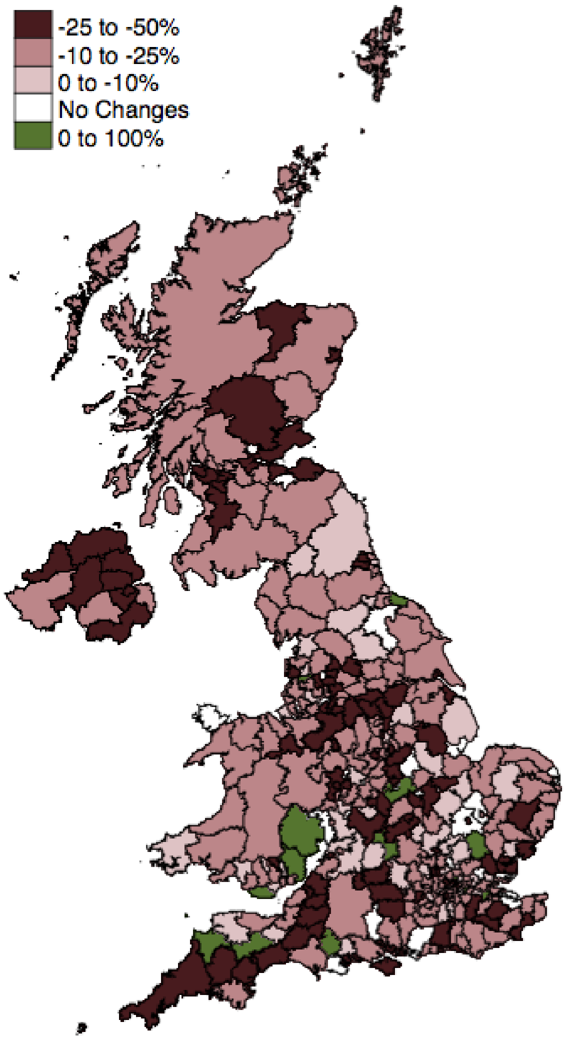
Figure A-2: Distribution of Commissions Across Borrower Types




Note: Commission rates are expressed as a percentage of the total loan balance. Internal remortgagors are borrowers refinancing with the same lender, while external remortgagors are borrowers refinancing their mortgage with a different lender.

## A.2 Geographical Changes in Branch Networks

Figure A-3: Branch closures and opening at the local authority level.




Note: Percentage change in total branches within a local authority district between December 2014 and January 2017. Data gathered from Experian Goad and Shop*Point datasets.

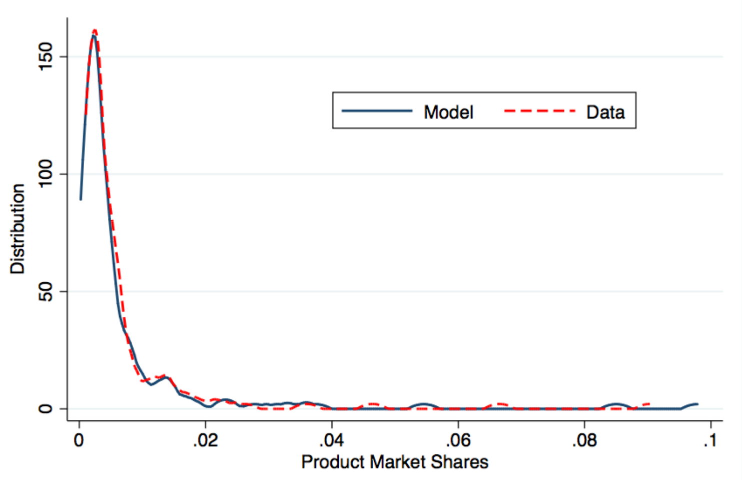
# Appendix B

# Appendix Chapter 2

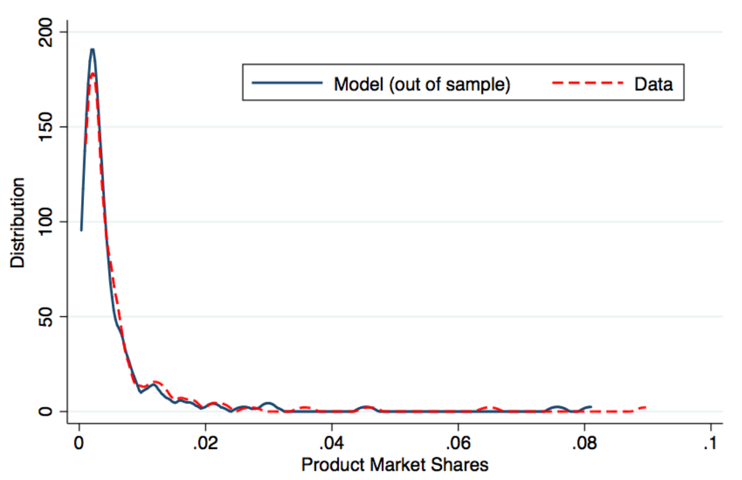
## B.1 Fit of the model

Figure B-1: Model Fit

PANEL A: Training Sample (25% random sample)

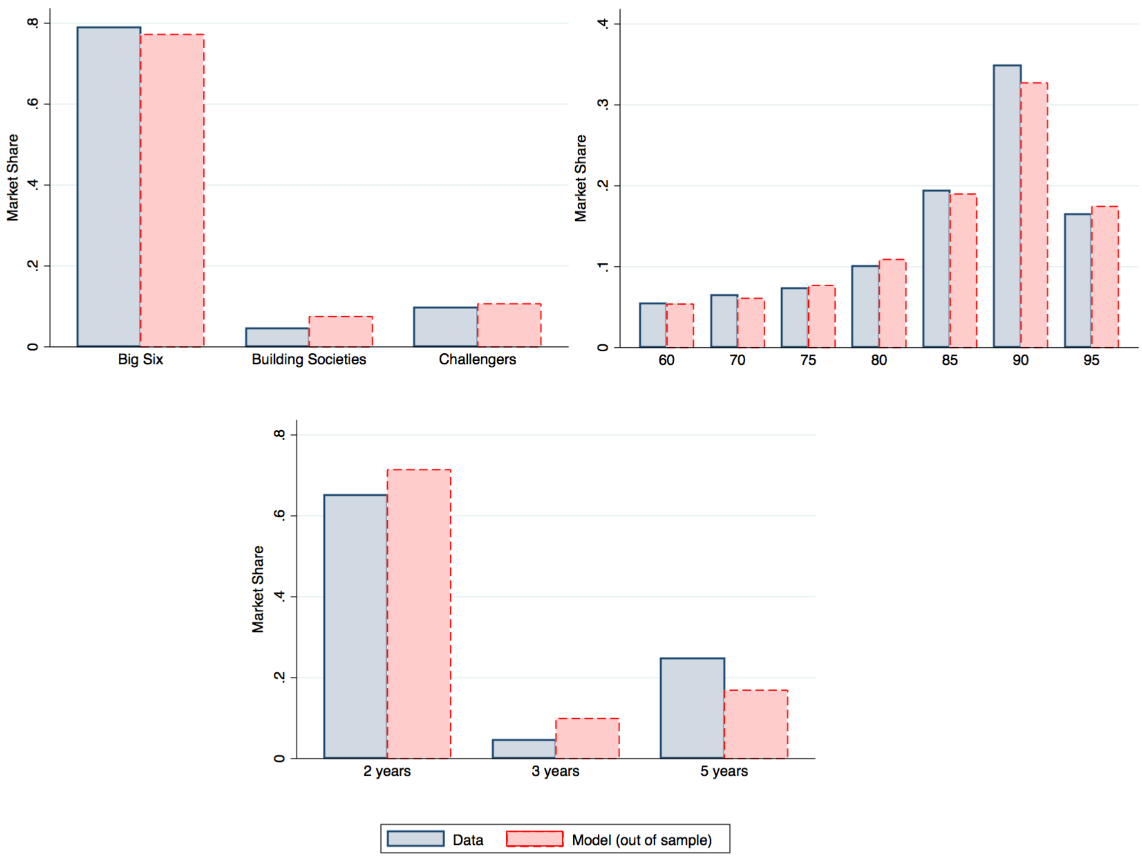



PANEL B: Cross-Validation Sample (Out-of-Sample Fit)




Note: The red solid lines are the observed market shares in the data computed as the sum of originations for each product in each market divided by the total number of households. The blue dashed lines represent the estimated market shares from the model calculated as the sum of the individual predicted probabilities. Panel A uses a 25% random sample, while Panel B is based on the remaining 75% that was not used in the estimation.

Figure B-2: Out-of-Sample Fit: Product Characteristics

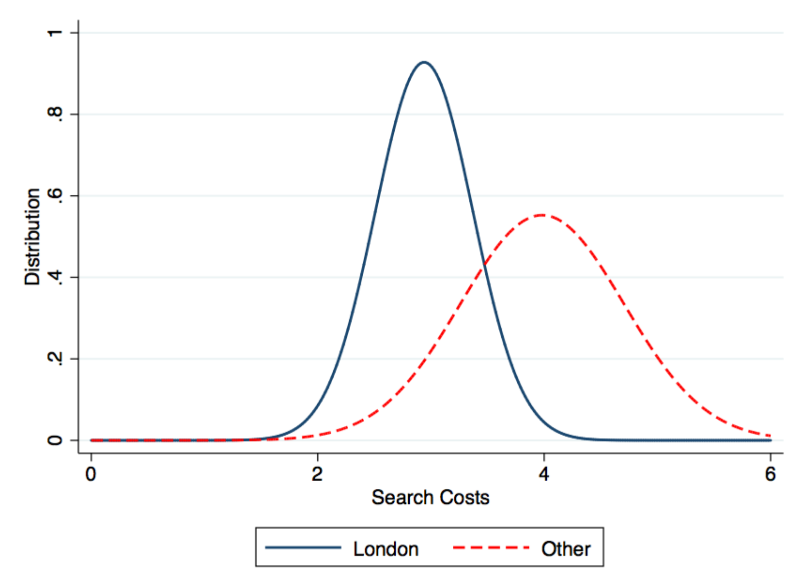



Note: I compare observed (solid line) and predicted (dash line) market shares across different product characteritsics. The upper left panel shows market shares for the Big Six, Building Societies and Challenger Banks. The upper right panel presents them across loan-to-value bands. Finally, the lower panel plots market shares across initial period deals.

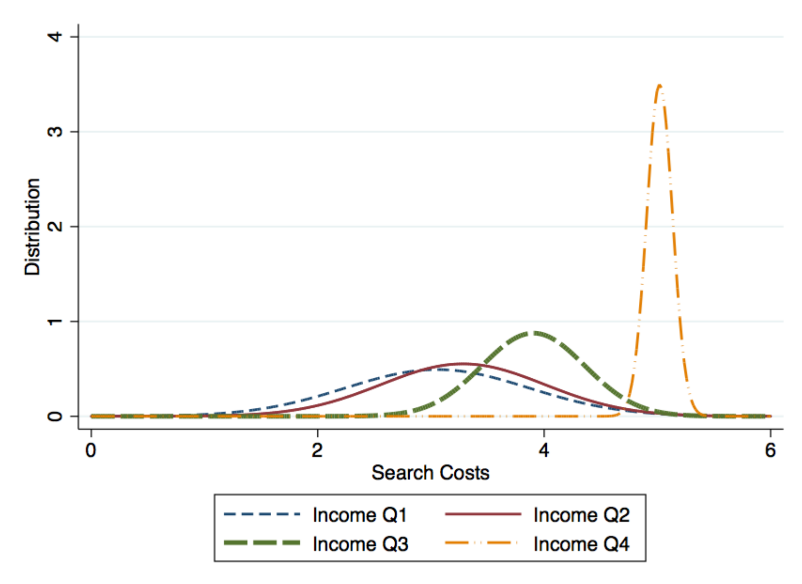
## B.2 Search Cost Distributions

Figure B-3: Search Cost Distributions Across Subpopulations

PANEL A: Geographical Variation

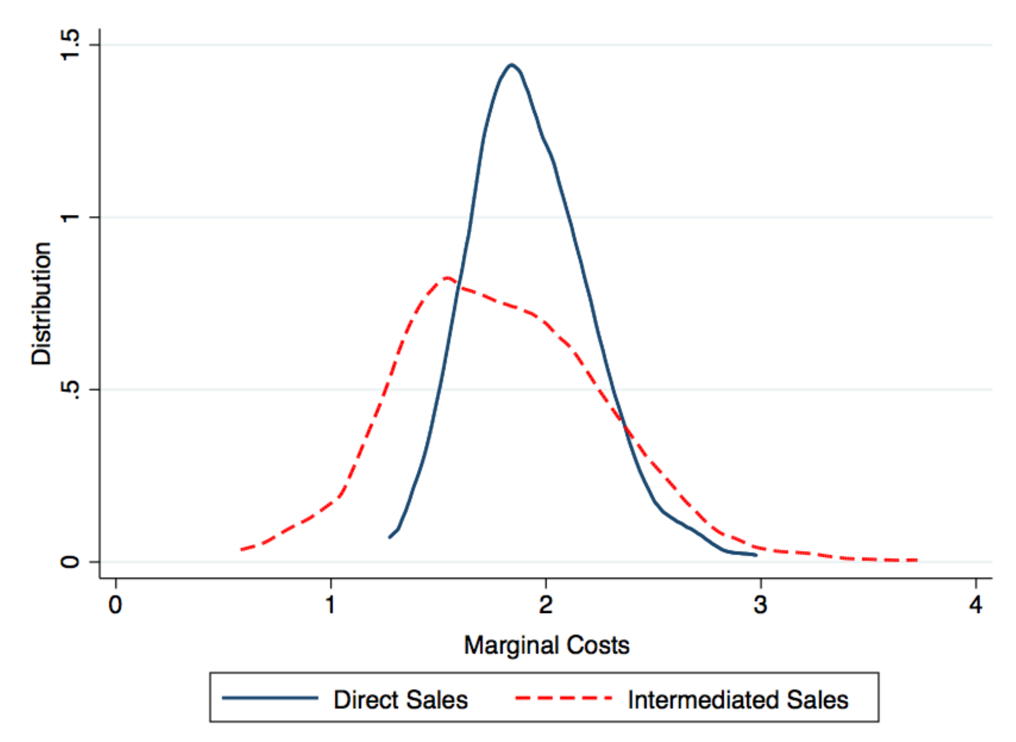



PANEL B: Income Variation



## B.3 Marginal Cost Distributions

Figure B-4: Marginal Cost Estimates



## B.4 Additional Counterfactual: Alternative Pass-Through

Figure B-5: Alternative Pass-Throughs for Broker Fees


Note: The solid line increases broker fees such that profits per mortgage sale remain the same as in the baseline with no restrictions for each broker. The dashed line sets broker fees equal to the median broker fee in the baseline (conditional on being positive).

# Appendix C

# Appendix Chapter 3

## C.1 No Changes in Idiosyncratic Risk

Identification of our estimates for coordination motives requires that there are no changes in idiosyncratic withdrawals during the weeks following the surprise announcement on December 8, 2014.

One potential concern is unemployment. If major layoffs took place immediately after the announcement, deposit withdrawals might be driven by liquidity motives differing from those in quiet times. Unemployment rates remain stable during December 2014 and January 2015, and had similar magnitudes to the same months the previous year.[1] Moreover, we find no correlation between changes in regional unemployment figures and changes in deposit withdrawals during this period.

Another concern, given the age of a large fraction of our depositors, is that after the announcement there was a change in payment of pensions. We have found no evidence of pension amounts changing during our period or delays/haircuts taking place after the announcement.

Moreover, we have checked the interest rates offered by our bank's competitors before and

[1] See Eurostat Database for detailed figures at the NUTS 2 level, available at `https://ec.europa.eu/eurostat/data/database`

after the announcement, and they are all similar to those we observed in quiet times. Therefore, there seem to be no changes in competition in the time-deposit market during our period.

## C.2 No Changes in Bank Fundamentals

Identification of our estimates for coordination motives requires that there are no changes in bank fundamentals during the weeks following the surprise announcement on December 8, 2014.

### C.2.1 Liquidity Measures

The bank tracks short-term liquidity through an index, the Liquidity Assets Ratio (LAR), defined as:

$$Liquidity\,Assets\,Ratio\,=\,\frac{Liquid\,Assets\;of\;up\;to\;30\;days\;maturity}{Short\;term\;borrowing} \tag{B1}$$

where *Liquid Assets* include cash, interbank placements with maturity up to 30 days, compulsory reserve requirements to Bank of Greece, unencumbered high quality liquid assets, excess collateral pledged to ECB, inflows from installment loans within 30 days and other assets with maturity up to 30 days; and *Short Term Borrowing* considers interbank deposits with maturity up to one year, time deposits with maturity up to one year, wholesale funding with maturity up to one year, and 80% of saving and current accounts.

The LAR index needs to be higher than 20% for the bank to be considered liquid. We have confirmed with the bank that the ratio was above the minimum threshold during the period for which we perform our coordination risk analysis. At that time, time deposits accounted for more than 15% of the bank's total liquidity.

The bank also monitored another liquidity index, the Maturity Mismatch Ratio (MMR), given by:

$$Maturity\,Mismatch\,Ratio\ =\ \frac{Assets -\ \ Liabilities\ of\ \ up\ to\ 30\ days\ maturity}{Short\ term\ borrowing} \tag{B2}$$

This index needs to be higher than -20%. It was the case that during our coordination risk period the index was significantly above this threshold.

Both indexes deteriorated soon after the January elections, and this trend intensified in early 2015.

### C.2.2 Funding Costs

Despite the deposit outflow after the surprise announcement, the bank did not face any funding problems. The bank was able to borrow from the ECB at similar rates in the weeks following the announcement (but before the election). Moreover, there were no changes on the interest rates on both time and demand deposits during this period. Finally, there was a slight decline on the value of the bank's collateral during this period. However, this fall did not pose a threat to the banks solvency.

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